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AN EFFICIENCY INDICATOR TOOL FOR MANAGING RESOURCE EXPENDITURE IN PUBLIC CENTRAL HOSPITALS

By

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ABSTRACT

Citizens generally assume that government has unlimited resources, but public health care services are always limited and constrained. Public hospitals are generally in dire need of opportunities to allocate resources efficiently in light of limited financial resources whilst in the private sector, affordability guarantees access (Alaba and McIntyre, 2012). Efficient hospital management should include harmonised health care activities and provision, based on application of knowledge and managerial skills, including problem-solving to achieve outcomes using resources in the most economical, efficient and effective way (Usman et al, 2015). This research investigated cause and effect relationships between the hospital efficiency indicators and some dimensions and sub dimensions of hospital performance, mainly costs and volume of health care activities.

Vector-Auto regression (VAR) system of models were applied to efficiency-indicator data for the four public central hospitals in Gauteng provided from District Health Information System (DHIS) over 28 time points which are quarterly intervals over 7 years (from 1st quarter 2008/09 to 4th quarter 2014/15). The rate of increment per quarter for each efficiency indicator was determined to be **R**44.02 for Expenditure per Patient Day Equivalent (ExPDE); 0.17% for Caesarean Section rates (C-Section); 0.31% for Bed Utilisation Rate (BUR) and 0.07 days for Average Length Of Stay (ALOS). The above estimates are generated in a predictive modelling context with smaller standard errors in comparison to those generated by traditional or conventional approaches and are therefore more precise. Linear Mixed Modelling also showed that correlating expenditure to efficiency would require hospital specific interventions due to significant 'hospital specific characteristics or random effect' (intra-class correlation) for each efficiency indicator. It was inferred that, whereas there might be common fixed costs associated with the operation of central hospitals, the cost pressure of providing for services is affected differently at each central hospital.

Inferences of managers' subjective responses on their understanding and utilisation of efficiency-indicator information showed that a manager with a medical background or within patient care is 1.14 times more likely to comprehend efficiency information compared to one with a business or management background. Interaction with efficiency data in current role is 1.10 times more likely for managers in patient care than those in administration / support. After controlling for hospital specific effects, changes are recommended for determination of targets for Caesarean section rates, as well as for the current set of efficiency indicators to be expanded. An Efficiency Indicator Management Tool (EIMT), where predictive modelling capability is a major output of the research study, is presented as a strategic implementational tool to promote evidence-based data decision-making in public hospitals. This research is significant in that it realised how efficiency indicators can be adopted to guide hospital expenditure in a cost-effective way.

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COMMONLY USED ABBREVIATIONS

ALOS: AVERAGE LENGTH OF STAY
BAS: BASIC ACCOUNTING SYSTEM
BOD: BURDEN OF DISEASE
BOR: BED OCCUPANCY RATE
BUR: BED UTILISATION RATE
C-Section: CAESAREAN SECTION
CH: CASUALTY HEADCOUNT
CHBAH: CHRIS HANI BARAGWANATH HOSPITAL
CMAH: CHARLOTTE MAXEKE ACADEMIC HOSPITAL
CPI: CONSUMER PRICE INDEX
CSR: CAESAREAN SECTION RATE
DGMAH: DR GEORGE MUKHARI ACADEMIC HOSPITAL
DHIMS: DISTRICT HEALTH MANAGEMENT INFORMATION SYSTEM
DHS: DISTRICT HEALTH SYSTEM
ER: EMERGENCY ROOM HEADCOUNT
EU: EUROPEAN UNION
ExPDE: EXPENDITURE (COST) PER PATIENT DAY EQUIVALENT
GCA: GRANGER CAUSALITY ANALYSIS
GDoH: GAUTENG DEPARTMENT OF HEALTH
GDP: GROSS DOMESTIC PRODUCT
GLM: GENERAL LINEAR MODEL
GLMM: GENERALISED LINEAR MIXED MODEL
HC: HIGH CARE
HST: HEALTH SYSTEMS TRUST
ICU: INTENSIVE CARE UNIT
IPD: INPATIENT DAYS
IPS: INPATIENT SEPARATIONS
KW: KRUSKAL WALLIS
LMM: LINEAR MIXED MODEL
LTP: LONG TERM PLAN
NDoH: NATIONAL DEPARTMENT OF HEALTH
NGO: NON-GOVERNMENTAL ORGANISATION
NHI: NATIONAL HEALTH INSURANCE
NIDS: NATIONAL INDICATORS DATASET
OLS: ORDINARY LEAST SQUARES
OPD: OUTPATIENT DEPARTMENT (HEADCOUNT)
PAF: PERFORMANCE ACCOUNTABILITY FRAMEWORK
PDE: PATIENT DAY EQUIVALENT
PFMA: PUBLIC FINANCE MANAGEMENT ACT
PHC: PRIMARY HEALTH CARE
PIDS: PROVINCIAL INDICATORS DATASET
SBAH: STEVE BIKO ACADEMIC HOSPITAL
STP: SERVICE TRANSFORMATION PLAN
THC: TOTAL HEADCOUNT
UHC: UNIVERSAL HEALTH CARE
VAR: VECTOR AUTO REGRESSION
WHO: WORLD HEALTH ORGANISATION

DECLARATION

I declare that the thesis titled **"***An efficiency indicator tool for managing resource expenditure in public central hospitals***"** is my own work and that all sources that I have quoted have been indicated and acknowledged by means of complete references.

Signature

Date: 14 November, 2016

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND TO THE STUDY

Section 27(1)(a) of the South African constitution (Act No. 108, 1996) guarantees all the right to access health care as noted also by Harris, Goudge, Ataguba, McIntyre, Nxumalo, Jikwana and Chersich (2011); that requires that a substantial budget be committed towards the (public) health care delivery platform. However, challenges have been experienced in that regard (Mayosi, Lawn, Van Niekerk, Bradshaw, Abdool Karim and Coovadia, 2012). The challenges have ranged from limited resources against an increasing demand of services, to a public hospital system entrenched in a myriad of issues such as rapid population migration growth, a growing need for funding citizens' health care in ageing populations and a burden of disease spiraling out of control. A strict fiscal constraint owing to depressed economic growth and the poor Rand value exchange have resulted in a shrinking tax revenue base. The country's performance against key health indicators has also remained consistently poor in comparison to other countries with similar levels of investment and expenditure in health care (Christian and Crisp, 2012). Evans, Tandon, Murray and Lauer (2000) describe how the performance of countries in maximising population health and resources can be measured; but promoting quality improvement in that regard, has seen focus being directed on collection and reporting of information more for the sake of compliance; scientific evidence on cause and effect in various dimensions of efficiency has remained unattended (Spiegelhalter, Sherlaw-Johnson, Bardsley, Blunt, Wood and Grigg, 2012).

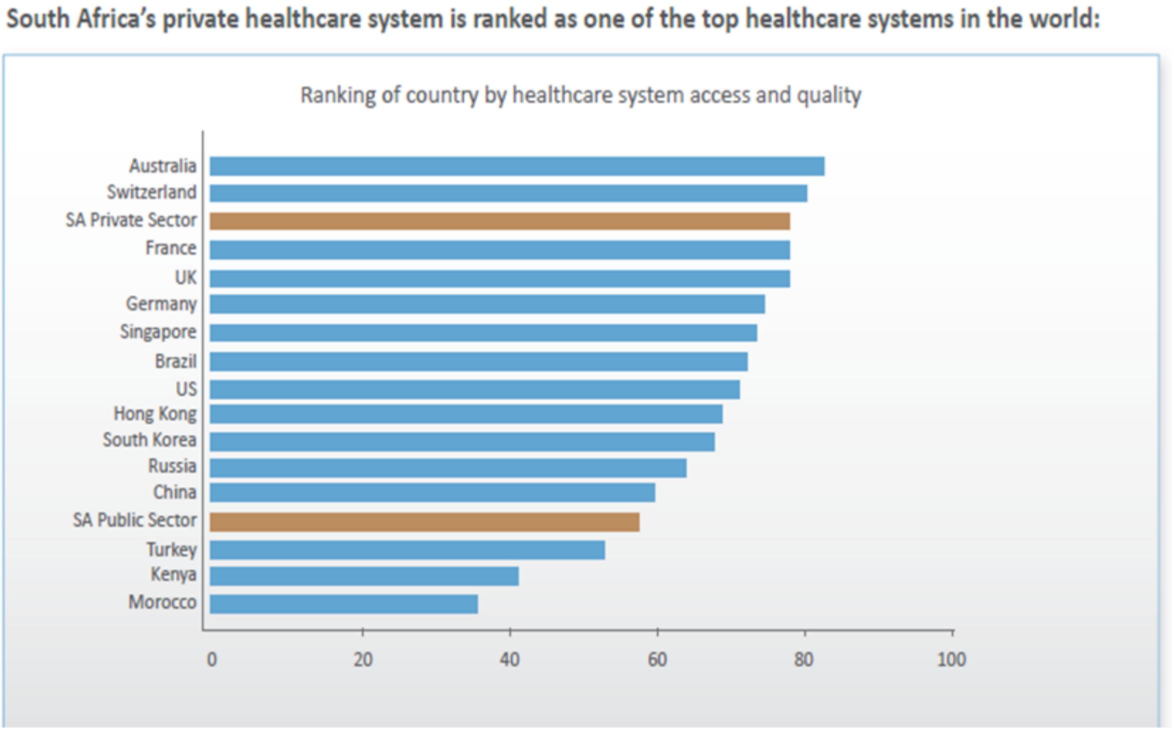
As the demand for health care is often unlimited in a free public health care environment (Serafini, Fantin, Brugiolo, Lamanna, Aprile, and Presotto, 2015); government must therefore allocate resources efficiently, including identifying ways to improve on service delivery performances while curtailing costs according to Christian and Crisp (2012). For that reason public hospitals have for some time now, constantly faced tough choices and decisions when it comes to rationing of available scarce resources (Orgill, 2012). The HIV / AIDS pandemic has greatly increased the pressures on public hospitals in South Africa as the country has the largest Anti-Retroviral Therapy (ART) programme in the world, with about 1·8 million people estimated to be on ART as of April 2011 (Mayosi et al, 2012). Given such numbers of patients, higher acute levels accompanied by more complications and slower recovery rates, there is therefore added strain on limited resources within public health facilities. In a chapter entitled "*Public hospitals in South Africa: stressed institutions, disempowered management*", Von Holdt and Murphy (2007) revealed that public hospitals in South Africa are highly strained. This is not only due to excessive workloads, but also perceived management weaknesses such as increased operational costs as well as poorly managed interventions. The Health System Trust (HST) Report of 2011 also identified limited management capacity as one of the systematic challenges contributing to poor performance within the public sector.

Rispel and Barron (2012), identified major weakness within the South African public health system to include non-alignment of organisational design to health service delivery including sub-optimal management exacerbated by a dearth of human resources, therefore precluding the possibility of improving performance. An article entitled "*South Africa's protracted struggle for equal distribution and equitable access - still not there*", by Van Rensburg (2014), noted that there is unequal distribution of Human Resources for Health (HRH) due to severe public-to-private drainage, exodus to developed countries, rural-urban migration, inappropriate skills mix and poor-wealthy settings (state dependent vs medically insured). Poor working conditions and remuneration have also been identified as among factors documented to push health workers out of the public sector (Hongoro and McPake, 2004). The Von Holdt and Murphy (2007) research also determined that a large component of the stress faced by the public hospitals may be attributed to the changing health environment in which they operate, such as rapid urbanisation evidenced by a dramatic increase in the population as reflected in the Census 2011 migration patterns (Stats, S.A., 2012).

South Africa has one of the highest GINI coefficient in the world, ranging between 0.64 to 0.69 (Van and Moses, 2012), which by implication, does little to reduce differentials in accessing health care. As a result, South Africa's health care system has been characterised as fragmented and inequitable owing to the huge disparity between the private and public health sectors. Private hospital beds have steadily increased in cost due to increased market concentration whereas public hospitals by contrast, have faced budget pressures as the vast majority of the South Africans rely entirely on public health facilities (Plaks and Butler, 2012). The situation is perceived to have given rise to a gap (perceived or actual) between the performance, quality and standard of health care offered in public compared to private sector hospitals, characterised by increasing operational costs against diminishing standards on the part of the former.

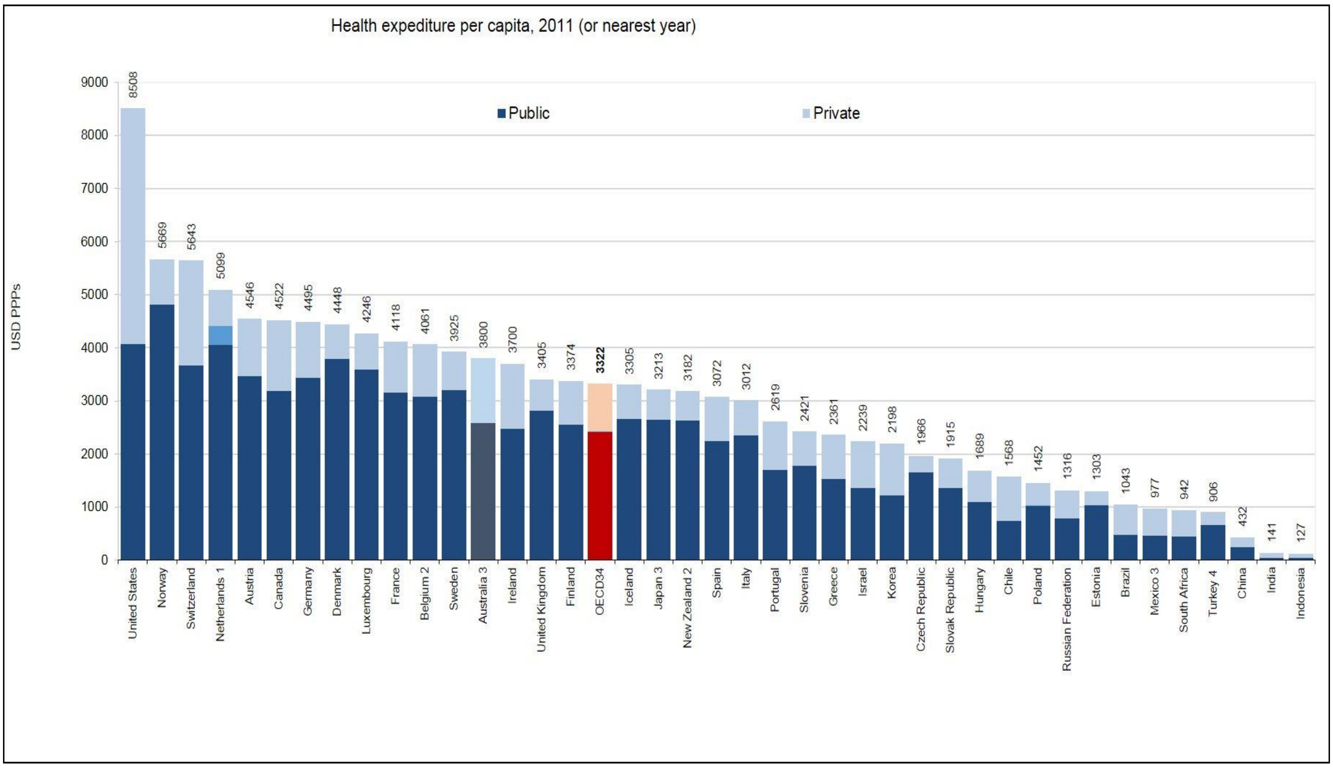
Pillay (2006) noted a huge divide between private and public health sectors especially inequity in the health systems, highlighting the need for strengthening cross-subsidisation between the sectors. Inequities have also been observed between and within provinces, between urban and rural areas as well as between the health care systems at the different levels of care (primary, secondary and tertiary). Those differences have not been scientifically qualified though. The author also noted that National Health Insurance (NHI) would be necessary to reduce such inequities, in particular the disproportionate distribution of resources. According to Murray and Frenk (2000), health care performance is related to the level of health expenditure. Figure 1.1 and Figure 1.2 below shows the disparity between the private and public health care systems in South Africa, as well as the health expenditure differentials between the two, three years later.

Figure 1.1: *Comparison of the performance of the South African public sector health care.*



Source: Pool Stream database, Monitor Group (2008).

Figure 1.2: *Contrast of public vs private health expenditure per capita (SA and OECD counties).*



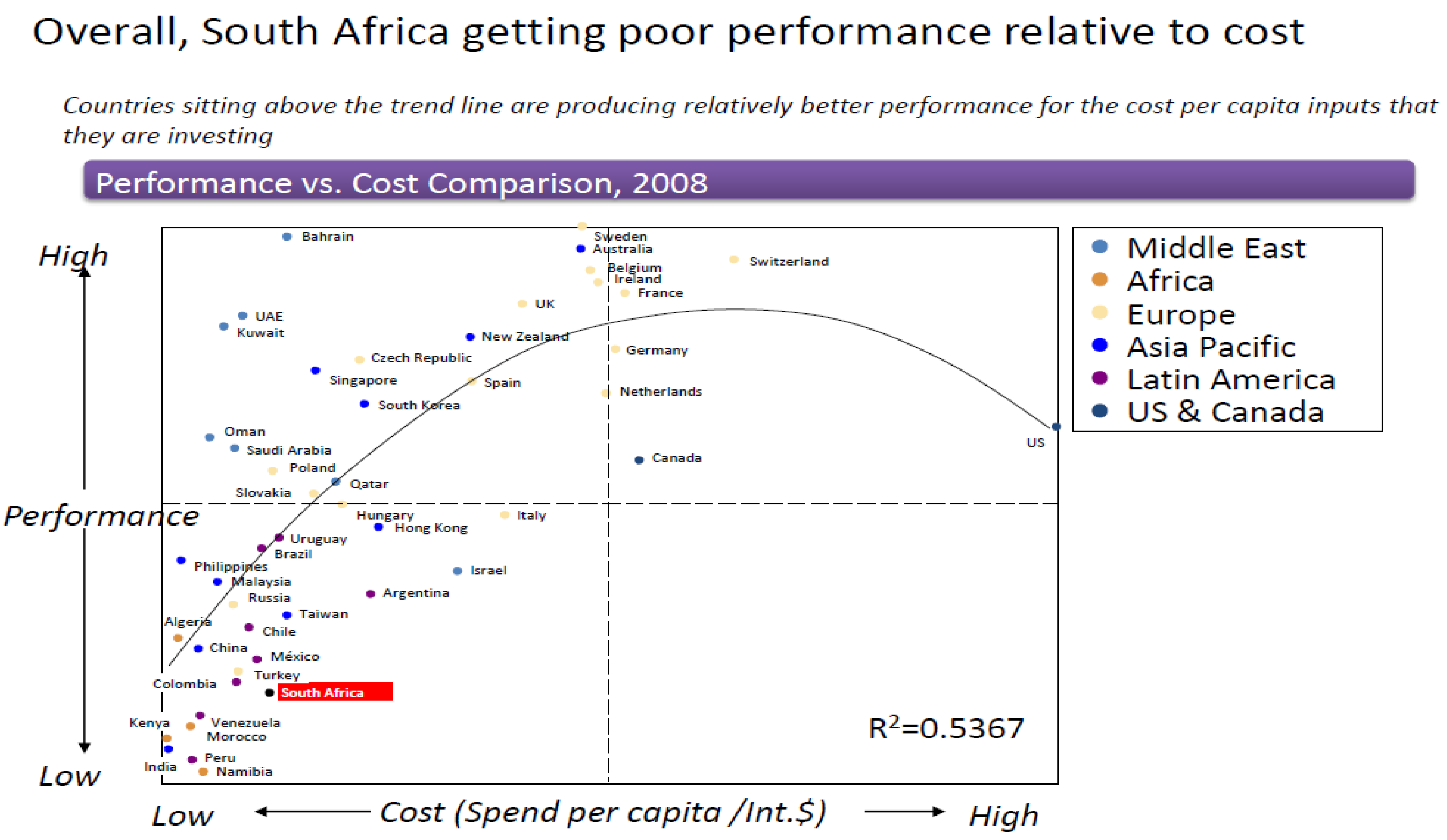
Source: OECD Health Data 2011 (WHO Global Health Expenditure Database).

It is clear from Figure 1.1 that South Africa's private health care system provides better care and is highly rated in the world, with the public sector one lagging behind. Health inequities emerge in that the public sector serves 84% of the population (McIntyre, Govender, Buregyeya, Chitama, Kataika, Kyomugisha and Chitah, 2008) whilst the private serves the remainder. Figure 1.2 shows that in 2011, the total health expenditure per capita (that is, the sum of public and private health expenditures as a ratio of the total population) was U$942 and that even though the spending levels between the two sectors are almost at similar levels. Another observation from Figure 1.2 is that there are countries such as Turkey and China, that have lower health expenditure per capita than South Africa and yet they obtain better performances, a matter later on discussed relative to Figure 1.3. The above trend is not peculiar to South Africa; a similar situation exists between public and private sectors in Australia (Chua, Palangkaraya and Yong, 2011); for that reason, the South African health care system is often characterised as fragmented and inequitable. The effects of the skewed expenditure and ultimately, service level inequalities between public and private health care sectors are widely documented by among others, De Jager and Du Plooy (2011). Knight and Maharaj (2009) had earlier on noted that, caution should be exercised when making comparisons between South Africa and other countries where the gap between the public and private health care is not as wide.

There is a financial burden inherent in the provision of quality health care and so the net effect of the differential apportioning of resources, is that a greater portion of the population is left to receive care of lesser quality due to heavy patient loads at overburdened, understaffed and ill-equipped public health facilities given that for every ten patients, eight depend on public health care facilities sharing an equal amount in health spend as the other two patients in private health care. Improved hospital performance should also be premised on competencies in resource management and efficiency in the use of such resources (Veillard, Champagne, Klazinga, Kazandjian, Arah and Guisset, 2005).

Therefore, service and funding platforms need to be efficiently configured to optimise available public resources including exploring opportunities to redirect revenue from private to public services to drive efficiencies in the latter. In the absence of any intervention, stark differences between public and private hospital services will inevitably be perpetuated for the foreseeable future. It must however be noted that increases in cost-of-care are not always accompanied by an increase in quality and so the highest quality of care is not necessarily the most expensive. As shown in Figure 1.3 below, countries such as Turkey and China have better health performances and health indicators despite spending less on health expenditure (on cost per capita input basis) than South Africa. The indicators adopted by some of the top performing countries are highlighted and contrasted later on in Table 2.1 in the literature review.

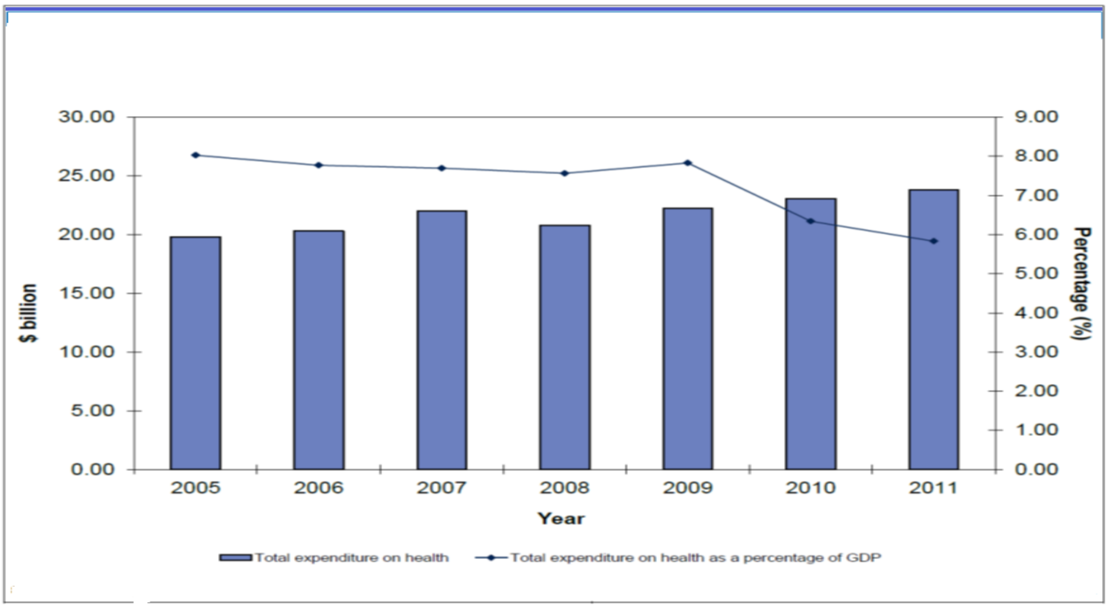
Figure 1.3: *South Africa is getting poor performance relative to cost.*



Source: Discovery Health Pool Stream Database, Monitor Analysis (2011)

Figure 1.3 above also implies that most critical health indicators in South Africa can be expected to be worse than those of comparable middle-low income countries that spend much less than South Africa on health care, as inferred upon by Christian and Crisp (2012). On average South Africa spends between 8.5% and 8.7% of the Gross Domestic Product (GDP) (Naidoo, Singh and Lalloo, 2013) on health care; a figure that is above the 5% recommended by World Health Organisation (WHO). Figure 1.4 below shows the total health expenditure from 2005 to 2011 as well as the total expenditure as a function of GDP.

Figure 1.4: *South Africa's total health expenditure (2005 - 2011).*



Source: Country Statistics, Market Line (2013)

The voted budget increases slightly between 2005 – 2011, but in real terms, it was getting lesser and lesser in value due to poorer GDP growth as evidenced by the dotted line. Pillay (2006) noted that although there had been an overall increase in spending in the health sector, the increments had not translated to improvements in health care services. The poor performance has been attributed mainly to the inequities between the public and private sector as well as to poverty given that 26.3% of the population lived below the poverty line of **R**305 per person per month during 2008/9 according to the South Africa Country Profile (2013). Increased cross-border migration further compounded the situation by stretching the limited resources ultimately placing increased dependency on the state for health care services. The above and factors highlighted earlier on, threaten to push public health care financing to excess cost growth, that is, the extent to which the increase in health care spending exceeds the growth in the economy. In fact, despite spending a significant proportion of GDP on health care, South Africa is among only 12 countries in the world where the under-5 years' old mortality rate has increased in the last two decades (Coovadia, Jewkes, Barron, Sanders and McIntyre, 2009).

Public health care expenditure in South Africa is funded through a portion of general taxes with expenditure on services consisting primarily of provincial health expenditure that is sourced through the provincial equitable share, conditional grants and other sources from the province's own revenue. National Tertiary Services Grant (NTSG) as per Division of Revenue Act (DORA) of 2014 compensates tertiary facilities for additional costs associated with improved access and equity in addressing the burden of disease by providing for designated central and national modernised and transformed tertiary services. Allocations to provinces are based on a formula that includes indicators of need for health and other services under the purview of the provinces. Nevertheless, the DORA framework places emphasis on an efficient health management information system for improved decision-making.

Therefore, improving on efficiency measurement in order to raise health indices implies that strategic, tactical and operational health managers must plan effectively, direct activities and use resources effectively and efficiently, which is a highly technical process that requires reliable information. At the heart of the difficulty of planning using efficiency information is the attribution problem and subsequently an inability to articulate the appropriate control measures in mitigation. A study by Pillay (2008) entitled "*The skills gap in hospital management in the South African public health sector*" noted a lack of management capacity within the public sector in South Africa. That, together with the existence of a significant gap between private and public sectors, attests to a need for further training of managers in understanding indicators as this has implications for the management of public resources.

Public health care performance measures show how well a country achieves health care goals relative to the maximum it could be expected to achieve, given its level of resources and non-health system determinants. According to Ioan, Nestian and Tita (2012), public health care services is the extent to which set objectives are achieved in the provision of specific packages of health services to solve a need on the part of the patient (efficacy) in the best possible way (quality) and in the most economical manner (efficiency) within a given budget. Davis, Milne, Parker, Hider, Lay-Yee, Cumming and Graham (2013), distinguish between efficiency and effectiveness and define effectiveness as doing the right things and efficiency as doing things right. Whichever way, resource utilisation must be adequately planned for so that resource allocation is done systematically. According to Nixon and Ulmann (2006), evidence for a causal link between expenditure and health outcomes remains elusive, frustrating attempts to measure the overall effectiveness and efficiency of health care management. Among the main hurdles in conceptualising solutions is a lack of appropriate knowledge, as not much is known about linkages or relationships between efficiency indicators and hospital operational activities. Adindu (2013) pointed out that health care managers must be equipped with specialist training in health management to acquire knowledge and skills needed for effective and efficient management of complex health care organisations.

Improving hospital operations also implies improving on health indices management, which in turn requires capacity to plan for and use resources effectively and efficiently, a highly technical process that requires reliable information. Given that the major proportion of the public health services expenditure is invested in national (central) hospital level care; the need for control measures at that level has also been a growing field in the last decade, including the need for evidence-based decision-making, quantifiable improvement and information. All these are elements useful for benchmarking, which should translate to needs-based budgeting and reduction of disparities in health care usage (Simou, Pliatsika, Koutsogeorgou and Roumeliotou, 2014).

The World Health Organisation (WHO) Report of 2010 acknowledges that whilst significant action to enhance equity can be taken; the roots of health inequalities lie in the social conditions outside the health system's direct control. This generally places hospitals in a position where they must constantly adapt to various dynamics in order to fulfil their obligations in ever-changing contexts such as policy shifts, or trends in demand and supply of health services including disease patterns. An ever-increasing demand for services in the public health care system implies a growing need for rational and efficient distribution of health care resources and improvement of the general health of the population. Adindu (2013) argues that health management involves technical and social processes for achieving health objectives through effective and efficient use of health resources in view of social, economic, political and cultural realities. There is therefore a continuous need to provide reliable and updated information on performance of available services for quality improvement of public hospitals; after all, one of the main roles of any government is to allocate scarce resources efficiently without impairing its fiscal solvency (Christian and Crisp 2012).

By using health expenditure as a hospital health care system's input to the production of health outcomes and efficiency; the interpretation of efficiency differs slightly to the interpretation of efficiency from several of the current production function studies. In such studies, efficiency mainly relates to technical efficiency or whether the observed combination of inputs produces the maximum possible output (Bem, Ucieklak-Jez and Predkiewicz, 2014). Efficiency in the context of this research combines both technical and allocative efficiency in relation to the choices made about the mix of interventions purchased with the available health expenditures. Therefore, hospital efficiency indicators are proxies for a broad range of interventions from responsiveness, fair-financing and financial management, health inequality to organisational or hospital management issues related to the delivery of health care services. Responsiveness in this context also refers to improving dimensions of the interactions of the populace with the health system. As with health outcomes, both the level of responsiveness and its distribution are important elements of the public health care service delivery.

1.1.1 PUBLIC HOSPITAL SERVICES PROVISION

The role of the National Department of Health (NDoH) in South Africa is to develop policy and channel funding to the provincial departments, who in turn manage public health care facilities (Von Holdt and Murphy, 2007). The National Health Act 61 of 2003 guides the range of health services to be provided at the relevant public health establishment. In order to enhance efficiency whilst expanding access to public health care services, there exists a hierarchy of hospital service delivery through an appropriate referral system, underpinned by district hospital services (being the most accessible to the surrounding communities) provides for the basis upon which hospital care is established. Regional, tertiary and national central hospitals provide the specialist, super-specialist and highly specialised care respectively. As noted by Burger, Bredenkamp, Grobler and Van (2012), access to public health care has since widened and improvements in the health service system and promotion of health care utilisation are well documented and applauded internationally (Datamonitor, 2010). As per the Government Gazette 35101 of 2nd March 2012 number **R**.185, public hospitals in South Africa are categorised as follows:

District Hospitals: These hospitals receive referral from community health centres and clinics as well as provide generalist Level 1 (L1) care. L1 care is delivered by general practitioners, medical officers or primary health care nurses, in the absence of a specialist other than a family medicine specialist. A district hospital consists of between 30 and 400 beds, facilities with fewer than 30 beds will normally be classified as Clinics or Community Health Centres (CHCs).

Regional Hospitals: These hospitals receive referrals from district hospitals and provide specialist support to the district hospitals as well. The hospitals provide Level 2 (L2) care, which is services requiring the expertise of general specialist-led teams that includes general surgery, orthopaedics, general medicine, paediatrics, obstetrics and gynaecology, radiology and anaesthetics.

Tertiary Hospitals: Tertiary hospitals receive referrals from regional hospitals and provide sub-specialist support to such hospitals. Tertiary hospitals provide Level 3 (L3) care, that is services requiring the expertise of clinicians working as sub-specialists or in rarer specialities such as in surgery, urology, neurosurgery, plastic-surgery and cardio-thoracic surgery.

Specialised Hospitals: Provide care only to certain specialised groups of patients, suffering from diseases such as acute and chronic psychiatric / mental health, tuberculosis (TB) as well as specialised spinal injury and acute infectious diseases.

National Central Hospitals:

National Central hospitals offer tertiary care but are superior to tertiary hospitals in that they consist of very highly specialised referral units that together provide an environment for multi-speciality clinical services, innovation and research and are also not geographically constrained, hence the notion 'national'. As a result, tertiary services provided at central hospitals should in theory, be high cost and low volume (Nathan and Rautenbachet, 2014) and requiring high technology and / or multi-disciplinary teams of people with scarce skills to provide sustained care of high quality. Central hospitals also act as academic flagships. Kuwabara, Matsuda, Fushimi, Ishikawa, Horiguchi, Hayashida and Fujimori (2011), noted that there was greater use of resources in academic hospitals due to expenditure on trainee education, which requires more time and resources compared to other types of hospitals. Therefore central hospitals are generally at the epicentre of health care evaluation being the most sophisticated in any country, and requiring disproportionately large amounts of resources as well as a well-functioning supportive hospital referral system. As of 2014, there were eight national central hospitals in South Africa, four in Gauteng, two in Western Cape, and one each in Free State and KwaZulu Natal. The four in Gauteng not only represent 50%, but are also the more advanced and busier ones.

Figure 1.5: *The hierarchy of hospital service provision.*

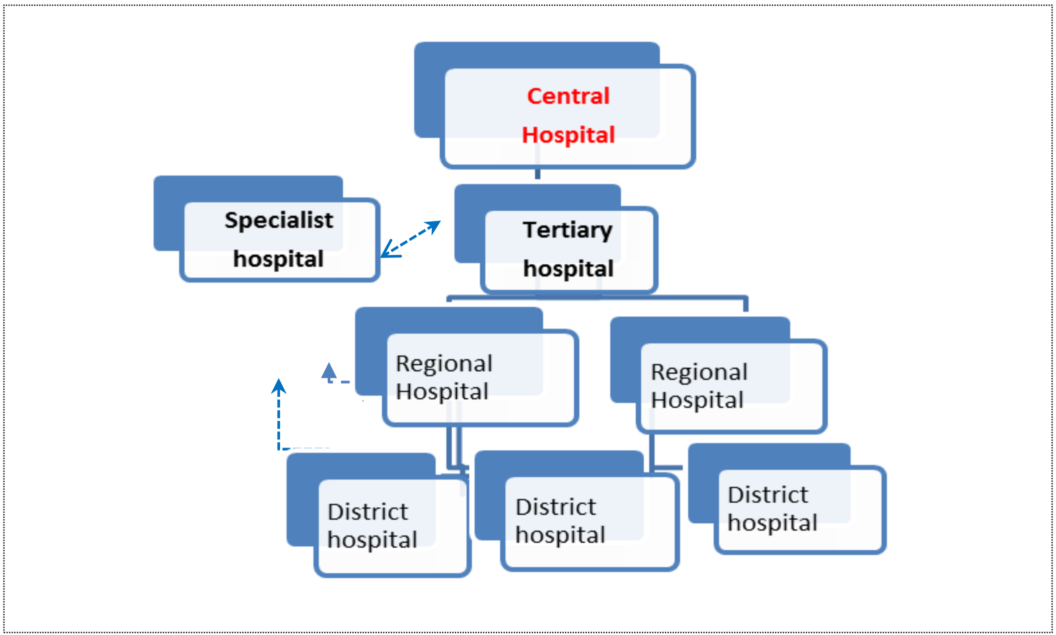


Figure 1.5 above shows the hierarchy of hospital service provision. The expectation is that patients enter the system of care at lower levels and are referred upwards to the appropriate level of care where necessary. In practice, both the weaknesses of the referral system and the lack of comprehensive hospital coverage mean that higher level hospitals end up accommodating patients that ought to be treated in hospitals at lower levels and this distorts the cost structure of service provision at that level as lower level services are rendered at a higher scale of costs.

Gauteng:

Gauteng has interesting geographical dynamics being the only province in South Africa with three metropolitan (metros) cities; City of Johannesburg, City of Tshwane and Ekurhuleni, which are in the central, northern and eastern parts of Gauteng. There is considerable demand and utilisation of public health care services within and across the metros' borders as well as on the outskirts where informal settlements tend to be more concentrated. In 2014, the public health care system in the province provided health services to 9,626,600 uninsured people who made up 75.8% of the 12.7 million residents based on Statistics South Africa's 2014 estimates; through a network of 377 fixed clinics and community health centres (CHCs), 10 district hospitals, 10 regional hospitals, three tertiary hospitals and four national central hospitals. The four are Dr George Mukhari with 1652 approved beds, Steve Biko Academic (832 beds), Chris Hani Baragwanath (2888 beds) and Charlotte Maxeke (1018 beds). In addition, there were 146 licensed private facilities, including 85 private hospitals, 22 sub-acute facilities and 40 unattached operating theatres in the same year.

When comparing hospital efficiency as defined earlier on; as much as possible this should apply to hospitals within the same category so that interpretation of the results can be contextualised by considering factors which include the package of services rendered, the supporting infrastructure around the hospital, differences in the geographical service area, transportation routes and level of affluence in the population as well as the hospital referral system (Nathan and Rautenbachet, 2014) and to some extent policy. It is also critical that packages of service to be delivered at each level of care are adhered to, to allow for assessment of allocative efficiency (Alaba and McIntyre, 2012). In developing packages of services, there are a number of questions considered:

- Is the service effective (needed) at that hospital level?
- Is the service cost effective at that hospital level?
- Is there a skills mix to provide better service than in other levels of care?

In line with the above, efficiency inferences across hospitals would be biased if the service package were to be ignored as for example, for similar conditions, severity would be more intense at the higher (central) than at the lower (regional) level and requiring more resources to address the condition. In addition, to avoid patient-overlap (that is patients who are referred to the next level of care hospital), the study focused on the very last level of care. Another matter is that different provinces have different policies such as in referral policy, discharge, management organogram, budget allocation strategies and so on. Variations in all those confound the efficiency design (Spiegelhalter et al, 2012) due to inter-province heterogeneity. The four central hospitals in Gauteng, which constitute half of the total number of central hospitals in the country, and being the more complex ones, are therefore the observational units of analysis in this study.

1.1.2. INDICATORS AND THEORY OF CHANGE

In order for one to understand the performance of health systems, Murray and Frenk (2000) prescribe that one should understand the factors that potentially explain the system. Veillard and colleagues (2005) defined an indicator as '*a measurable element that provides information about a complex phenomenon which is not easily captured*'. The authors group indicators into two (i) a '*core*' basket gathering a limited number of indicators relevant, responsive and valid in most contexts and premised on sound scientific evidence for which data is available (ii) a '*tailored*' basket gathering indicators suggested only in specific contexts because of varying availability of data, varying applicability or varying contextual validity (cultural, financial, organisational settings). Hospital indicators can be summarised into the following common sub-categories, which are all dimensions of performance:

- Input indicators measure the amount of physical resources consumed during the generation of the (health) outcome.
- Output indicators denote the quantity of results of the process activities.
- Outcome indicators measure the quality of the end result.

According to the United Nations, indicators can be classified as follows (Vuk, 2012):

- **Performance indicator:** Refer to a particular characteristic or dimension used to measure intended changes defined by a programme results framework. Performance indicators are used to observe progress and measure actual, rather than expected, outputs and outcomes. They indicate 'how, 'whether' or 'to what extent' a unit is progressing towards its objectives, rather than 'why' or 'why not' such progress is being made. A key theme to be demonstrated later on from the literature review is that performance indicators are not an end in themselves, but rather are subject to a range of diverse purposes.
- **Impact indicator:** A variable or set of variables used to measure the overall long-term impact of an intervention. Impact indicators often use a composite set (or group) of indicators, each of which provides information on the size, sustainability and consequences of a change brought about by an intervention.
- **Proxy indicators:** Cost, complexity and / or the timeliness of data collection may prevent a result from being measured directly. In such instances, proxy indicators, which are variables that substitute for those difficult to measure directly, may reveal performance trends and make managers aware of potential problems or areas of success. This is often the case for health outcomes including health performances.
- **Operational indicators:** These focus on factors related to hospital operations and are more likely under the direct control of management, and constitute the practical application component for hospital managers.

The usefulness of indicators depends on the configuration of variables, including purpose, context and culture in which they are applied and how the results are used in relation to other postulated relationships. Equally, a hospital can be thought of as a production unit that transforms labour and capital inputs into inpatient and outpatient services, with input prices and levels of health outcomes used to explain the total operating cost of the hospital unit (Vitikainen, Linna and Street, 2010). Efficiency indicators in that context, provide information as to whether right priorities are being met effectively and efficiently or not. Generally, most indicator operational frameworks use process indicators, as these are easier and more feasible to measure and because of the disadvantages of outcome indicators taking too long to manifest, especially in the field of health outcomes (Simou et al, 2014; Ludwig, Merode and Groot, 2010).

Indicator measurement provides a means to define what hospitals actually do, and to compare that with set targets in order to identify opportunities for improvement. Without reliable indicators to measure health care service quality and performances, accountability for policy choices or tracking of scientific evidence becomes difficult if not impossible to establish. Research by Adindu (2013) showed that health management involves technical and social processes for achieving health objectives through effective and efficient use of health resources in view of social, economic, political and cultural realities. Ioan et al (2012) noted that certain conditions must be observed when selecting indicators for hospital efficiency performance assessment; the selection of indicators must:

a. Allow for the creation and implementation of actual and efficient system/s of control and measurement of the indicators.
b. Allow for useful interpretations (and analyses) of medical or administrative decisions that affect the functioning of the system of activities in the hospital.
c. Align and adapt operational activities to the main strategic objectives, as well as introduction of improvements in the system of care, including informing plausibility to new strategic imperatives.

An efficiency indicator framework can be central in addressing equity, fairness, affordability, appropriateness and effectiveness in the delivery of health care services (Mayosi et al, 2012). Even though literature suggests that efficiency indicators are a proxy for management accountability and therefore, better suited to give aggregate levels of performance if well understood; it is apparent as shall be presented later on, that the impact of efficiency indicators on various performance domains has mostly been viewed from correlational or association point of view and seldom on causality (cause and effect). The major problem, is not the absence of indicators but rather that of attribution, that is whether the indicators are measuring what they purport to be measuring.

Isolating the impact of health care outcomes is difficult and furthermore, isolating this to one particular delivery platform even more cumbersome (Adair, Simpson, Casebeer, Birdsell, Hayden and Lewis, 2006). The challenge is to identify the causal effect or the ‘why’, ‘what’ and ‘how’ of an indicator framework that is capable of successfully bringing about the desired change or intervention. Understanding how change happens and the potential for influencing change requires a comprehensive description and illustration of how and why a desired change is expected to happen in a particular context. Theory of Change (TOC) articulates the assumptions about the process through which change will occur and specifies the ways in which all of the required early and intermediate outcomes related to achieving the desired long-term change will be brought about and documented as they occur and is further demonstrated on page 26. TOC uses backwards mapping requiring researchers to think in backwards steps from the long-term goal to the changes that would be required to cause the desired change.

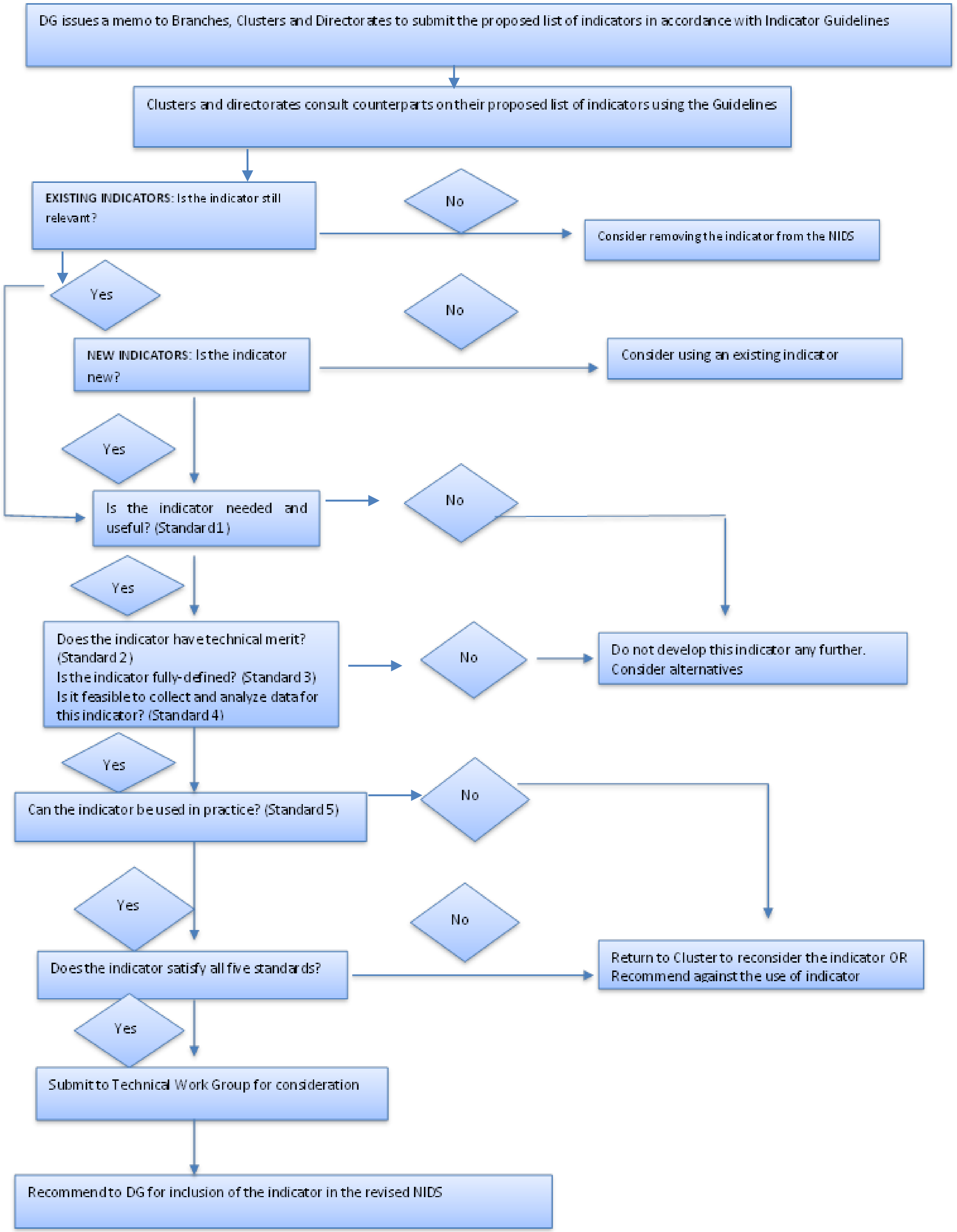
1.1.3. INDICATOR DEVELOPMENT IN DEPARTMENTS OF HEALTH

The development of indicator measurements assists in understanding the performances and impact of various programmes, interventions and policies in general. The World Health Organisation (WHO) bulletin of August 2003 entitled "*How can hospital performance be measured and monitored*?" (Shaw, 2003) recommended that:

- Indicators require reliable methods of measurement against validated standards.
- The reliability of indicators is determined primarily by the accuracy, completeness and timeliness of data collected.
- Valid comparisons of performance between institutions demand rigorous standardisation of assessment criteria and methods.
- Performance failures are more often a result of failures in systems and processes rather than of individual competence or knowledge.

In South Africa, the District Health Information System (DHIS) was adopted nationally as the health information system used to pool information and efficiency data from various sources used in the public health sector to track health service delivery. There are over 500 variables collected monthly but often examined quarterly. DHIS was adopted as the routine health information system for South Africa in 1999. The policy that governs DHIS is called the District Health Management Information System (DHMIS) policy of 2011. Figure 1.6 below shows the indicator development process flowchart followed in generating new indicators or reviewing existing ones as enshrined by the District Health Management Information System (DHMIS) policy.

Figure 1.6: *Sketch of the indicator development flowchart as prescribed by the DHMIS policy.*



The DHMIS policy looks at the following when developing or reviewing indicators:

- **That the indicator is needed and useful:** Is there evidence that this indicator is needed and if so, at what level? How would information from this indicator be used?
- **That the indicator has technical merit:** Does the indicator have the ability to pick up changes in the source of measurement such as the activity in a hospital?
- **That the indicator is fully defined:** Is the method of measurement for the indicator clearly defined, including the data elements and the calculation where applicable?
- **That the indicator is feasible:** What are and how well are the tools and mechanisms required to collect, interpret and use data for the functionality of this indicator?
- **That the indicator can be used in practice:** In what area of performance does, the indicator review, for instance is it management, clinical or overall performance?

That DHIMS policy dictates that the National Department of Health (NDoH) is responsible for determining the National Indicator Data Set (NIDS) which stipulate indicator variables that must be captured in DHIS as a national imperative. Each provincial Department of Health is expected to add more indicators to be captured on DHIS for their Provincial Indicator Data Set (PIDS). NIDS indicators must measure specific performances in areas essential to effective health care delivery and necessitating national response, whilst PIDS indicators must measure key performance results in provincial operations, programmes, and strategies. The DHMIS policy also stipulates that the Director General (DG) or Head of Department (HoD) shall have the overall responsibility for improving resources management through such information, as part of enhancing the monitoring of health sector performance. The DHIS is therefore an integrated, comprehensive national health information strategy for the country, with tools in the form of six Health Information System (HIS) components: resources, indicators, data sources, information products, data management, dissemination and utilisation framework. The HIS components are expected to realise indicators that guide a number of interventions; such as in assessing quality of care, generating evidence for policy making and evaluation, determining how the orthogonal use of resources can be optimised or even for accounting for expenditure in a cost effective and guided manner.

There are four "*management or efficiency indicators*" within DHIS which are meant to guide operational efficiency in hospital management. These indicators are postulated to be proxies for management accountability at aggregate levels of hospital performances, unlike clinical indicators that are used at individual patient level or ward level to assess quality of care. It is generally expected that information as to whether right priorities are being met effectively and efficiently or not, could also be inferred from the efficiency indicators. It must also be noted that hospital efficiency indicators are not optional but rather prescribed as a matter of national policy, hospitals are expected to report on them on a quarterly basis.

Indicators are not absolute, as they cannot exist in isolation (Veillard, Guisset and Garcia-Barbero, 2003). That means indicators alone cannot give the full perspective but are crucial components and often the first in flagging situations requiring intervention. Currently, there is no scientific basis and knowledge guiding targets or thresholds for existing hospital efficiency indicators. At times, hospitals derive targets of their own, a situation unsuitable for comparative analytics. One common approach in setting targets is to adopt some local or national average as a target for a given period. This is an indication of poor understanding of indicators, which is cited for limited use for efficiency information (Dlamini, Garrib, Govender, Herbst, Mckenzie, Rohde and Stoops, 2008). This research emanates from a request from national level, to investigate and generate evidence around the efficacy and use of efficiency indicators as none is known of and documented in the "management accountability" context; especially in the South African environment. According to Christian and Crisp (2012), inefficiency in the South African public health sector contributes significantly to the country's relatively poor health outcomes, because efficiency information is poorly understood and often overshadowed by health care financing and payment issues.

1.1.4. SIGNFICANCE OF AREA

As earlier on indicated, a major problem even in the body of literature, is not the absence of indicators but rather that of attribution to performance; that is whether the indicators are measuring what they purport to be measuring. When the value of scientific soundness in indicator measurement is lacking, there is an inclination towards turning very good indicators into targets by focusing only on the final state of the indicator, bypassing the theory of change in pursuit of only the end outcome. The cause - effect mechanism (that is, how it happened or could have better happened) gets side-lined and the efficacy of intervention strategies becomes suspect. This research is therefore significant in that it seeks to contribute towards closing the gap identified by Mihut (2013), that is to ensure that administrative indicators (as are hospital efficiency indicators) allow for the identification of ineffective administrative activities over which hospital management could pay more attention with a view to take measures to improve and streamline them. For that to happen however, the knowledge gap identified in theory to address limitations in hospital efficiency indicators would need to be addressed, that is, do the indicators measure what they purport to be measuring? What is the rate of change in what they measure and how should hospital managers infer from efficiency information? The latter question is important because differences in the design, content and management of health systems in literature translate into differences in a range of health outcomes (Murray and Frenk, 2000). Hibbert, Hannaford, Long, Plumb and Braithwaite (2013) however noted a lack of consensus on the number of indicators that are necessary for monitoring administrative activities in a health care environments.

1.1.5. PURPOSE OF THE STUDY

The absence of alignment between available public health care resources and strategies necessary to ensure effective use of such (financial) resources as a management attribute (Simou et al, 2014) has led to a myriad of health performance challenges. Hussey, De Vries, Romley, Wang, Chen, Shekelle and Mcglynn (2009), noted the absence of clear strategies that use indicators in that regard. The purpose of this study is to bridge that gap by developing a tool that builds on the work done by Ioan et al (2012), on the relevance of key performance indicators in a hospital performance management context, where the dimension of performance is hospital expenditure. Maximiszing the use of existing resources and accounting for expenditure in a cost-effective manner should be a deliberate process, yet poor understanding of hospital indicators often leads to a culture of very little regard for using indicator-information for decision- making (Dlamini et al, 2008).

According to Mihut (2013), to improve public hospital management, it is recommended that expenditure is not only defined medically (by expenditure or cost per patient per hospital day); but rather also in terms of cost of maintenance, operating and all other associated costs. This brings in a new perspective of total health expenditure different from the conventional approach; were any cost incurred in the provision of health care services should be factored in the expenditure calculation per unit time. Such costs include salaries, all fixed and variable costs incurred as the inputs for calculations necessary to reach the conclusion and build the model. Such a data element exists and is called “expenditure per patient day equivalent” or “cost per patient day equivalent” and is further defined in the variables’ section. Adindu (2013) asserts that defining health care management is open to different interpretations and argues that changes in thinking, perspectives, context and time influence the definition; yet the underlying principles are all consistently about the effective and efficient use of organisational resources to meet the health needs of people.

1.2 FOUNDATION

A 2008 evaluation of the use of DHIS information in KwaZulu Natal established that health care workers and managers were not utilising DHIS data; rather a culture of reporting than using the information for decision making was predominant (Dlamini et al, 2008). The research cited a lack of understanding of the theory of indicators as the main reason and further warned that such a situation compromised measurement, reporting and interpretation including correlating hospital activities to outcomes and strategies. According to Pillay (2008), all managers, perform four generic tasks: planning, organising, leading and controlling. Organising entails arranging and coordinating human, material and information resources aimed at achieving desired goals. Controlling involves measuring performance and monitoring progress relative to set objectives. Yet, in most public hospitals, the planning process involves nothing more than some simple deterministic spreadsheet calculations and as shown by Young, Brailsford, Con Connell, Davies, Harper and Klein (2004); such an approach typically does not provide the appropriate information necessary for strategic decision making in a complex health care delivery platform.

The term efficiency as widely used in economics, refers to the best use of resources in production and in conceptual terms of a product. A productive process is said to be efficient when it realises the best possible use of the resources. Ensuring effective management systems and quality improvement strategies is crucial for improving hospitals' performance. It is acknowledged that among the major challenges facing the public health care system, is the lack of strong linkages between resource shifts and outcomes in an efficient, effective and sustainable manner (Van and Moses, 2012) in order to enhance hospitals' operational performance.

Generally, efficiency indicators ought to operate in a system-like manner and should be complimentary, not conflicting as they provide for more than a single perspective of the same system. If hospitals neglect to improve on efficiency interventions, resources will be wasted, costs will skyrocket and standards of both management and hospital performance will decline. Already most critical health indicators in South Africa are worse than those of comparable middle-low income countries that spend much less on health care (Christian and Crisp, 2012) as depicted in Figure 1.3. Economic efficiency is a proxy for resource and performance management and is typically assessed in terms of allocative and technical efficiency. Technical efficiency refers to production of maximum amount of output from a given amount of inputs or alternatively, producing a given output with minimum quantities of inputs (Bem, Ucieklak-Jez and Predkiewicz, 2014). Allocative efficiency occurs when the combination of inputs minimises the cost given input prices. Accurate data in health care utilisation is necessary so that planning and execution of operational activities can be reconfigured to attain allocative efficiency (Alaba and McIntyre, 2012).

The four (management) efficiency indicators as outlined on page 16 are Average Length of Stay (ALOS), Bed Utilisation Rate (BUR) also known as Bed Occupancy Rate (BOR), Expenditure Patient Day Equivalent (ExPDE) and Caesarean Section (C-section) rates. The four efficiency indicators mostly track the flow of patients and accompanying expenditure through the system of care to get an overall measure on operations as proxies for health care performance. ALOS, ExPDE and BUR are generally regarded as proxies for hospital efficiency in that they measure how cost-effective hospital operations are (OECD, 2010). That is, they seek to ascertain if there is value for money in the provision of health care services. C-sections are associated more with the effectiveness of the hospital in dealing with obstetric complications in the population (OECD, 2011b).

Whilst a more rigorous mathematical examination and formulae of the four indicators will follow in subsequent sections; ALOS refers to the average number of days that patients spend in hospital. It is measured by dividing the total number of in-patient hospital days counted from the date of admission to the date of discharge by the total number of discharges (including deaths) in the hospital during a given quarter. The number of hospital beds provides a measure of resources available for delivering services to inpatients in hospitals; so BUR or BOR measures the average proportion of usable beds occupied. It is calculated by dividing the number of inpatient days plus half of the day patients by the usable bed days (number of actual usable beds multiplied by the number of days in the quarter). NIDS (2013) defines a Caesarean section, as "*the removal of the foetus, placenta and membranes by means of an incision through the abdominal and uterine walls*". In South Africa, it is expressed as a ratio of the total deliveries that took place in that facility per unit time (quarter) and is further divided into two:

- C-section in labour (also known as an emergency C-section).
- C-section, no labour (also known as an elective C-section).

Expenditure per Patient Day Equivalent (ExPDE) is calculated by dividing the total hospital expenditure by the Patient Day Equivalent (PDE). The latter is the equivalent number of 24-hour patients attended to by a hospital. If for instance, eight patients were each treated in the hospital for three hours per patient, then all eight patients would constitute a single PDE. This therefore allows for Day patients to be factored into the PDE and ultimately ExPDE calculation. Patients hospitalised overnight or in care (Inpatients), who occupy a bed when the midnight census is conducted are regarded as single PDE's. Therefore, ExPDE is the ratio of the total hospital expenditure to the PDE for the same period (that is quarter) and measure the average Rand cost per patient day. As indicated earlier on, the numerator (total hospital expenditure) includes all costs fixed and variable, salaries, consumables, costs emanating from litigation and so on. Table 1.1 below shows the numerator, denominator and a few selected factors postulated to impact on the four efficiency indicators as listed within DHIS as part of the NIDS dataset.

Table 1.1: *The 4 "efficiency" or management indicators.*

Indicator Name	Numerator	Denominator	Factors listed within DHIS possibly affecting the Indicator
Expenditure per PDE	Total hospital Expenditure	Patient day equivalent	Economic factors: Inflation, VAT, CPIX, Cost of fuel and so on. Data Elements: Emergency Headcount, OPD Headcount, Day Patient total, inpatient days total
Average length of stay	Inpatient days + 1/2 Day patients	Inpatient separations	• Emergency Headcount (we expect a certain proportion of emergency cases to be admitted in Hospitals). • Inpatient beds total (Or useable beds) - (if beds are available, then patient can be admitted) • Discharge – Depends on availability of transport
Inpatient bed utilisation rate	Inpatient days + 1/2 Day patients	Inpatient beds - total	Turnaround times for fixing broken beds, capturing of useable beds on the system.
Caesarean section rate	Delivery by Caesarean section	Delivery in facility total	• This indicator could be affected by patient medical condition • Size of patient (especially around abdomen) usually gynae recommends caesarean for petite patients. • Availability of theatre • Availability of personnel : gynae, Paediatrician, Midwife, Anaesthetists • ANC 1st visit before 2 weeks and follow up visit • Early booking and proper counselling during ANC visit could prevent some C-sections. • EMS response times for Obstetric patient

The ExPDE therefore by definition, provides a quasi-indication of efficiency (technical, allocative and cost) as it measures and compares the inputs (total financial resources available to the hospital as measured by reported expenditure) in relation to the outputs (volume and type of patients seen as measured by PDE).

As such, the ExPDE indicator is a composite process indicator, in that it links financial data with service-related data from hospital admissions and outpatients and as shall be explained later on; the above scenario precludes the focus of this research from being one in financial modelling. Financial modelling is mainly synonymous with cash flow projections, average cost of capital, depreciation schedules, debt service, inventory levels, rate of inflation and so on for decision-making and financial analysis. In addition, public hospitals in South Africa do not have profit-maximisation as a parameter when it comes to their cost functions as shall be explained later on in the delimitation.

Up until now, public hospital budgets have tended to be determined and allocated based on staff establishments and / or historical expenditure patterns (McIntyre, Govender, Buregyeya, Chitama, Kataika, Kyomugisha, Kyomuhangi, Mbeeli, Mpofu, Nzenze and Walimbwa, 2008). In theory though, budgets of public hospitals should be based largely on bed capacity and (correct) utilisation thresholds of the service package gazetted (funded); calculations of ExPDE would require careful consideration in such instances. For example, exclusion of inappropriate utilisation and accruals from the calculation would be a major step towards being efficient. Gaspar, Rocha and Freitas (2012) noted that hospitals are complex organisations where efficiency as an aspect of hospital performance is a feature far from being simple to measure and that it affects cost benefit analyses. According to the WHO bulletin of 2003, resource management requires that managers use data on performance, costs and volume of activity in order to decide on the best use of resources (Shaw, 2003). It is clear therefore that, efficiency is a key dimension of performance that it should inform the managerial frameworks; and so appropriate utilisation of efficiency indicators can suggest issues in need of performance management and quality improvement examination. However, inferences are also relative to the quality of the underlying data including the definitions used.

Hospitals are complex systems and improvements in their operational efficiency requires indicators that fit the purpose if such indicators are to add value given the time and resources devoted to generating such data. Indicators should therefore be designed to measure the achievement of predetermined objectives. In practice, the indicators are often selected or adopted based on whatever data is routinely available. Efforts to address such issues are constrained by a general lack of transparency about cost drivers, indicator dimensions and best practices in indicator synthesis (Boussabaine, Sliteen and Catarina, 2012). Standardisation becomes essential for measurements within hospitals in similar categories or offering the same service package. Until such aspects are addressed, the design of performance measurement systems will continue to focus more on (unreliable) rankings and comparisons instead of aiming to improve resource management and hospital performance operations.

1.3 RESEARCH PROBLEM

Citizens generally assume that government has unlimited resources, yet public services are always limited and constrained. In the private sector, affordability guarantees access (Alaba and McIntyre, 2012). As a result, public hospitals are generally in dire need of opportunities to allocate resources efficiently in light of limited financial resources. Even though indicator benchmarking is increasingly getting recognition as a resource management tool for making various interventions or improvements; little is known about its applicability in hospital settings (De Korne, Van Wijngaarden, Sol, Betz, Thomas, Schein and Klazinga, 2012). Hussey et al (2009) carried out a systematic review of hospital efficiency measures; their principal findings indicated a lack of evidence on scientific soundness. Nixon and Ulmann (2006) also observed that evidence for a causal link between expenditure and health outcomes had remained elusive; in particular, evidence on growth and magnitude (cause and effect) between cost of services and performance dimensions. The research problem can be stated:

- Is there a cause and effect relationship between hospital efficiency indicators (as a dimension of hospital performance) and hospital expenditure in and across the public central hospitals in Gauteng?

Research objectives

Hospital managers often receive voluminous data, but are unable to distil important evidence from the data to guide strategic objectives and measurable performance reviews; and therefore unable to eventually make informed decisions. A common explanation as to why indicator evidence is seldom used or not used effectively in the management of hospital activities is postulated to emanate from a lack of evidence philosophically grounded and underpinned by rational analyses. The result is a lack of appropriate control measures scientifically determined to address the root causes that may be identified as a result of indicator information. The research objectives seeks to determine:

i. The effect of efficiency indicators and their linkages to hospital operations.
ii. The extent efficiency indicators purport to be measuring what they are intended to measure.
iii. Factors or gaps that influence managerial operational activities in response to efficiency-indicator information.
iv. Strategies and interventions required to synthesize efficiency-indicator information from a resource management accountability point of view.
v. Develop a model that utilises efficiency indicators to enhance on forecasting hospital expenditure as part of evidence-based decision making within public hospitals.

1.3.1 RESEARCH QUESTION

Efficiency indicators are meant to inform and guide changes in hospital activities for purposes of health service planning, monitoring and reporting. Measuring changes in indicators should enable hospital managers to determine improvements in the monitoring and evaluation of efficient performance. Currently available performance measures are limited in their scope and health care budgets are getting more and more constrained. As a result, ensuring efficiency of services provided by public hospitals is of great importance. Pursuant to that, the research question seeks to realise a resource framework that undertakes an in-depth investigation of the causal nature between (financial) resource inputs and the health outputs and is stated:

i. Apart from describing the change, can hospital efficiency indicators explain changes in expenditure and guide managerial strategies at public central hospitals in Gauteng?

Sub-questions:

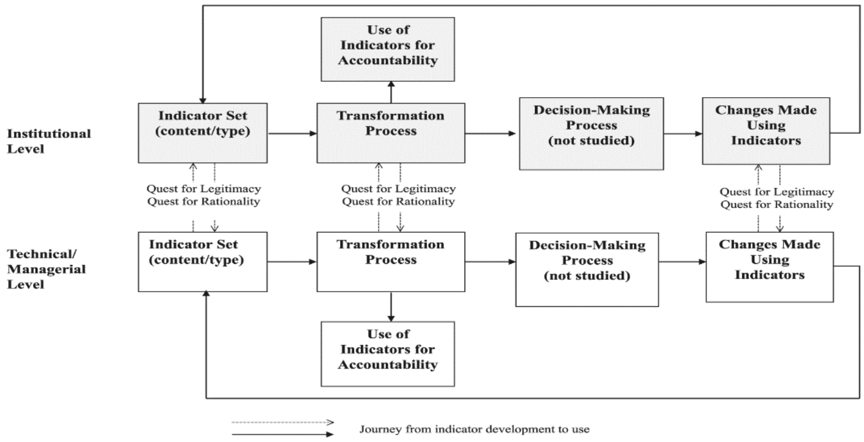
ii. What is the impact (variation, magnitude and lag) of the efficiency indicators across the hospitals and subsequent association to resource expenditure?

iii. What institutional challenges do hospital managers as decision-makers face as they interact with efficiency-related hospital activities?

iv. What implementation strategy for efficiency indicators is optimal and best suited to enhance evidence-based management within public hospitals?

Adapting efficiency indicators to ascribe cause and effect to model expenditure is known to be difficult partly due to the disjuncture between indicator development and the subsequent use of indicator information (Van and Moses 2012), as depicted in Figure 1.7 below.

***Figure 1.7**: Sketch of indicator synthesis gap from indicator development to usage.*



Source: http://www.emeraldinsight.com/content_images/fig/0010410810001.png [accessed 13/08/2014]

Due to the absence of known relationships and indicator models relating to operations within public hospitals; there has often been skewed resource allocation patterns (McIntyre, Govender et al, 2008). As already indicated, Shaw (2003) highlighted the need for managers to use information such as costs and volume of activities in order to decide on the best use of resources.

1.3.2 RESEARCH HYPOTHESIS AND THE UNDERPINNING THEORY

The purpose of this research is to evaluate expenditure as a leading management "efficiency" indicator and explore causal relationships to bed utilisation, average length of stay and C-section rates. Other variables are also included (as they may have auxiliary information) and these are defined and expanded on in the section on variables. Cost effectiveness as an element of expenditure has traditionally always been viewed as an indicator or predictor of efficiency. This view however, does not go without controversy and the reasons emanate from the fact that increased expenditure may not necessarily translate into better hospital performance; health outcomes and indicators may still take a dip irrespective of the expenditure levels. However, other researchers such as Magnussen (1996) and even more recently Hibbert and colleagues (2013), argue that there is a lagging effect; that is, improvements in health indicators manifest over a much longer period of time subsequent to the expenditure.

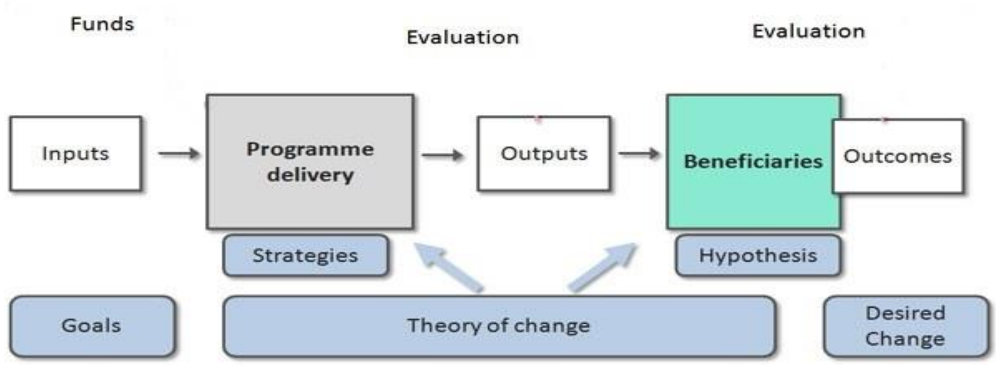
The procedure for testing statistical causality was proposed by Granger in 1969; "Granger-causality" suggests that whilst the past can cause or predict the future; the future cannot cause or predict the past. As explained in section 3.3.1 under Granger Causallity Analysis; **X** causes **Y** if the past values of **X** can be used to predict **Y** more accurately than simply using the past values of **Y**. In other words, if past values of **X** statistically improve the prediction of **Y**, then we can conclude that **X** "Granger-causes" **Y**. Therefore, in explaining the theories underpinning this study; this research is about causality between ExPDE (as **Y**) and each of the other efficiency indicators, that is ALOS, BUR, C-sections (as **X**); that is, does expenditure predict ALOS, BUR, C-sections (or vice-versa). The hypothesis tests for the significance of the parameters:

H_0: **X** does not Granger-cause **Y** against H_A: **X** Granger-causes **Y**

H_0: **Y** does not Granger-cause **X** against H_A: **Y** Granger-causes **X**

There are different permutations to the set up and these are expanded on in the above mentioned section 3.3.1. In answering the 'why', 'what' and 'how' aspects of the study; the underlying theory of causation between inputs, outputs and outcomes depicted in Figure 1.8 below must be examined. Quite often relationships between financial inputs required for the provision of health care, the design of performance measurement systems and activities within the hospital (as envisaged by the theory of change) leading to the achievement of specified targets clinical or administrative are vague and complex. Even though indicators are of different types, having different characteristics and objectives, operationally, they are related and the relationship requires mapping because ascribing cause and effect health care system performances is known to be difficult due to the complicated pathways inputs have to follow before achieving outcomes (Van and Moses 2012). A "*pathway of change*" represents the change process and is the skeleton around which the other elements of the theory are developed within the Theory of Change (ToC) as shown in Figure 1.8.

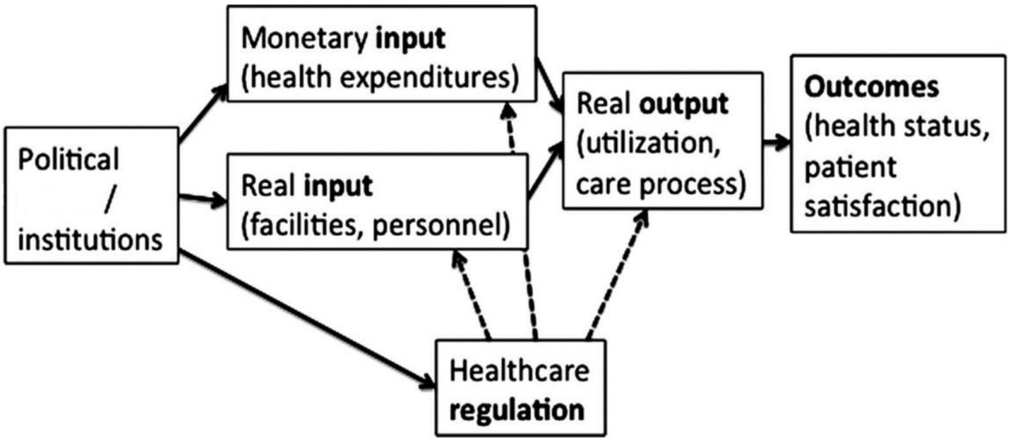
Figure 1.8: *Indicators' theory of change.*



Source: Modified from www.excitant.co.uk.

Figure 1.9 below shows the general approach adopted in the absence of evidence regarding the provision and financing of health care, from political ideas (policy) influencing institutional plans to strategies and outcomes as the ultimate goal.

Figure 1.9: *Diagram showing a general approach to health care system financing.*

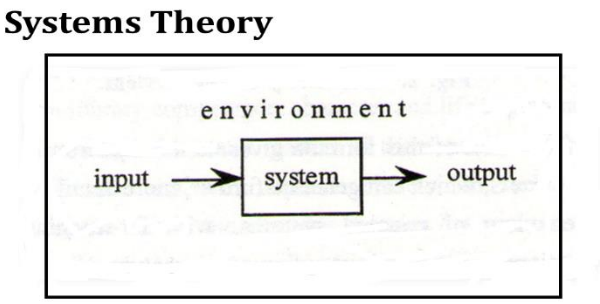


Source: Modified after Marmor T, Wendt C. Conceptual frameworks for comparing healthcare politics and policy. Health Policy 2012;107:11–20.

Several approaches have been suggested to establish a conceptual framework to guide health care systems' objectives; these include the WHO health system framework and the WHO / World Bank / Global Fund health system monitoring tool (Shaw, 2003). However, determining how indicators should effectively guide hospital operations in achieving set outcomes is a matter of on-going debate. Zelman, Pink, and Matthias (2003) reviewed the use of the balanced scorecard for instance; widely regarded a prominent innovation in strategic performance measurement systems and adopted as one of the most significant management innovations of the 1990's.

Zelman et al (2003) concluded that whilst the theory and concepts of the balanced scorecard were relevant to health care settings, there was a need to modify the scorecard so as to reflect institutional realities (indicators appropriate to their own services, programs and operating environment). In doing so however, there was a need for valid, comprehensive and timely data capturing. Figures 1.8 and 1.9 can also be examined by way of systems theory as shown in Figure 1.10 below. Systems theory framework was developed by Ludwig von Bertalanffy in the 1930s (Von Bertalanffy and Rapoport, 1963) and can be used to describe relationships between the components in a system.

Figure 1.10: *Systems theory framework.*



Source: Sadowski, P. (1999) Systems Theory as an Approach to the Study of Literature: Origins and Functions of Literature. Lewiston-Queenston-Lampeter: The Edwin Mellen Press.

In systems theory, knowledge can be gained on how hospitals function as components of the health care system in converting or processing resources (inputs) into health products and outcomes. Hayajneh (2007), held the view that systems theory, concepts and principles could be applied to understand and explain hospitals and their operations and allows one to clearly assess, visualize, analyse and understand the structure, processes and feedback loops that make up a system. That is so because a system is a collection of independent but interrelated elements or components organised in a meaningful way to accomplish an overall goal (performance).

Murray and Frenk (2000) argue that in health care, performance is related to the level of health expenditure; but very few frameworks articulate or provide for accountability mechanisms with respect to public expenditure in linking the cost-effectiveness of the theory of change in health care. Accountability is the obligation to demonstrate and take responsibility for performance in light of commitments and expected outcomes. Since the dawn of the new millennium, a number of frameworks for measuring health system performance have been proposed. However, the Performance and Accountability Framework (PAF) is fast gaining attraction as a mechanism used by governments to deliver more appropriate, efficient and effective public services owing to the fact that (i) Expectations must be predefined (ii) Decisions should be made using evidence and (iii) Continuous improvement must be institutionalized among other reasons (Hidalgo, 2013).

1.3.2.1 THE PERFORMANCE AND ACCOUNTABILITY FRAMEWORK (PAF)

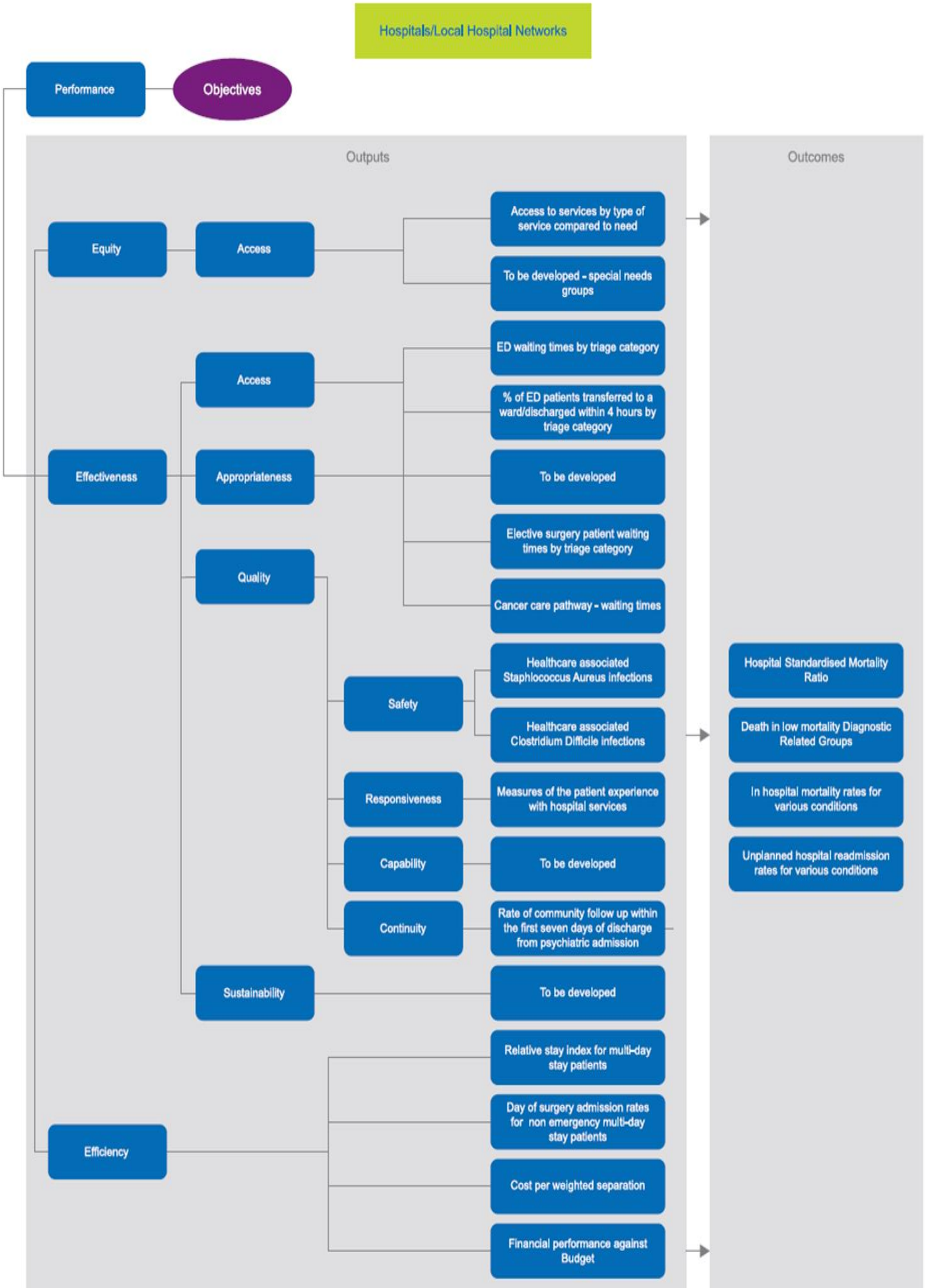
Performance and Accountability Frameworks (PAF's) take account of a range of mechanisms used to deliver more appropriate, efficient and effective public services. Within the health care environment, the framework was popularised by the United Nation's Central Emergency Response Fund, at the request of private donors and member states as a means for formalising a clear set of accountability to ensure that the flexibility and straightforward nature of the fund was complemented by an appropriate level of transparency, efficiency and accountability (Tye, 2013). The framework has been in place since 2010 and makes use of a logic model approach as a means of clarifying accountability and performance expectations around a set of predetermined outputs, outcomes and impacts. In so far as indicator measurements are concerned, the intrinsic goals of health systems must first and foremost be clearly articulated and must be measurable (strategic objectives and strategic indicators); this is in line with efficiency targets which must in theory, be predetermined and set quarterly or annually in advance for the central hospitals based on policy (Murray and Frenk, 2000).

The performance and accountability process can be conceptualised as an ongoing cycle, which provides a model to translate intentions into action and results by continually refining goals and strategies to improve performance and ensure accountability. Four basic elements of the cycle are (i) planning objectives and actions (ii) managing or delivering services (iii) reporting on the performance of the service provided (iv) reviewing and evaluating the outcome of the process. The four basic elements of the cycle resonate with the four generic tasks all managers are expected to perform according to Pillay (2008): planning, organising, leading and controlling. The PAF is more suitable for the research objectives in that not only do performance indicators measure an Organisation's performance in delivering their outputs; but should present a concise picture of performance. This may include how much was done, how well it was done and what it achieved. This makes PAF very applicable to local (South African) context, see Figure 1.11.

In addition, efficiency indicators as a dimension of performance indicators are meant to be (i) within the direct control of or significantly influenced by the operating entities (ii) clearly linked to hospital mandates and (iii) measurable or verifiable. The appropriateness of the types of measures used, either qualitative or quantitative, vary according to the strategic objectives and operational activities. Even though a PAF depends on sound structures and processes through the entire performance cycle, it is clear that this approach is better suited to drive the research objectives earlier presented. The use of PAF enables an analytic assessment that examines:

- The appropriateness of planned performance criteria and their limitations.
- Factors affecting performance.
- Measurements through a combination of health care delivery and patient health outcomes.

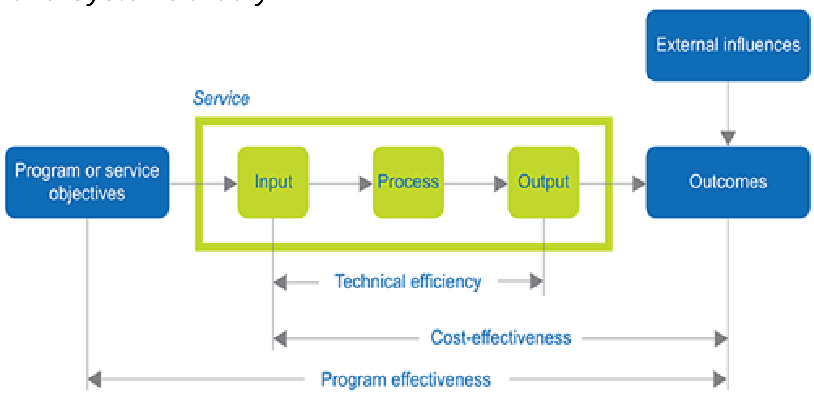
Figure 1.11: *The Performance Accountability Framework.*



Source: http://nhpa.gov.au/internet/nhpa/publishing.nsf/Content/PAF

In the context of this research, the four output measures that will be used to track efficiency are average length of stay, caesarean sections rates, bed utilisation rate and cost or expenditure per patient day equivalent. Though the framework is aimed at reporting performance information at an organisational level, it can still be used to support lower level activities such as at the level of a ward (Hidalgo, 2013). Figure 1.12 below shows how the PAF accommodates Systems theory.

Figure 1.12: *PAF and Systems theory.*



Source: http://nhpa.gov.au/internet/nhpa/publishing.nsf/Content/PAF

According to Murray and Frenk (2000), the performance of the entire health care system must be related to the performance of various sub-components, including Organisations such as hospitals as components within the health care system. The PAF therefore mimics the service components or sequence of steps involved in transforming inputs into outputs and outcomes in order to achieve the desired policy and program objectives. The framework should assist in identifying gaps in assessing performance by way of appropriate indicators. Though the use of PAF in health care settings only gained momentum around 2011 (Hidalgo, 2013); its applicability in other fields had since been adopted. For instance, Colin, Sattar, Fisher and Mayo (2001) used PAF a decade earlier to get clear and concise ways of understanding the performance of Community Development Finance Institutions (CDFIs). That study showed that having a menu of indicators would make performance assessment more straightforward and benchmarking work better when based on shared standards; there was scepticism when it comes to having a common set of indicators.

Performance in a public hospital setting, illustrates the quality of health care services, strategic objectives, the efficiency and effectiveness within which such services and targets are provided to attain the desired health outcomes is the overall goal (performance). However, there has not been much research on how to measure target setting and outcomes, which rely on several activities (Adair, Simpson, Casebeer, Birdsell, Hayden and Lewis, 2006). In that regard, the problem of attribution is especially pertinent to healthcare performance measurement because there are many determinants and indicators of a health outcome, where the causal relationship to health care performance remains unclear.

According to Murray and Frenk (2000), causality is compounded by differences in the design, content and management of health systems translating into differences in a range of outcomes and process flows. Process measures show the extent an organisation is aligning operational activities to evidence-based guidelines and linking that to improved outcomes. Outcome measures gauge the impact health services have on those in need of it. Emphasis on one or more of these types of indicators may be appropriate for different purposes, for instance, process indicators may be more appropriate for timely feedback over a shorter period of time as outcome indicators mostly involve a time lag (Adair et al, 2006).

In most empirical studies, relationships such as in the above theories are often correlational in nature or derived by ordinary regression models. According to Murray and Frenk (2000), for instance, hospital performance is related to the level of health care expenditure; but Obermann, Chanturidze, Richardson, Tanirbergenov, Shoranov, and Nurgozhaev (2016), argued that indicators only describe change, but fall short when it comes to explaining the change. Regression parameters generate coefficients for “rate of change”; but to the explain “change”, this study will make use of “Granger-causality”. Another gap arising in literature pertains to the lead or lag time between inputs and outcomes. Lag differencing once causality is established in this study, should be able to shed new knowledge in that regard.

1.3.3 AIMS AND OBJECTIVES

Efficiency in a hospital is about optimal use of inputs to yield services that are appropriate; that is, inputs relative to maximal outputs (Veillard et al, 2005), which is a performance measure issue. In economic analysis, performance indicators must offer real, relevant and accurate information regarding the performance by way of using analyses and diagnosis techniques. Ketelaar, Marjan, Signe, Liv, Deane and Martin (2011) identified a gap in that regard and highlighted the fact that there was little tradition of information use for decision-making at the facility level in most developing countries. That creates a situation where managers’ report on improvements in performance levels without necessarily getting to be more efficient in their operational activities.

The aim of this research is to employ Granger-causality (which uses time-series analysis and structural equations) to model relationships between expenditure (as a financial performance dimension) and other operational activities and indicators. The time to manifestation (lag) emanates from a need to investigate cause and effect relationships to determine time to manifestation of effects within and across different central hospitals in Gauteng. The focus on variability across hospitals is to determine if there are significant hospital effects; these would indicate different practices and guidelines between the central hospitals.

Efficiency dimensions are postulated to concern main hospital operations as auxiliary management variables; whereas clinicians have traditionally been the decision-makers in the use of health care resources (Flynn, Smith and Davis, 2002). In part, this is attributed to the fact that no clear overview is available to guide hospital managers in implementing efficiency inferences and strategies on management frameworks. The objective of determining an efficiency indicator model for managing resource expenditure in public central hospitals is in part aimed at:

I. Contributing to addressing the long standing gap identified in theory, that is to realise a tool for hospital managers in public hospitals to enable complex decision-making knowing the cause and effect of efficiency indicators on hospital expenditure.
II. Realise a tool that can address the gap highlighted by Obermann et al, 2016, that indicators can only describe change and not explain the change.
III. Realise a resource framework that undertakes an in-depth investigation of the causal nature between resource inputs and the health outputs at central hospitals in Gauteng.

If hospital efficiency indicators are monitored and evaluated on a routine basis, individually and collectively, and within the proper context; they can serve as the basis for strategic planning activities within hospitals for managers as they seek to identify and act on early (indicator) warning signs. These may include signs of inappropriate expenditure patterns and areas of operational weaknesses warranting specific course of action as part of guiding a prioritised array of critical resources and performance measurements. The frequent production and collection of efficiency data or any information does not always guarantee its utilisation; yet it is vital that information is processed and interpreted correctly for appropriate decision-making to improve and strengthen health systems (Klazinga, Fischer, and Ten Asbroek, 2011).

1.3.4 MOTIVATION

Indicator frameworks are complex by design because they are structured according to multiple dimensions. It is thought that monitoring performance imposes an inherent pressure to improve practice but the extent that is true is disputed and under researched (Boyce and Browne, 2013). Whilst understanding efficiency data is essential for equitable resource allocation and in particular, a needs-based model to guide the allocation of health care resources using a mix of indicators (McIntyre, Chitah, Mabandi, Masiye, Mbeeli and Shamu, 2008); there is little agreement in literature about how indicators can be adapted in resource management (Hamlin and Sawyer, 2007). Maximising the use of existing resources and accounting for expenditure in a cost-effective manner should be a deliberate process, yet poor understanding of hospital indicators often leads to a culture of very little regard for using indicator-information for decision-making (Dlamini et al, 2008).

Research by Afzali, Moss and Mahmood (2009) concluded that even though measurement methods in hospital efficiency assessment have been widely argued in literature, few authors have offered a framework to specify variables that reflect development of indicators in hospital operations including their effectiveness. A scenario where a lot of (indicator) data is collected and reported on, but never utilised is indicative of a potential knowledge gap. In literature, this gap is in understanding and synthesising indicator dimensions and their relationships to the constructs the indicators are intended to measure. Anema et al (2013) identified several bottlenecks behind the low uptake of indicator information in hospital management, including poor data quality, breakdown in communication and a lack of feedback. Gilson and Daire (2011), appealed to managers to make decisions based on health care needs within the confines of policy and resource frameworks that are scientifically proven, as opposed to leaning towards political instructions or repeating the same thing over and over again as a cultural norm.

Governance models dependent on performance information for policy decision-making assume the existence of high quality data and so, by implication, performance indicators ought to be reliable and valid (Anema et al, 2013). This research aims to support and guide policy and hospital decision-makers whose task it is to respond to a myriad of health performance challenges by enhancing technical competencies. That is, to help understand, operationalize and strategize operations premised on hospital efficiency data and react with informed intervention strategies. Economic efficiency is a proxy for resource and performance management and is typically assessed in terms of allocative and technical efficiency. An investigation by Lotfi, Kalhor, Bastani, Zadeh, Eslamian, Dehghani and Kiaee (2014), inferred that hospitals are costly to operate and efficient use of resources can help in saving costs. Even more more importantly, it was determined that reprioritisation of financial resources must be an on-going exercise that should always be well-informed at every stage.

The research motivation is driven by sentiments that currently available performance measures are limited in their scope, that health care efficiency and its measurement are under pressure due to rapidly increasing health care expenditures. As a result, ensuring efficiency of services provided by public hospitals is of great importance in the current financially challenging period. The major and current predicament within the public health care system does not appear to be a lack of evaluative tools; but rather in the understanding the concept of causation of the indicators to operations within the value chain of hospital activities and operations. Allocative planning processes require decisions to be made about how resources should be spent so that the different types of resources available for delivering and achieving health outcomes are carefully balanced, that’s a part of resource management (Usman, Memon and Shaikh, 2015).

1.3.5 ORIGINAL CONTRIBUTION

The study seeks to provide for a mechanism, a framework or model for informing how resources ought to be allocated from an expenditure point of view. The research will make an original contribution by profiling hospital efficiency indicators to realise a fair distribution of financial resources through a non-intensive resource utilisation strategy / model. Given that the research will focus on effective use of (financial) resources as a management attribute (Simou et al, 2014); a predictive model that guides hospital expenditure is therefore expected as part of an original contribution. An Efficiency Indicator Management Tool (EIMT) to address the disjuncture between indicator information and its subsequent utilisation is to be realised in a predictive modelling context as part of an efficiency decision-making strategic tool for the hospital managers. The latter will bridge the divide in literature, that no clear overview is available about strategies for implementing indicators in hospitals (Hussey et al, 2009).

The priority is to bridge a gap in theory as identified by Obermann at al (2016), by using cause and effect relationships to explain changes within constructs measured by indicators. Development of indicator frameworks has progressed rapidly even though most of the indicators used to test the performance of hospitals are still to be fully understood beyond describing the correlational association between the indicators and their constructs. The researcher is not aware of any study in which Granger-causation has been used in that regard. Granger causality analysis will be used to generate unique effects through stochastic dependences among random variables. Such an approach is plausible in that economic or financial variables for instance ExPDE or cost of drugs are not only contemporaneously correlated to each other, but are also correlated to each other's past values. Granger-causation has two elements namely (i) that the cause occurs before observing the effect and (ii) that the cause contains information about the effect that is unique and is in no other variable.

The impact of efficiency indicators in hospital operations remains largely unknown and as pointed out by Adindu (2013); the application of scientific management principles and emphasis on effectiveness and efficiency in the management of health care services permeating systems have not received serious attention in the majority of African countries. A major challenge facing the public health care delivery platform currently is the strengthening of linkages between resource shifts and outcomes in an efficient, effective and sustainable manner (Van and Moses, 2012). According to Spiegelhalter et al (2012), at least three challenges brought about by the measurement of statistical indicators within hospitals are (i) defining the target (ii) transforming the target into numerical language and (iii) correctly and accurately aligning the measurements of the indicators' constructs to the relevant operational activities. A predictive tool realised from hospital efficiency indicators in a predictive model is expected as part of an original contribution.

1.3.6 SIGNIFICANCE

This research is significant in that it seeks to achieve a new perspective on the role efficiency indicators can play in guiding hospital expenditure in a cost-effective way, thus leading to more effective management decisions in so far as service utilisation (how much is spent by patient type) is concerned. Rational health allocation decisions have to date, been compounded by historical budgeting with trends and baselines levels that were set before the advent of democracy, especially in South Africa's most populous province. Since then, the norm has always been to adjust the budgets annually by an inflation correction factor from one preceding year to the next, irrespective of the dynamics around need and / or utilisation levels of the health care services. Correcting that status quo has been hampered by a lack of appropriate methodology that links utilisation of services to the need in an efficient and cost effective manner. In addition, the corrective approach would need to be broad enough to include aspects other than just clinical costs of treatment. Efficient hospital management should also be about harmonised health care activities and provision, based on application of knowledge and managerial skills, including problem-solving, to achieve outcomes using resources in the most economical, efficient and effective way (Usman et al, 2015).

Indicator frameworks are complex by design because they are structured according to multiple dimensions. In literature, the body of evidence available to support evidence-based management decision-making in the public health care sector is sparse, limited in scale and lacking generalisability as noted by Yozgat and Sahin (2013). In today's management framework, there is a need to understand and appreciate the intrinsic characteristics of efficiency indicators and generate simplicity of design, validity of purpose, ease of implementation and directness of interpretation (Betran, Torloni, Zhang and Gülmezoglu, 2015). Administrators running hospitals are generally in dire need of approaches to achieve that in light of limited financial resources (Usman at al, 2015). Understanding efficiency indicators and the properties enables prompt and targeted interventions that may help to focus on more efficient management and usage of resources.

Through the knowledge acquired, opportunities to allocate resources efficiently, improving hospital operational performances and guiding hospital budgetary allocation will be enhanced. The EIMT tool should assist determining the appropriateness of expenditure of the allocated budget by way of indicators, taking into account factors such as patient type and volume, level of financial or human resources available to a hospital and so on. These are among factors that must be accounted for in order to achieve a desirable level of hospital efficiency. According to Klazinga et al (2011), in order to avoid misuse of indicators, their meanings as well as their embedding in governance and managerial structures and processes must be known.

1.3.7 IMPACT ON THEORY

Theory requires that indicators be designed to measure the achievement of predetermined objectives and not the other way round. For that to be corrected however, the knowledge gap identified in theory to address limitations in hospital efficiency indicators would need to be addressed, that is do the indicators measure what they purport to be measuring? Implications for the rate of change in their measurements and how hospital managers should infer information from efficiency data are aspects that must be understood. For that reason, factors or gaps that influence managerial operational activities in response to efficiency-indicator information and the development of strategies or interventions required to close such are issues envisaged to be addressed by the research.

Currently, efforts to address the above are constrained by a general lack of transparency about best practices in the public sector of health care (Boussabaine et al, 2012). As a result, there is poor evidence, if not a complete disconnection between alignment of public health care financing (including costing relative need for health care services) and the specific action, policy development and strategic interventions. This is mainly attributed to the complex breakdown and nature of the causal pathway between synthesis of efficiency data on one hand; and how it affects operations on the ground on the other hand. Such issues are far from being straightforward to measure or estimate (Gaspar, Rocha and Freitas, 2012). That is, evidence for a causal link between expenditure and quality health outcomes remains elusive, and frustrates attempts to measure the effectiveness and efficiency of the health care system in general (Nixon and Ulmann, 2006).

Another reason as to why the use of indicators has often been regarded as problematic is that research in response to the effectiveness of indicator information on the functioning of health care system is rarely carried out. One of the reasons for this is a lack of common perspectives. This research seeks to model changes and variability across hospitals in efficiency indicator values and the magnitude of such variation, including modelling the rate of growth in the constructs measured by the efficiency indicators. It is envisaged that such a contribution will narrow the gap advanced by Hernández and San Sebastián (2014), Bonca, and Tajnikar (2010) which is that scientific evidence on cause and effect in efficiency dimension or measurement is still lagging behind. James and Rigoberto (2007) observed a tendency amongst managers, to think that 'one-size fits all' implying therefore that indicator information applied equally to all types of hospitals. The extent managers recognise the limitations of individual metrics will therefore be tested, as well as their comprehension of indicator dimensions and sub-dimensions relative to activities in the hospital through a questionnaire. In this way, identification of the key dimensions of hospital performance including the "theory of change" framework and a conceptual model of performance standards and measures of the data will be realised.

1.4 METHODOLOGICAL APPROACH

The research methodology specifies the way in which the research is conducted in order to achieve the objectives formulated. The main analytical approach will use Granger-causality test, which involves using F-tests to test whether lagged information on one variable provides any statistically significant information about another variable that is lagged. This can be achieved in a number of ways, for example through the autoregressive specification of a bivariate vector auto-regression to estimate an unrestricted equation. The test has two components (i) the cause occurs before the effect and (ii) the cause contains information about the effect that is unique, is in no other variable. The second aspect is the unique principle that makes it different from techniques such as Data Envelopment Analysis (DEA). DEA has limitations when interpreting the results in that the method utilises a non-parametric function, and so is difficult to apply statistical tests of hypothesis regarding possible factors associated with that variation and therefore, cannot ascribe causality of the variation (Hernández and San Sebastian, 2014), as is the main focus of this research study and thus unable to describe and explain changes in constructs.

Managers' questionnaire responses (qualitative) and efficiency indicator data (quantitative) over seven years from four central hospitals is analysed for the empirical investigation of efficiency phenomena by way of Granger-causality Analysis (GCA), Generalised Linear Mixed Models (GLMM) and Kruska-Wallis (KW). GCA is used to generate unique effects through stochastic dependences among random variables using lagged values to determine significance effects on the current value of another variable to the existence of causal mechanisms underlying the data. Structural Equation Modelling (SEM) and Generalised Estimating Equations (GEE), which are integral components of GCA will enable testing of various models for triangulation purposes (Aristovnik 2014).

1.4.1 POPULATION AND DATA SOURCES

The DHIS, being the single verified data management system for health services, is considered the gold standard of health care data elements in South Africa. Data will be retrospectively drawn from quarter 1 (2008/09) to quarter 4 (2014/15) that is 28 quarterly time points. Data for Steve Biko Academic Hospital (SBAH), Dr George Mukhari Academic Hospital (DGMAH), Chris Hani Baragwanath Academic Hospital (CHBAH) and Charlotte Maxeke Academic Hospital (CMAH) is to be drawn from the DHIS. Dolmas (2010) defines an observational unit as the entity on which measurements are obtained from; therefore the above four central hospitals in Gauteng are the observational units. Dolmas (2010) also goes on to define the unit of analysis as the entity that is being analysed in a scientific research. The research study seeks to infer on efficiency indicators (together with other auxiliary indicators as outlined in the methodology) and given that efficiency indicators are characteristics of central hospitals, each efficiency indicator and each sampled manager therefore constitutes a unit of analysis. The former objectively and the latter subjectively.

The second data profile will be the phenomenological inference based on responses to a semi-structured questionnaire. This exploratory section aims to investigate the paradigm of subjective knowledge, experiences, and interpretation of indicator information by hospital managers, that is Chief Executive Officers, clinical managers, heads of departments / or clinical areas as well as managers from quality assurance, programmes, monitoring and evaluation as well as policy and planning. The responses per observational unit will constitute the subjective assessments on level of comprehension and utilisation of efficiency information by managers, institutional challenges faced as well as inform the implementation strategy best suited to enhance (efficiency indicator) evidence-based management within public hospitals in line with the objectives of the study research. Relating the objective efficiency indicators from DHIS to the subjective responses from the hospital managers imply a mixed study design as the objective measures are quantitative in nature whilst the subjective questionnaire responses from the managers are qualitative. One of the appeals of such a mixed approach is that it can help triangulate the measurement methodology by using different measures of the same performance concept to provide a better understanding of the research problem or issues than either research approach alone. This is further explained in the methodology chapter.

1.4.2 VALIDITY AND RELIABILITY

Problems intrinsic to indicator measurements include scientific, validity and reliability concerns pertaining to the collection of statistical information (Hibber et al, 2013) and so, as a result, even the most commonly indicators have been exposed in the literature as problematic in terms of attribution. A measure is valid if it measures what it is supposed to measure and accomplishes that without accidentally including other factors. Reliability on the other hand, refers to the likelihood that an indicator will yield the same value each time it is assessed in the same set of (performance) conditions. Reliability is therefore the degree to which measures are free from error and inclined to yield consistent results (Thanasegaran, 2009). Two dimensions underlie the concept of reliability; repeatability or stability over time and internal consistency or homogeneity of the measures (Zikmund, 2003). Though validity and reliability are often used alongside measurements (Leedy and Osmond, 2010); the probability that one will obtain statistical significance (that is whether differences obtained are due to chance or not as measured by the p-value) is imperative. The p-value provides for scientific evidence as to the extent to which conclusions drawn from the data are determined. Methods of assessing reliability include test-retest, alternate-form and split-half (Robinson, 2016). Repeatability, or stability-over-time reliability, may be measured with the test-retest method. Internal consistency or homogeneity may be measured by using either the split-half method, alternate-form method, or Cronbach’s alpha method. The latter is a reliability coefficient that measures inter-item reliability or the degree of internal consistency / homogeneity between variables measuring one construct / concept, that is the degree to which different items measuring the same variable attain consistent results. The coefficient varies from 0 to 1 and a value of 0.6 or less generally indicates unsatisfactory internal consistency reliability, a more acceptable reliability estimate ranges from 0.7 to 0.8 (Thanasegaran, 2009). SAS and SPSS softwares shall be used and the Scale Cronbach values determined. Other statistics often used are part-whole correlation and squared multiple correlation coefficient (Brace, Kemp & Snelgar 2012). More details are provided in section 3.3.2 under “Datasets”.

Face validity seeks for consensus that a measure is related to the dimension (or sub-dimension) it is supposed to assess. Content validity infers if the measure relates to the sub dimension of performance it is supposed to assess and considers whether or not the items on a given test accurately reflect the theoretical domain of the latent construct it claims to measure. Contextual validity looks at whether the indicator is valid in different contexts and examines if the indicator relates to other indicators measuring the same sub dimension of hospital performance. Construct validity is directly concerned with the theoretical relationship of a variable / measure to other variables or measures. When comparing the measured construct to other constructs based on hypothesised relationships; one expects to see either convergent or discriminant validity. In convergent validity one seeks to ascertain that two measures that are supposed to be measuring the same construct are indeed doing so and are therefore related (Dolma, 2010). Convergent validity coefficients should arise when considering two constructs hypothesised to be related, else discriminant validity coefficients if unrelated. Criterion validity consists of predictive validity or concurrent validity; but more generally refers to the ability to draw accurate inferences from test scores to a related behavioural criterion of interest.

Researchers look for a high degree of correlation between the criterion variable and scores on the testing instrument, in order to assert good criterion validity. Validity coefficients are ultimately derived from the correlation between these components. Veillard et al (2005), highlights measures that can be taken to enhance validity and reliability survey instruments, this was undertaken during the piloting of the questionnaire and include evaluating:

- Face validity - is the indicator set acceptable as such by its potential users?
- Content validity - are all the dimensions covered properly?
- Construct validity – In what way do indicators relate to each other?
- Relevance - does the indicator reflect aspects of functioning that matter to users and are relevant in current health care context?
- Sensitivity - are hospitals able to act upon this indicator if it reveals an implementation problem?
- Reliability - is there demonstrated reliability (reproducibility) of data?

1.4.3 LIMITATIONS AND DELIMITATIONS OF THE STUDY

Limitations are potential weaknesses in the study out of the researcher's control, and can influence the research outcomes if not controlled for or limited. Delimitations on the other hand, are characteristics that limit the scope and define the boundaries of the study, Simon (2011). Delimitations therefore, are choices made by this researcher and describe the boundaries set for the study. The study is limited and delimited in the following ways:

- The study is limited to central public hospitals in Gauteng and not to other hospitals to avoid variations in and adjusting for (i) patient-overlap and the hospital referral system; for instance a patient may be referred elsewhere but still remain in care of a hospital, ALOS would therefore need to be reconciled between the two facilities (ii) case mix; patients suffering from the same condition may differ in severity depending on the service package of the level of hospital treating the case, thus generating different cost structures to treat the case (iii) different cost structure; hospitals' budgets and expenditure are premised on the funding formulae. So there are differentials within allocations and mechanisms relating to the service package. For instance, a normal delivery at a central hospital is more expensive as it is attended to by a super-specialist whereas at a district hospital it could be done by a nurse (iv) different operational modalities, structures and treatment protocols across different provinces. This is because different provinces are permitted by policy to derive their own hospital protocols, management establishments included. For instance, other central hospitals in other provinces attend to mental health / psychiatry patients but in Gauteng, these are seen in specialist hospitals and institutions such as Life Esidemini. This is significant because ALOS for mental health / psychiatry can range between 90 and 120 days, which would skew current GDoH data set, if combined with that from outside of the province. Facilities such as psychiatric hospitals, TB hospitals and rehabilitation hospitals have exceptionally high ALOS and are categorised as 'specialised' hospitals (see Figure 1.5) and are excluded in terms of service package. They are therefore not a part of this study.

- Introducing hospitals from different provinces would also necessitate sufficient numbers from each province and additional terms to account for inter-provincial heterogeneity (but Gauteng has four out of eight of the hospitals as discussed already). The introduction of weights could be feasible (though that would generate large standard errors as there are no such hospitals in other provinces), but introducing weights was not a focus of this research. Another reason why only one province was ideal emanates from the fact that longer ALOS are typically medical admissions with lower average costs per day than surgical admissions since there are no theatre costs included, and so the acuity of care is relatively lower. However, the split of ALOS between facility types is not uniformly measured between provinces with some provinces having no data at all in that regard.

- The focus of this study differs from financial analysis perspective; which looks at the financial capacity (cash flow projections, depreciation schedules, debt service, inventory levels, rate of inflation, capital structure and so on) of an organisation to meet its mission and financial performance. In financial analysis, one of the most important characteristics is the financial performance and condition of an entity and also, revenue indicators measure the amount and mix of different sources of revenue. Public hospitals in South Africa are funded by the state based on service package, equitable share and levels of utilisation and neither generate operational revenue of their own nor do they have profit-maximisation as a parameter to their cost functions. Whilst hospitals seek to recover a fraction of the costs from those patients able to pay for health care services (as determined by the 'means' test) and medical aid patients; tariff amounts that can be claimed for are determined by law and gazetted in the Uniform Patient Fee Schedule (UPFS) tariffs for paying patients attending public hospitals. The tariff charges are not in any way aligned to the true cost of the treatment or procedure or what it actually costs the state to provide that service. Furthermore, any fees collected from the patients are meant for the treasury though part of that revenue can nevertheless be retained, subject to motivation being submitted and approval being granted. Quite often, the revenue is a small percentage of the voted funds required to operate the facilities as most patients are often exempted, section 27(1)(a) of the constitution prevents citizens from being denied access to services. None of the indicators used are cost indicators; ExPDE does not capture the amount and mix of different types of costs but rather aggregates all such to create a single measure of operating expenses; the unit cost of which is 24-hour patient. The ExPDE alongside ALOS, BUR and C-sections can therefore be regarded as utilisation indicators, measuring the extent to which assets (fixed and financial) are fully utilised.
- In South Africa, the efficiency (management) indicators are defined and prescribed by the national Minister of Health. Though other auxiliary variables are included, the focus was only on those designated as management indicators by the National Department of Health. Efficiency indicators may still be used at the same time for clinical inferences alongside other clinical indicators; however, they are only "efficiency" indicators when they are so designated for purposes of management frameworks (whether right priorities are being met effectively and efficiently or not). In the public health care system in South Africa, only the four (studied in this research) are so designated currently. The output of this research will assist in informing policy makers on the efficacy of those four, including whether or not there is a need to review the set (that is, add or subtract from the set). This is a matter revisted in the discussion and recommendation sections of the study.

- This research study seeks to utilise (objective and quantitative) data extracted from the DHIS and survey responses (subjective and qualitative) through a questionnaire. Though a pilot was necessary prior to implementation to ensure the research gets to the heart of the research problem as questionnaires tend to be weak on validity and strong on reliability (internal consistency), managers' responses were taken as given with no attempt to validate them.

- Methodologically, measuring hospital efficiency whether by way of Stochastic Frontier Analysis (SFA) or Data Envelop Analysis (DEA), has not always addressed 'fairness' in relation to the service package, indicators such as ALOS or resource usage (Kuwabara et al, 2011), unlike GCA. However, Granger-causality also has its own limitations and results and conclusions drawn from it should be considered as suggestive rather than absolute. The above is important in light of the fact that Granger-causality may produce misleading results when the true relationship involves three or more variables or when the lagged length is too long, as too many lags compromise the power of the test. As a result, the causality test has been known to be sensitive to model specification, generating "spurious" relationships (Bressler and Seth, 2011).

- Performance has several dimensions; this study will mainly focus on the dimension of efficiency. Mathematically, it can be shown that indicators that are mathematically derived such as in taking averages (ExPDE, ALOS and BUR) must be calculated from a large enough sample size to mitigate against sampling variability. The four efficiency indicators, ALOS, C-section, ExPDE and BUR are all obtainable from DHIS per hospital. Hospital expenditure is recorded in the Basic Accounting System (BAS) and is classified under eight budget programmes which are Administration, District Health Services, Emergency Health Services, Provincial Hospital Services, Central Hospital Services, Health Sciences and Training, Health Care Support Services and Health Facilities Management. The efficiency indicator Expenditure per Patient Day Equivalent (ExPDE) is derived by dividing the total hospital expenditure per quarter by the PDE for the same quarter, data quality has in some instances been suspect.

- DHIS data elements for quarter 1, 20 and 21 for ExPDE were suspect. This is attributed to a move from an old manual system to the new system (quarter 1) and "down-time" that occurred in the absence of any back up (quarter 20 and 21). Whilst it would have been possible to generate values through statistical methods such as "data amputation" for those periods; the preference was not to do so, on the basis that (i) all other data elements were not affected (ii) ExPDE was a response variable, trend analysis would mitigate for those time periods as part of the stationarity condition.

1.4.4 CHAPTER 1 SUMMARY AND CONCLUSION

The background and rationale to the imbalance between the private and the public health care leading to the overburdening of the later and the subsequent need to be efficient was highlighted. The hospital service provision outlining the structure of the public hospital delivery platform, an introduction of the indicators' theory of change and indicator development process followed. The significance of the study and role of indicators in theory, background and purpose of study were presented. Table 1.2 below summarise the indicator constructs.

Table 1.2: *Criteria for indicator selection.*

Level	Criteria	Issues addressed by the Indicator
Set of indicators	Face validity	Is the indicator set acceptable as such by its potential users?
	Content validity	Are all the dimensions covered properly?
	Construct validity	How do indicators relate to each other?
Indicators	Importance and relevance	Does the indicator reflect aspects of functioning that matter to users and are relevant in current healthcare context?
	Potential for use (and abuse) and sensitivity to implementation	Are hospitals able to act upon this indicator if it reveals a problem?
Measurement tools	Reliability	Is there demonstrated reliability (reproducibility) of data?
	Face validity	Is there a consensus among users and experts that this measure is related to the dimension (or sub-dimension) it is supposed to assess?
	Content validity	Does the measure relate to the sub-dimension of performance it is supposed to assess?
	Contextual validity	Is this indicator valid in different contexts?
	Construct validity	Is this indicator related to other indicators measuring the same sub-dimension of hospital performance?
	Burden of data collection	Are data available and easy to access?

Source: A performance assessment framework for hospitals: the WHO regional office for Europe PATH project (2005).

The variables of the study were defined followed by a preliminary examination of the gaps in literature in relation to the role and efficacy of indicator measurements. This led to the research aims amd research objectives. The Performance and Accountability Framework (PFA) follows from the research theory and was presented as the main theoretical and conceptual framework. The problem of attribution pertinent to healthcare performance measurement was highlighted. The gaps in literature were further articulated to highlight the motivation behind the gaps. The anticipated original contribution to be made and how that impact on theory followed. The methodological approach outlined the statistical approach to be employed. The target population was defined and the sources of data identified. Phenomena relating to validity and reliability was contextualized and finally, the scope of the study outlined with limitations and delimitations explained.

Chapter 1 begins by highlighting a comparative view of the efficiency of national health systems and the fact that there are countries doing better in terms of achieving their potential, in relation to their inputs. This association of overall efficiency with resource inputs is also evident from the country rankings where industrialised countries are dominant and among the best performers. In South Africa, there are major disparities in financing between the public and private health sectors, with the latter spending the same level as the public sector serving 84% of the population. This aspect highlights the need for efficiency measures to underpin resource requirements planning and ration resources towards ensuring the best outcomes and impact. Efficiency or management indicators are postulated to guide that process, as a crude process of identifying determinants to becoming more efficient.

Indicator frameworks are complex to design because they are structured according to multiple dimensions. Efficiency is postulated a dimension of performance and the focus of the research is to examine how hospital efficiency indicators can explain the rational of hospital expenditure (are right priorities being met effectively and efficiently or not) as a dimension of operational performance. The efficiency indicators ALOS, BUR, ExPDE and C-sections mostly track the flow and expenditure of patients through the system of care to get an overall measure of the cost effectiveness of operations as proxies for evaluation of health care delivery system performances. It is motivated for, that currently no clear overview about strategies for implementing indicators as a resource monitoring strategy in hospitals exists due to uncertainty of attribution and a general lack of transparency in indicator dimensions and best practices. The observational units are the four central hospitals in Gauteng; which are at the top end of the hospital referral chain of the integral national health system.

The Performance and Accountability Framework (PAF) is presented as the theoretical link between operational activities and performance. The problem of attribution is especially pertinent to healthcare performance measurement in that isolating the impact of healthcare outcomes is difficult; as a result, that theoretical link remains a grey area that is not well understood that needs to be researched further. Prominent issues highlighted when it comes to indicator frameworks include the need to take into account a variety of issues such as a comprehensive description and illustration of how and why a desired change is expected to happen in a particular context, the process through which the change will occur, the disconnect between such processes and indicator frameworks; even more importantly though, how all of the above impact on management approaches and methods for planning, performance and evaluation of hospital performances. In the next chapter, the relevant literature is critically reviewed and conclusions intermittently presented.

CHAPTER 2: LITERATURE REVIEW

This chapter is dedicated to reviewing the literature on indicators, the performance dimensions and more specifically the four efficiency indicators. The constructs of performance indicators, concepts developed so far in literature and their application in management frameworks will be examined. The literature review is bound and informed by the research problem, question, aims and objectives of the study as presented in chapter 1. The section begins by looking at the 10-point evaluation checklist presented by Saunders, Lewis and Thornhill (2012) and is shown in Figure 2.1 below.

Figure 2.1: *10-point evaluation checklist for literature review.*

Relevance and Value

- ✓ How recent is the item?
- ✓ Is the item likely have to have been superseded?
- ✓ Are its research questions and objectives close to your own?
- ✓ Is the item excluded by your relevance criteria?
- ✓ Have you seen references to this item (or its author) in other items that were useful?
- ✓ Does the item support of contradict your arguments? For either, it is still worth reading!
- ✓ Does the item appear to be biased? Even if it is, it may still be relevant to your critical review!
- ✓ What are the methodological omissions within the work (e.g. sample selection, data collection, data analysis)? Even if there are many it still may be of relevance!
- ✓ Is the precision sufficient? Even if it is imprecise it may be the only item you can find and so still of relevance!
- ✓ Does the item provide guidance for future research?

Source: Adapted from Saunders, Lewis and Thornhill (2012).

In line with the above checklist, a systematic review approach is adopted using comprehensive inferences from literature, evaluating its contribution, analysing and synthesising the findings and reporting on the evidence. A critical review of the literature should depict the evidence in support of or against any gaps noted, as well as support and provide the rational for the research's hypotheses. That way, conclusions relating to the aims and objectives of the study are possible.

Copnell, Hagger, Wilson, Evans, Sprivulis and Cameron (2009), studied the inventory of hospital indicators and noted significant gaps in measurement despite the large number of available indicators identified. Apart from the indicator constructs themselves, evidence presented by Veillard et al (2005), showed that the way an institution is organised, in particular; the management configuration influence the delivery of health care services as well as the performance of the overall health care system. Attributes most affected are listed as accountability, cost effectiveness, sustainability as well as quality improvement strategies. That study also noted that most health systems were lacking in respect of most of the attributes.

2.1 EFFICIENCY (INDICATORS) AS A DIMENSION OF PERFORMANCE

Hibbert et al (2013), undertook a literature review on "*what can the academic research and grey literature tell us about the impact of performance measurement regimes on the quality of healthcare*?", three issues were raised (i) purpose of performance indicators (ii) mechanisms and barriers of performance indicator usage (that is, the theoretical link between performance measurement and improvement) and (iii) evidence of impact of performance indicators (that is, the empirical support for performance measurement). Whilst the study determined the existence of substantial literature dealing with the design, properties and scientific soundness of individual indicators; there was much less consideration of how indicators are actually used in practice. It was unclear as to the impact indicators have on the behaviour of those that engage with the indicator measurements, including the effect on operational activities of health care services. It was noted that there was on-going debate as to the exact purpose of indicators, including if they should be used for accountability, quality improvement or other purposes.

Historically, Ernest Amory Codman is credited as the first doctor to pursue hospital performance measurement and improvement systematically (Donabedian, 1989), following up on patient outcomes to determine how they could be improved. However in his approach, emphasis was placed only on the final end-outcome disregarding initial status and the value-chain of hospital care leading to the final outcome. It can be argued that the health delivery landscape has changed significantly since then, but not the objective. It is thought patients' stay in hospital facilities have been reduced owing to modern medical care and technology but on the other hand, outcome measures have been found to be getting harder to track as patients tend to leave the hospital environment relatively earlier compared to Ernest Codman's times (Simou et al, 2014). That also implies outcome indicators tend to have less than optimal validity and reliability, as they are often harder to measure, making process indicators a better proxy for outcome performance measurement in the modern era.

By 2005, Veillard et al (2005) had developed a flexible and comprehensive tool for the assessment of hospital performance, referred to as the Performance Assessment Tool for quality improvement in Hospitals (PATH) with 6 interrelated dimensions; clinical-effectiveness, safety, patient-centeredness, responsive governance, staff orientation, and efficiency. Two principal uses of the indicator systems employed in PATH are (i) a summative mechanism for external accountability and verification in assurance systems (ii) a formative mechanism for internal quality improvement. However, whilst PATH support hospitals in assessing their performance, making inferences on their own results and translating them into actions for improvement; it is criticised from a number of fronts including the fact that an indicator system must have 'measurable elements' that provides information about a complex phenomenon. Constructs such as clinical effectiveness or patient-centeredness are abstract and not easy to objectively measure.

Today, hospitals seek cost-effective strategies and methods for identifying interventions that achieve the greatest level of health impact per unit of expenditure. In Gauteng, hospital case managers focus on identifying potential high cost patients as early as possible, in an attempt to seek alternative treatment plans. This is an attempt to manage benefits for the patient as well as ensure cost effective use of resources (Flynn et al, 2002), therefore, the patients are more closely monitored. According to Bonca and Tajnikar (2010), there are strong benefits in monitoring process measurements within a hospital as close as possible to the point of care and selecting relevant processes and outcomes in order to be more proactive. For instance, BUR can be useful in guiding the planning and operational management of hospital beds in a way that improves patient welfare when admitted in a hospital. Research by Usman and colleagues (2015), called for further separate research that may lead management to respond appropriately to counter protracted ALOS to mitigate against unnecessary resource consumption.

The WHO bulletin of August 2003 on indicator principles entitled "*how can hospital performance be measured and monitored?*" noted the following:

- Performance assessment requires reliable methods of measurement against validated standards.
- The reliability of indicators is determined primarily by the accuracy, completeness and timeliness of data collected at facility level.
- Valid comparisons of performance between institutions demand rigorous standardisation of assessment criteria and methods.
- Performance failures are more often a result of failures in systems and processes rather than of individual competence or knowledge.

In South Africa, a rudimentary understanding of health information is an obstacle to effective health care management and performance (Dlamini et al, 2008; Pillay et al, 2008). Comprehension of hospital performance also depends on the specification of the output but, as noted by Magnussen (1996), Hibbert et al, (2013), several challenges exist with health outcomes:

- Outcomes are often not well (measurably) defined.
- Even when they are, they manifest over a much longer period, making it difficult to ascribe causality.
- In certain instances, relationships, for example those between resource consumption and outcomes are not well understood.
- As indicated earlier on, sources of data used in cost efficiency analyses often do not support meaningful assessments of health care outcomes (Ludwig et al, 2010).

According to Dlamini et al (2008), concerns regarding the technical capacity (both in leadership and management) within the public health sector have been raised; yet the extent managers at public hospitals decipher efficiency information or are familiar with such processes remains undetermined. As a result, the true value of information systems such as the DHIS has not been ascertained from a hospital “efficiency” point of view. The authors retain the view that if efforts to ensure the transformation of efficiency data into standard indicators fit for making rational decisions about service delivery and quality of care are to bear fruit in public hospitals, then hospital managers should be encouraged and capacitated to interact with key hospital indicators and monitor their performance (Dlamini et al, 2008).

One problem in line with the observations made by Dlamini et al (2008), is that the vast majority of training sessions conducted in health care management up till now, continue to be clinical, administrative or public health centred and lacking in efficiency designs necessary in addressing resource allocation challenges. As a result, the gap envisaged to be covered by this research study has largely remained unattended. The role of hospital efficiency data in strengthening attributes of health systems and assessing predictors of efficiency indicators should be a significant element in realising optimal management configurations in relation to the use of financial resources, as it’s a part of evidence-based policy determination. In the United Kingdom for instance, accident and emergency departments are monitored to ensure that 95% of patients admitted are discharged or admitted elsewhere in the hospital within four hours (Blunt, Edwards, and Merry, 2015). The logic behind this being to prevent a build-up of strain on staff and resources. Emphasis is also placed on discharging patients safely and quickly from the hospital. As noted much earlier by Hofer (2006), such an approach reduces delays in recognising deteriorating performances and allows for the immediate implementation of corrective strategies.

Relationships between the skill levels of hospital managers and their empowerment to carry out effective and strategic tactics necessary for optimal distribution of resources are well documented by Toygar and Akbulut (2013). Prior to that, a study by Pillay (2008), aimed at determining the skills and competency levels of hospital managers in South Africa, found that public sector hospital managers were more likely to report that they required further development in comparison to their private sector colleagues. In addition, managers in the private sector perceived themselves as more competent in comparison to those in the public sector. More than half of public sector hospital managers (55.3%) had a medical / health related background, whilst the majority of managers in the private sector (67.2%) had a commerce / management background. The report noted that, in an attempt to improve public sentiment about the public sector, public sector agencies were aspiring to emulate the private sector philosophy and management approach in a quest to enhance efficiency and effectiveness.

Theory suggests that inadequacies such as those observed in the South African hospital referral system where deficiencies affect patient flow across the public hospital system, could be minimised if hospital managers and administrators better understood and utilised efficiency data generated by the DHIS. Quite often, management is often criticised for merely reacting to events as opposed to proactively anticipating and linking ideas with practice in the workplace (Mah'd et al, 2014). Findings by Greyvenstein and Cilliers (2012), were that managers often preoccupied themselves with figures around performance and then seek to drive change from the boardrooms. It was noted that such an approach was flawed and lacking in terms of leadership attributes. The concept of management and / or leadership styles has often been posed when it comes to innovation in organisations, health care in particular (Aarons et al, 2015). That could imply that leadership is equally an important factor with respect to indicator management in hospitals and that formed the basis for which a questionnaire for managers was necessary in this research.

Though leadership is associated with organisational and staff performance, the impact of leadership on public services is assumed but evidence is often anecdotal and evaluation is still rudimentary for a number of leadership development approaches. For that reason, this is an area that has never been well articulated. Transformational leadership is a technique of leading an organisation where subordinates or followers are inspired and motivated, based on the theory that workers are motivated by rewards and discipline (Ingram, 2013). Transactional leadership is based more on reinforcement and exchanges and focuses on team-building, motivation and collaboration with employees at different levels of an organisation to accomplish change for the better (Ingram, 2013). It has been hypothesised that positive transformational leadership would be associated with more positive attitudes toward implementing evidence-based practices and that effective leadership is one of the most crucial factors that leads an organisation towards success (Aarons, 2006; Mah'd et al, 2014). The use of efficiency indicators as a part of evidence based decision-making management frameworks resides more with the latter than the former.

Veillard et al (2005), noted that hospital reforms in performance management needed to be based on scientific evidence and placed emphasis on the development of systems monitoring the performance of health care services as well as practice models for assessing improvements. Yet addressing the role and impact of efficiency indicators on hospital performance in a public hospital context remains a grey area (Bem et al, 2014). Therefore, even though leadership is critical for effective implementation of innovative strategies in organisations including health care facilities, the concept of leadership and management in implementation science seems not fully developed (Aarons et al, 2015). As a result, whilst leadership in organisations is important in shaping acceptance of innovations such as evidence-based practices, the full extent of the diverse leadership elements necessary at various management levels within public hospitals remains unclear.

Hofer, Hayward, Greenfield, Wagner, Kaplan and Manning (1999) noted that most indicators used to monitor hospital performances are resource intensive and efforts to develop new indicators are generally directed at the evaluation of health plans and not constructed to help find and fix problems with the quality of care and outcomes within health institutions. Four categories of barriers in determining linkages between performance measurement and operational activities were identified by Hibbert et al (2013), these are (i) matters intrinsic to the indicator such as the lack of scientific validity / reliability) (ii) problems with quality of data (iii) problems with the use and interpretation of the data and (iv) the confounding influence of organisational and contextual factors such as a culture of compliance without comprehension. From the above, it is clear that whilst new ways of organisational and management changes that contribute to increased efficiency and quality performance are necessary; the need for standardised indicator models is apparent. Currently, not much is known about the applicability of efficiency information in hospital settings (De Korne et al, 2012) as existing frameworks are not well developed.

Calls to examine the manner and extent hospital managers and administrators are able to decipher and translate such information in their daily operations have been getting louder, but new health care techniques and technologies require different management and leadership approaches as well (Aarons et al, 2015). Hernández and San Sebastián (2014), postulated that managers need information on how well their units are utilising the resources they receive in order to strengthen the performance of health care services. Mayosi et al (2012), advocated for the strengthening of the comprehensive and integrated DHIS to provide good quality, reliable and timeous evidence for tracking and improving health service delivery; yet, for example in the Netherlands, hospitals are solely responsible for reporting indicator measurements (Anema et al, 2013). A major setback in that regard, is the skepticism associated with self-reporting. Also, if each hospital decides on its own indicator system then again, too many indicators can adversely impact hospital operations and confound comparisons (Bonca and Tajnikar, 2010). Indicators from one system may not automatically imply a valid reflection of the underlying health care process that it is intended to measure especially across a different system (Anema et al, 2013).

In performance measurement, it is recognised that indicators can be measured from more than a single perspective and so a single standard of measurement of efficiency is never the end goal, rather a suite of quality and cost measures may be a better proxy for efficiency. As a result, efforts ought to be directed towards in-depth investigation of efficiency frameworks. It is equally important that in solving the current health care service delivery challenges problems, focus is not only directed at enhancing the efficiency of resources usage by understanding the cost of services required, but also getting an understanding of how the same resources can be used to provide optimal levels of service in a guided manner.

2.2 GATEKEEPING OF PERFORMANCE INDICATORS

Generally and as noted by Hibbert et al (2013); public health care performance frameworks should reflect government's and health care system's strategic goals. The factors influencing choice and dimensions of indicators may change over time, such as when there are policy changes and changes to the broader strategic goals or priorities of the public health care system itself which is often structured according to multiple domains. As a result, the matrix of indicators largely depends on the availability of data and purpose as determined by the entities or authorities entrusted with such a function. Table 2.1 below shows some of the indicators for top performing countries from Figure 1.3. Denmark has the highest number at 197 and Australia has the least at 17 whilst Scotland has almost the same number at 18. The context of those indicators differ significantly, Australia's indicators include dimensions of effectiveness, appropriateness and efficiency. In Australia, the Performance and Accountability Framework (PAF) was developed to structure the indicators by healthcare organisation type and rolled out in 2012. The framework includes almost 50 indicator sub dimensions of performance about hospital and community activities. The National Health Performance Authority (NHPA) is the authority entrusted under the National Health Reform Act 2011 (2) as an independent agency to monitor and report on health care system performance in Australia.

The Canadian health system has 101 performance indicators presented in 4 domains (i) health status (ii) non-medical determinants of health (iii) health system performance and (iv) community and health system characteristics. Altogether, there are 8 domains of health system performance (i) acceptability (ii) accessibility (iii) appropriateness (iv) competence (v) continuity (vi) effectiveness (vii) efficiency and (viii) safety (Canadian Institute for Health Information). In Denmark, the Danish National Indicator Project (DNIP) manages the indicator portal (Hibbert et al, 2013). Danish performance indicators are collected and reported through a range of separate national registers and databases, but all the indicators are read from a clinical perspective (Mainz, Krog, Bjørnshave and Bartels, 2004).

In England, the National Institute for Health and Care Excellence (NICE) is responsible for managing the development of indicators, including prioritising areas for new indicator development, developing and selecting indicators, advising on thresholds and ensuring broad consultation with individuals and stakeholder groups (National Institute for Health and Clinical Excellence, 2013). In the Netherlands, the National Institute for Public Health and the Environment, commissioned by the Ministry of Health reports on the performance of all 125 indicators of the healthcare system. The indicators are only reported at the national level (National Institute for Health and Clinical Excellence, 2013). The indicators are contained within three overarching themes which are quality of care, access to care and healthcare expenditure and efficiency.

Table 2.1: *Core performance indicators for selected top performing countries (from Figure 1.3).*

	Canada	**Denmark**	**England**	**Netherlands**	**New Zealand**	**Scotland**	**USA**	**Australia**
Number of indicators reported	SC- 101 indicators CHRP – 21 indicators Healthy Canadians – 70 indicators	197 but majority in Danish.		125 indicators – National only 65 local indicators (difficulty translating)	34 national indicators	18 national indicators	The Commonwealth Fund – 43 indicators. Hospital Compare – 87 indicators	Indicators for Local Hospital Networks – 17 Indicators for Medicare Locals
Dimensions/ Domains reported	a) acceptability; (b) accessibility; (c) appropriateness; (d) competence; (e) continuity; (f) effectiveness; (g) efficiency and (h) safety	Under development	NHS Outcomes – 5 domains CCG- adds to the overarching NHS Outcomes framework QAO framework – 4 domains – clinical, organisational, patient care experiences, additional services	Three overarching themes - quality of care, access to care and healthcare expenditure	Diverse themes. Atlas domains: maternity, gout, demography, cardiovascular disease, poly-pharmacy and surgical procedures.	Described as Quality Ambitions: Safe, person-centred and effective.	The commonwealth Fund – 4 domains access, prevention and treatment, costs and potentially avoidable hospital use, and health outcomes. Hospital Compare – 7 dimensions – General information, Timely and effective care, Readmissions, complications and death, Use of medical imaging, Survey of patients' experiences, Medicare payment, Number of Medicare patients	PAF – safety, effectiveness, appropriateness, quality, access, efficiency, equity, competence, capability, continuity, responsiveness, sustainability. ROGS – effectiveness, appropriateness, quality, access, efficiency, equity

Source: Performance indicators used internationally to report publicly on healthcare organisations and local health systems (2013).

In New Zealand, there is a National Health Committee (and other ministerial advisory committees) that advice the Minister of Health on measures designed to improve the performance of health services (Hibbert et al, 2013). The measures are meant to ensure that government priorities are focused on accountability including quality improvement. Scotland has a Quality Measurement Framework to structure and coordinate the range of measurements that are administered by NHS Scotland (and operates alongside a range of private healthcare services) across the country (Gillam, Niroshan and Steel, 2012). Among the outcomes indicators reported on, are resource use indicators.

The United States of America (USA)'s Department of Health and Human Services' Agency for Healthcare Research and Quality (AHRQ) reports nationally on healthcare performance across four dimensions of quality of care, which are effectiveness, patient safety, timeliness and patient-centeredness (117). There are 43 indicators covering the four dimensions of health system performance, and these include costs and potentially avoidable hospital use, health outcomes and many others, including 87 indicators for clinical care. In the USA, health care is provided by multiple organisations with the majority of healthcare facilities owned by private organisations. In fact, 62% of the hospitals are considered non-profit, 20% are government owned and 18% are for profit (Sparer, 2011). Even though the USA is dominated by private hospitals, but as shown in Figure 1.3, the public hospitals' performance is quite good relative to South Africa. In theory, that may seem to suggest that bringing resources under state control is not necessarily an enabler for achieving better performance. Such an argument has huge implications for legislation with respect to private sector contribution.

Whilst the development of performance frameworks in health care has largely been welcome, criticism is levelled at the fact that often the frameworks are inclusive lists of multiple, and often overlapping indicator constructs (Murray and Frenk, 2000). That makes causality difficult to determine. Besides, some frameworks are premised on the availability of indicators. The disadvantage of this is that the performance construct that is realised, merely replicates the conceptual and technical inadequacies of the available measures. Such approaches are unsatisfactory for a comprehensive and meaningful assessment of health performance indicators.

A number of studies in literature have examined whether certain characteristics of hospitals, such as the number of beds (commonly used as a capital variable), the presence or absence of academic involvement, and geographic region predict a high level of performance or not (Jha, Orav, Dobson, and Epstein, 2009; Vitikainen et al, 2010). Those studies found that the quality of hospital care varied widely across different indicators and that individual hospitals vary in their performance according to indicators and conditions (that is, there is a significant hospital effect). In such instances, the success of policy in guiding the hospital sector towards best-practice depends on the ability to distinguish efficient from inefficient services (Copnell et al, 2009).

What is clear from Table 2.1 is that there is not a single ‘composite’ indicator to show the performance of a health system. Rather, a dimension-based approach with a mix of indicators provides for a more holistic picture of the constructs. The complication is that dimensions require balancing according to the health system’s goals and priorities, beginning with the broad domains describing what the indicators should measures (Hibbert at al, 2013). For that reason, Hibbert and colleagues (2013) concluded that indicator frameworks are complex to design because they are structured according to multiple dimensions and there is no consensus on the optimal number of indicators that should be in use and will differ depending on several factors.

Much of the current evidence on the effectiveness of performance indicators is based on observational or experimental data. Some experience suggests that guidelines to standardise management of common conditions may reduce length of stay and episode costs without detriment to clinical outcome. In such cases, indicator frameworks can be used to suggest issues for performance management; they should not rely on single sources of data but should use a range of information. Using a range of information has a disadvantage when it comes to interpretation, caution must be exercised in this situation. Hospital performance must be defined in a manner that supports the achievement of specified targets, either clinical or administrative through synthesis of the best available evidence, including policy options related to the profiled constructs. The publication of performance statistics as “league tables” should aim to encourage improvement and to demonstrate a commitment to transparency and accountability; that way, the design of performance measurement systems should improve hospital performance.

Bonca and Tajnikar (2010) indicated that standard business performance indicators could be improved if hospitals are treated as process organisations in the same way private hospitals operate. In the period 1998 to 2004, 20 new private hospitals opened in Gauteng province, meaning that, of the province’s 157 hospitals then, 128 were private (Stuckler, Basu and McKee, 2011). Yet, research by Naidoo et al (2013) showed that, despite serving only 16% of the total population, the private sector holds 84% of the total ICU/HC beds in the whole country. To address the stark contrast between health service provision in the public and the private sectors, several observers have hypothesised the need to redirect the flow of funds from private to public on the assumption and guarantee that the funds will be used efficiently and appropriately (Christian, 2012; Pillay, 2008). Unfortunately, unlike the private sector, the use of hospital efficiency indicators for decision-making and apportioning appropriate interventions in public hospitals is currently constrained despite efficiency information being regularly collected because efficiency data and patterns are seldomly understood. As a result, not much is known about the applicability of efficiency information in public hospital settings and even within the body of literature; many areas of indicator synthesis remain unaddressed.

2.3 EFFICIENCY INDICATORS (THE BIG 4)

The District Health Management Information System (DHMIS) policy read in conjunction with the District Health Information System (DHIS) standard operating procedures (SOP's) define hospital 'efficiency indicators' as management indicators meant to guide and ensure resources are used in the most effective, economical and efficient manner (English, Masilela, Barron and Schonfeldt, 2011). There are four efficiency indicators (often called "the big 4") nationally prescribed as part of the NIDS dataset in South Africa and are operational indicators in nature; that is they focus on factors related to hospital operations. Operational indicators are more likely under the direct control of management. The big four indicators are (i) Average Length Of Stay (ALOS), which is the average number of days for admissions in hospital (ii) Bed Occupancy Rate (BOR), more commonly known as Bed Utilisation Rate (BUR). That is the proportion of inpatient-bed days used as a proportion of the maximum available bedding capacity (iii) Caesarean Sections rate (C-Sections rate), delivery by C-section as a proportion of total deliveries in the hospital and (iv) Expenditure per Patient Day Equivalent (ExPDE), which is the cost of inpatient services per patient day. As earlier on indicated, these are meant to guide more efficient management interventions; but efficiency data and patterns are seldom understood, particularly in the context of public hospitals.

The number of hospital beds provide a measure of the resources available for delivering services to inpatients in hospitals as the bed occupancy rates are an important parameter for cost determination and is of immense relevance in effective decision-making. In most countries, the positive population growth with ageing populations or increasing-stable life expectancy implies that even without a reduction in the number of hospital beds, there is an increase in the demand for hospital bed occupancy and raising BOR. Generally in South Africa, the distribution of hospital beds is skewed against the public sector (Naidoo et al, 2013). The authors determined that there are more Intensive Care Units / High Care (ICU/HC) beds in the private sector (66%) as compared to the public sector (34%) despite the latter servicing about 84% of the population.

A study by Usman et al (2015), attributed an increased rate of hospital-acquired infections and hand-hygiene compliance failures to a high BUR, as overcrowding begins to set in. It is also known that the empirically determined BUR is positively related to the admission and inpatient separation rates. That study further called for research to investigate the essence of BUR and ALOS in hospitals to determine the association with various demographic factors in medical and allied wards. The study submitted that the two measures were useful in guiding the planning and operational activities of hospitals, but efforts to guide that are constrained by a general lack of transparency about cost drivers and best practices in the health care sector. The study also noted that hospitals are largely unfamiliar with efficiency methodologies and recommended that technical assistance be provided to hospitals.

In theory, BUR is a function of supply versus demand (of tertiary beds in the context of this research). Therefore the development of a model that capitalises on BUR would be beneficial in that for example in Gauteng, the Outpatient Department (OPD) headcount is at its lowest in the first two months and the last two months of the year. Such information if modelled resource-wise, would imply for example that staff leave could be maximised during such periods. Table 2.2 below shows the distribution of beds by level of care in Gauteng whilst table 5 shows the distribution of the beds at the four central hospitals that constitute the units of observation for the research.

Table 2.2: *Allocation of beds by level of care in Gauteng as of 2012.*

LEVEL OF CARE	APPROVED BEDS (ACUTE BEDS)	
	No.	%
DISTRICT	2 965	18.4
REGIONAL	4 605	28.5
TERTIARY	2 182	13.5
CENTRAL	6 390	39.6
TOTAL ACUTE BEDS	**16 142**	100

*Source: Regulations Pertaining to Categories of Hospitals, 2012

Table 2.3: *Distribution of beds by central hospital in Gauteng as of 2012.*

National Central Hospital Beds			
District	Hospital name	Approved beds*	Useable Beds
Johannesburg	Charlotte Maxeke	1018	794
	Chris Hani Baragwanath	2888	2308
Tshwane	Dr George Mukhari	1652	1236
	Steve Biko	832	790
TOTAL NATIONAL CENTRAL HOSPITALS BEDS		6390	5128

*Source: Regulations Pertaining to Categories of Hospitals, 2012

The distribution of beds is important in order to give context to factors such as the extent of service package, differences in the geographical service areas as well as the supporting infrastructure around the hospital, transportation routes and level of affluence in the population (Nathan and Rautenbach, 2014). Such factors should be borne in mind in relation to the configuration of supply and demand of health care services. It must be pointed out that generally, central hospitals are not confined to serving a defined (surrounding) geographical population.

Internationally, maximum value for BUR is usually benchmarked at 85% as at that point, the risk of bed shortages becomes unstable due to the cycle of peaks and troughs (Bagust et al, 1999; Mustafee, Katsaliaki, Gunasekaran, Williams, Virtue, Chaussalet and Kelly, 2013). The 85% threshold is determined through stochastic simulation which implies that at 85% bed occupancy, a hospital is technically full. The remaining 15% is reserved for erratic and volatile demand at short notice - termed surge capacity. Surge capacity mitigates against higher than normal admissions of day patients or a sudden demand due to a disaster or epidemic and so on. The 85% threshold is also supported by Usman et al (2015), who found that bed utilisation is most efficient when it is not allowed to exceed 85%. Beyond that, problems arise in handling both emergency and elective admissions. Serafini et al (2015), also support this threshold and argue that an optimal balance between care efficiency and safety is achieved at this level.

A high BUR does not always suggest any performance inferences in that BUR can still be high owing to the hospital offering more than the designated volume of services; in fact, the implications of high BUR for average costs and hospital efficiency are ambiguous without information on other service indicators. A high BUR may reflect relatively efficient situations, as when many patients with modest ALOS (that is, a high bed turnover rate) are served. DeLia and Wood (2008) noted that countries with limited surge capacity tend to have relatively large and growing populations, that is, growth in hospital capacity responds to growth in population. However, it is undeniable that the supply of hospital beds drives utilisation and, where there are more hospital beds per capita, more people can be expected to be admitted (and readmitted) although higher re-admissions rates are associated with poor outcomes. The downside is that this can be very costly and serves to discourage the notion of efficient use of resources in the wake of growing populations.

From above, it is clear that there is a conundrum when it comes to BUR. It is sensitive to demands in health care services for example, if the demand on hospital admissions were to decrease (assuming that populations are getting healthier), then would the hospitals would require fewer beds? If so, that would lead to a contraction in BUR, presenting a complete contradiction. The question is what causal link exists between population growth parameters and the BUR demand? In addition, how does that impact manifest itself in other hospital operations and indicators? Strategies for managing BUR differ across settings. In the UK, it is kept low due to a four hour target on admission to discharge or refer to another section of the hospital. The technique involves the treating doctor estimating the date of discharge and profiling any deviations – the result is one can model BUR and ALOS but doing so regularly would be cumbersome. DeLia and Wood (2008), showed that BUR based on annual or monthly data can be misleading because of daily variations that may require smoothing of surges in demand, for that reason GDoH (as with this research) adopted quarterly time intervals.

In South Africa, given the skewed staff establishments (in favour of the private sector as earlier presented); a four hour target on admission to discharge or refer to another section of the hospital in public hospitals could place undue pressure on the already strained staff. In an attempt to focus on the four hour target and given the perceived inferior quality of care in the public hospitals already, such an approach may not be fruitful, but more research on the concept is necessary; if well supported and managed, the approach could potentially decrease the demand on BUR (and ultimately decrease ALOS). Of course, all ethical guidelines would need to be upheld.

In investigations on the impact of BUR on the operational cost of health facilities in France, Boussabaine et al (2012) concluded that the cost per bed was a dominant factor in assessing performance of health care facilities. Yet, the assumption that low BUR would lead to low operational costs was found to be problematic in that one would then have to find latent operational cost determinants in order to detect patterns of cost occupancy in hospitals. Generally, though, the complexity of the health care configuration (its size and the difficulty associated with collecting data and interpretation of results relating to the cost structure) as highlighted by Mustafee et al (2013), complicates efforts to apportion causality to the cost structure of providing health care services efficiently.

Boussabaine et al (2012) also identified important elements or latent variables that are predictors of BUR and operational performances applicable in a tertiary / central hospital such as the service package, nature of specialised services, type and number of specialists and the level and extent that technology is in use at that facility; such findings resonate with those by Nathan and Rautenbachet (2014). By using a variety of tools such as correlation analysis, analysis of variance (ANOVA), ordinary regression techniques and general linear models (GLMs), Boussabaine and colleagues (2012), modelled the relationship between BUR (as the dependent) and operational costs (water, internal and external maintenance) to form an efficient resource framework. Such an approach is recognised for establishing general associations but not causality. In particular, the effect of predictor variables on the response can be determined, but such an approach cannot ascribe cause and effect. This is important in that associations may exist even on attributes that do not Granger-cause each other and / or vice-versa. For example, statistically, cross-correlations examine the correlational manner two variables move in time even where at times; one possibly is not actually the cause of the other despite seemingly moving in the same direction. Parallels with this research is that ExPDE has as its numerator, total hospital costs per quarter and includes operational costs such as above, salaries paid out, costs of medications and consumables and the denominator is the PDE, a proxy for the number of 24-hour patients seen, that is the equivalent number of patients in care for 24 hours.

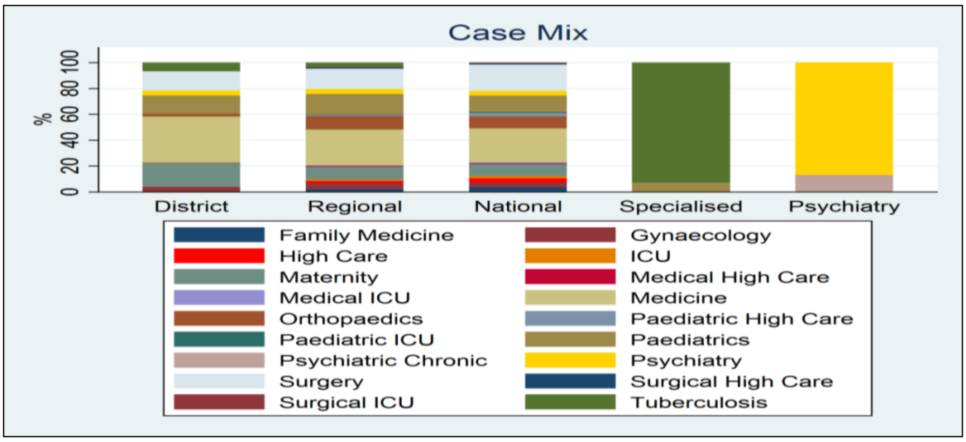
Due to the ever growing demand and budgetary constraints facing countries word-wide, there is a need to control growing health care costs globally (Vitikainen et al, 2010; Kuwabara et al, 2011). The need to manage BUR becomes increasingly essential. Apart from the lack of scientific evidence on the impact on costs, Litvak and Bisognano (2011) showed that with improved and more efficient BUR monitoring, hospitals in the USA managed to reduce staff stress levels, lowered rates of medical error and reduced incidences of medical malpractice. Within the OECD countries for instance, the number of hospital beds per capita has slightly decreased in the last decade, and this has been driven partly by progress in medical technology, which has enabled a move to day-surgery and reduced the need for hospitalisation (OECD 2011a). The reduction in hospital beds has been accompanied in many countries by a reduction in hospital percentage discharges and lowered ALOS. In the case of OECD countries, only in Korea, Greece and Turkey has the number of hospital beds per capita grown between 2000 and 2009 (OECD 2011c). South Africa is not a member of the OECD, but she cooperates with OECD's BUR strategies.

Whilst a hospital bed can be regarded as a unit upon which average values of all costs for treatment protocol can be premised on (based on specific assumptions); BUR and ALOS are often regarded as measures that reflect the functional ability of a hospital. ALOS is often used as an indicator of efficiency and is in all likelihood, the single greatest contributor to public health care expenditure (OECD 2011a; OECD 2010; Zemencuk, Hofer, Hayward, Moseley and Saint, 2006). Eliminating inappropriate hospital stay could translate to a decrease in both ALOS and BUR and therefore, free up resources for more patients. For that reason, ALOS is regarded as a good measure of hospital performance and a proxy of resource usage. ALOS is also a function of the discharge rate and as found by Usman et al (2015); there is a significant association between ALOS and nature of diseases as well as between ALOS and gender.

In South Africa, the calculation of ALOS includes days and discharges of healthy babies born in hospitals whereas, in most developed countries those are excluded. Within the OECD countries, babies (including neonates) are excluded otherwise they would actually reduce the ALOS (OECD 2011a). Over the past decade, ALOS in all OECD countries has fallen from 8.2 days in 2000 to 7.2 days by 2009 (OECD 2011a,d). Several factors explain this decline, including the expansion of early discharge programmes which enabled patients to be discharged but continued to receive follow-up care. For the OECD countries, profiling ALOS along specific diseases or conditions substantially removes the effect of case-mix and projects a more holistic picture of hospital efficiency. In the local context, home based care and ward based outreach teams provide for similar interventions at home and community levels. As a result, it is more informative to examine ALOS by clinical area or condition however, the impact of such interventions on ALOS in hospitals is yet to be scientifically quantified in the local context.

The distribution of case-mix by breakdown of ALOS by speciality, clinical area or by level of care shows a greater proportion of patients are medical and maternal patients. Surgical and orthopaedic patients contribute more compared to other patients as shown in Figure 2.2 below (Van Schaik, Madale, Day, Cois, Moodley, Massyn, Padayachee and English, 2014). No data is readily available at central hospital level; yet in order to accurately calculate the financial impact; data on the mix and volume of products consumed must of necessity be available.

Figure 2.2: *Caseload mix at all hospitals.*



Source: In-depth analysis of the Gauteng Province Hospital Efficiency indicators (2008/09 to 2012/13)

Hibbert et al, 2013 showed that reducing ALOS by increasing BUR would not only increase the turnover rate but also would extend hospital benefits to a greater number of people. In such instances, long hospital stays raise questions regarding efficiency and should provoke closer scrutiny. However, it is difficult to use ALOS in isolation as a direct indicator of efficiency because without information about case mix and severity and in the absence of standard treatment practices and treatment protocols for the same cause, there will always be variations. Variations between physicians of the same department, between hospitals in the same set of service packages and between provinces. Even after adjustments for case-mix and severity are made, interpretation would still be dependent on social and economic variables beyond the hospital's control (WHO, 2003). Crude adjusted measures nevertheless, do compensate for the fact that hospitals treating patients with greater severity would be more prone to experiencing for instance more deaths or higher complication rates, irrespective of how good they might be performing.

It is imperative however, that as a part of good hospital management practice, an effective strategy for allocating beds in a hospital exists (Usman et al, 2015), as that feeds into the narrative of profiling ALOS by clinical area or condition. For instance, a persistently high ALOS could be indicative of patients spending too much time in hospital, possibly due to problems with timeous referral to higher levels of care or to long-term chronic care facilities, inappropriate or incorrect treatment (resulting in longer recovery times), or a failure to discharge patients which would indicate inefficiency (Van Schaik et al, 2014).

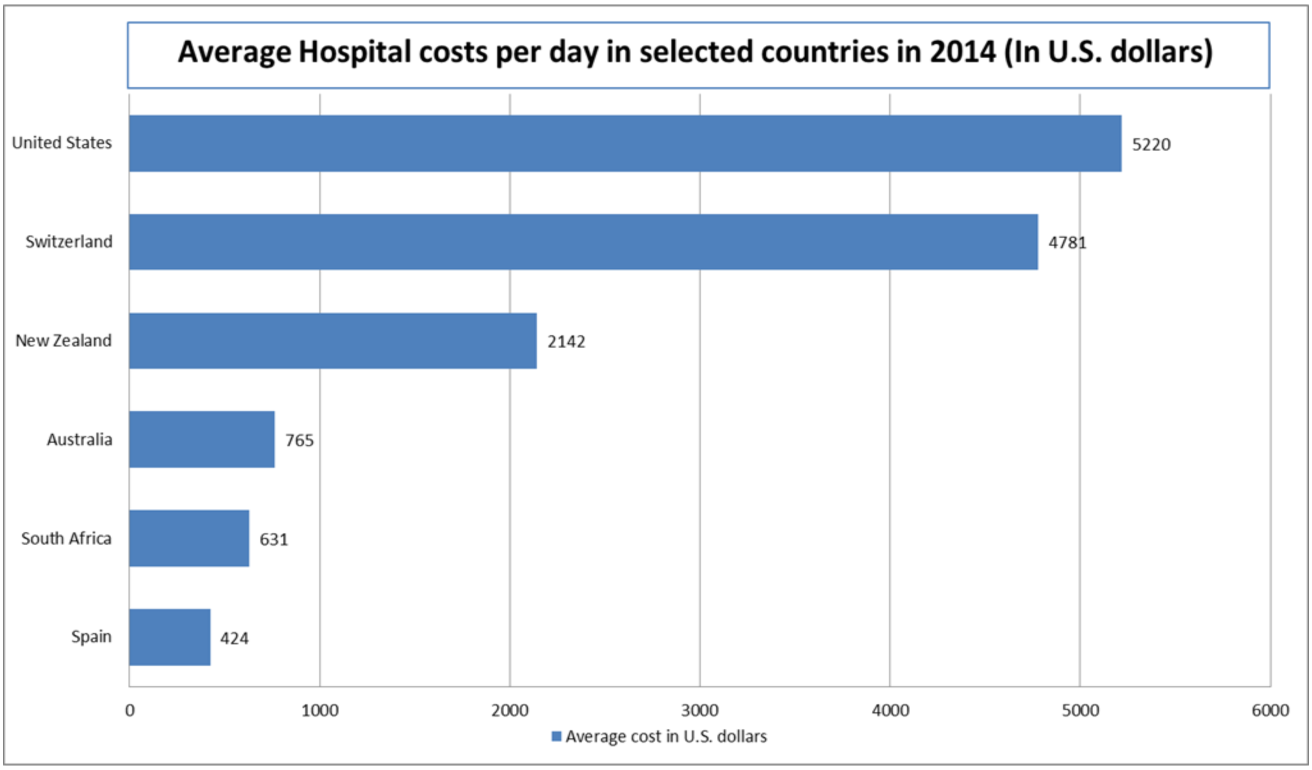
Singh and Ladusingh (2010) determined that for the same case-mix level, ALOS in private hospitals was significantly lower than in public hospitals irrespective of clinical condition. The latter could possibly be due to insufficient staff to discharge patients timeously or due to specialist type procedures being done by visiting specialists. Kuwabara et al (2011) showed that monthly per capita expenditure was significantly and negatively associated to ALOS. That research showed that the more patients with a higher ALOS requirement a hospital admitted; the more ALOS-efficient care was delivered. Given that ALOS is an important measure of health care utilisation and determinant of hospitalisation costs, Schwartz and Mendelson (1994) demonstrated that a reduction in ALOS is associated with a decrease in the number of inpatient days. In India, the public and private sectors co-exist but adjustments in the health care system to ease the pressure on the public sector created a mushroom of the private health sector establishments run by corporations. As a result, expenditure on hospitalisation between the public and private sectors differs significantly (Singh and Ladusingh, 2010). The implication being that public hospitals ought to adopt a cost-centre approach if resource tracking is to take effect.

The above suggests that a unit concentrating on severe cases tends to be more efficient than one with fewer severe conditions or patients. More research would be necessary if the causes for that are to be established, but there is the possibility of a positive effect or influence of the more specialised and highly trained staff simply being more concentrated and therefore, more diligent. That study identified risk factors by clinical condition to determine case-load for short, medium and long stay (levels of ALOS) using a negative binomial modelling approach. Such an approach is helpful in determining differences between groups and clinical conditions in ALOS variability, but is far from causal when addressing determinants of ALOS, but benchmarking ALOS by caseload seems reasonable.

Zemencuk et al (2006), demonstrated that ALOS can be positively skewed, with heavy tails showing extreme outliers (possibly due to big variations in case-mix) as many more patients will obviously stay fewer days than the median and fewer patients would have longer stays and even less severe cases extending way beyond the median. One can still argue that if BUR and ALOS are among the more important indicators of the health services utilisation, then a shorter stay should reduce the cost per discharge and shift care from inpatient day settings. However, shorter stays tend to be more service intensive and demand more resources and logically, tend to end up becoming more costly per day. If not correctly managed though, too short a length of stay could also cause adverse effects on health outcomes or reduce the recovery rate of the patient, leading to higher rates of readmissions which are more expensive ultimately. Chu, Maine and Trelles (2015) suggested for instance that should patients staying in care exceed two weeks on average; the cost implications can be quite severe on the health care system. Such inferences could also help monitor shifts in disease severity as well.

If meaningful and credible inferences are to be realised from hospitals' information systems, then data on levels of utilisation must be available (Alaba and McIntyre, 2012). Alongside that, arises a need for policy decisions to be premised on accurate administrative data such as the ALOS for enhanced hospital performance evaluation and associated budgets (Lu et al, 2015). For example, a reduction in PDE can be attributed to reduction in inpatient days allowing hospital managers to control costs through monitoring inpatient days or ALOS. A better understanding by hospital administrators of the association of the cost in relation to ALOS would enable demand planning, such as how many beds will be available (BUR) and for how long (ALOS), and use that information to develop treatment plans appropriately. ExPDE as a cost indicator, measures the amount and mix of different types of costs such as salaries, administrative costs and all other consumables. The ExPDE indicator also relates to utilisation measures such as the extent to which fixed assets (beds) are fully utilised, that is BUR. Figures 1.3 and 1.4 showed the contrast of South Africa's total spend on health care against performance, yet in Figure 2.3 below showing the cost per hospital day, South Africa's average cost per hospital day is higher than Spain, yet in Figure 1.3, Spain has better performances than South Africa. This contrast requires further investigation.

Figure 2.3: *Cost per hospital day for selected countries.*



Source: IFHP; HCCI © Statista 2016

Generally, expenditure information can mask inadequacies and deficiencies, and gives no bearing as to how it could have been better spent, causality could be more relevant in tracking the determinants and nature of the expenditure, that could be the case with South Africa possibly.

Contrasting Figure 2.3 against Figure 1.3 suggests that health care performance is not necessarily a function of increased costs per bed; for instance Spain's cost per bed is less than South Africa's yet from Figure 1.3, Spain has a much higher performance than South Africa. The magnitude of the difference in cost per bed between Australia and South Africa is rather marginal compared to the difference in performance looking at Figure 1.3. Such inferences suggest that rather the emphasis should be on the efficiency of the resources spent per bed rather than the quantity. Switzerland and the United States' costs per bed are relatively large, but so are the performances as well. That could arise owing to the fact that as presented in Table 2.1:

(i) There are established regulatory bodies to monitor and structure health care performances by constantly profiling appropriate indicators such as the National Health Performance Authority (NHPA)'s Performance and Accountability Framework in Australia, New Zealand's National Health Committee or the USA Department of Health's Human Services' Agency for Healthcare Research and Quality (AHRQ).

(ii) An appropriate number of indicators – Australia has 17, new Zealand has 34 and the USA has 43.

(iii) It must be borne in mind that the USA government only finances 20% of the hospitals and the financing model is such that the bulk of the health care costs are exclusive to government funding, hence the extremely high costs in both Figure 1.3 and Figure 2.3.

If developing countries were to try to be at par with USA, they would run the risk of "excess cost growth", that is health care spending would exceed the growth in the economy. Whilst as indicated earlier by Murray and Frenk (2000) that indicator frameworks are inclusive lists of multiple and often overlapping indicator constructs, there is a need for a balance interms of the number of indicators necessary to achieve appropriate profiling of health care performance. It may imply that the four efficiency indicators that South Africa adopted are too few.

To ascribe causality appropriately, it is necessary to have as many indicators as necessary to capture as wide the variability as possible. These are sampled and profiled, cost variables such as ExPDE, reflect whether a hospital or health care facility is in general, optimally managed. ExPDE can be regarded as a measurement of efficiency (technical, allocative, scale and cost) but, in light of the inadequacies and deficiencies presented by expenditure data if examined from a single perspective, Violán et al (2013) recommended that research using other indicators is necessary and so quite a number of auxiliary or proxy information must be collected. Braspenning, Hermens, Calsbeek, Westert, Campbell and Grol (2013), emphasised that knowledge as well as a rigorous system of indicators is a basic step in stimulating changes and improvements in health care.

A system of indicators such as the National Framework of quality indicators for public hospitals in Greece uses efficiency indicators together with some patient centred auxiliary variables. These include length of stay, hospital bed coverage, admission / discharge rate, cost of inpatient services per patient day (ExPDE), tests ordered at the emergency room per patient and Caesarean section rate (CSR) (Simou et al, 2014). This research study will investigate as a part of auxiliary variables; these indicators, as explained in greater detail in the variables section of methodology are Inpatient days (IPD), Total headcount (THC), Outpatient headcount (OPD), Casualty headcount (CH) or Emergency room headcount (ER) and Inpatient separations (IPS). In the case of South Africa, given the current state of public hospitals there is a need to ensure that apart from public hospitals operating within budgets, managers are sufficiently empowered to exercise responsibility and accountability for determining and managing a whole range of indicators for which they are held accountable.

Resource tracking of expenditure in hospitals enables the Provincial Head Office to monitor and assess whether (i) spending is appropriate (ii) there is harmonisation and alignment of strategic objectives, interventions and activities with expenditure (iii) the extent of the financing gap if any, so as to improve the allocative decision-making and guide resource mobilization efforts. Efficiency indicators can provide evidence to enable the above, but implementation of indicator syntheses is a complex process and requires a thorough exploration of the processes underlying a particular service, assessment of a myriad of issues combined with appropriate scientific developmental methodologies (Vuk, 2012). A research study by Van den Bergh (2009), made recommendations on how managers can utilise DHIS data for evidence-based management, but the focus was restricted to clinical outcomes and not the entire value chain of hospital operations as sought in this study.

Research carried out so far, such as examining the relationship between health care expenditure and health outcomes, though focused on evidence and caveats for causal link, tended to focus on linkages to clinical outcomes but not on managerial aspects such as how much should be spent - in relation to patient type and numbers, (Nixon and Ulmann, 2006). Generally, current research seems to be skewed towards measuring the performance of clinical outcomes with fewer studies focusing on underlying theories and concepts, or empirical studies on the use of indicators for quality improvement (Klazinga et al, 2011). In order for management to identify strategic organisational units, monitor and improve performances on activities performed, identify bottlenecks, implement budgeting in a more efficient manner and to distinguish between non-discriminatory factors of poor performance; it is necessary that a resource framework that undertakes an in-depth investigation of the causal nature between expenditure and the health outputs is first realised (Bonca and Tajnikar, 2010).

The Caesarean section rate (CSR) in South Africa is calculated as the ratio of deliveries by Caesarean section (C-section) to the total deliveries that took place in that facility per unit time (quarter in our context). That makes the indicator a facility-based indicator. C-sections are an important indicator of appropriateness of care and a proxy for the capacity and availability of resources as well as the clinical management protocols in use (Betran et al, 2015). It is one of the key maternal health indicators used in the evaluation of safe motherhood programmes and is used to track obstetric performance (Nathan and Rautenbachet, 2014). An estimated 18.5 million C-sections are performed annually worldwide (Chu et al, 2015), at times resulting in increased maternal mortality, maternal and infant morbidity as well as increased complications for subsequent deliveries. It has been noted that the rate of C-section deliveries varies enormously from one country to another mainly because of substantial differences in resources and traditions (Dahl and Rosseland, 2015). As of 2014, the C-section rate world-wide was estimated at approximately 14.8% per 1000 live births (Zizza et al, 2015).

The world-over, an increase in C-sections is evident with no clear scientific basis as to what is driving it. A similar trend is also observed in South Africa (Monticelli, 2012). Nationally South Africa's C-section rate is reported as 23.1% for the period between 2011 - 2013 (Gebhardt, Fawcus, Moodley and Farina, 2015). South Africa does not base the C-section rate on 1000 live births as is the norm in most countries, but uses the total facility deliveries as the denominator, making comparisons less straight forward. In India, C-section rates are based on the numerator of all the deliveries, including home and institutional deliveries (Narzary, Tsawe and Susuman, 2015). If India used the same denominator as South Africa (total deliveries in the facility as the denominator), the effective C-sections rate would be much higher and quite different.

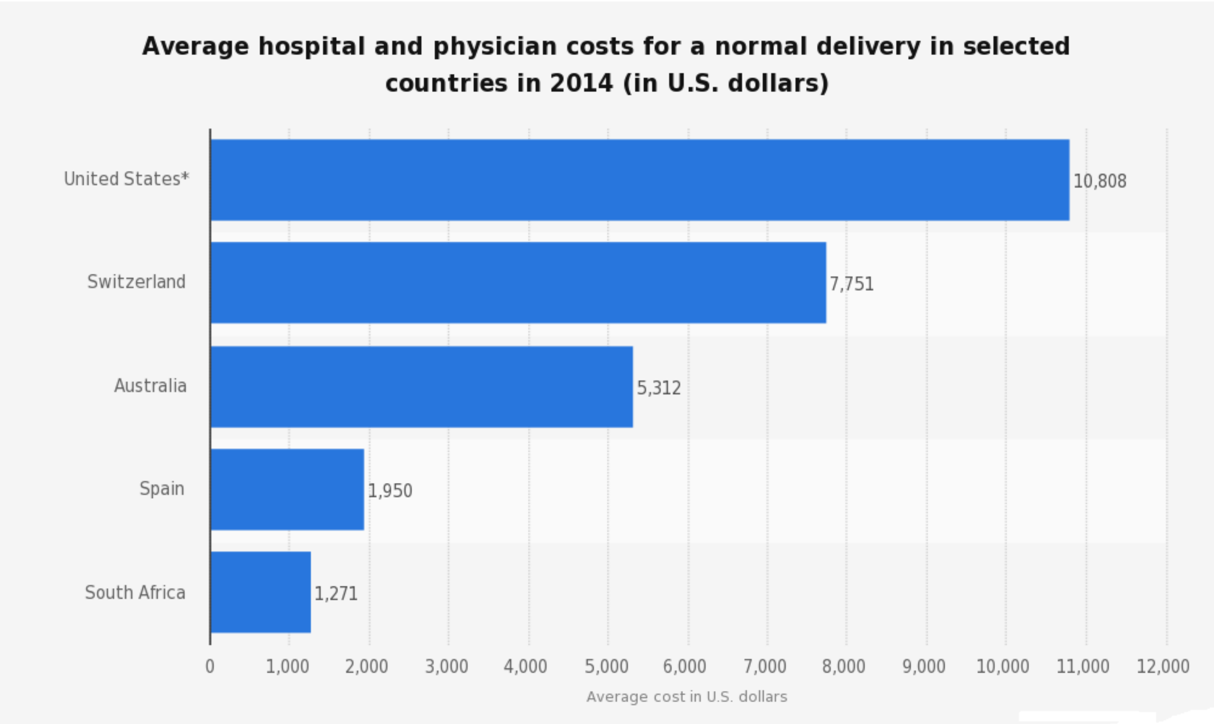
The facility indicator has a disadvantage in that it does not necessarily mimic obstetric issues and trends in the underlying community or geographical population serviced, as such there is a danger of over-estimating obstetric effects within the population. In their study, Nathan and Rautenbachet (2014) determined that even though C-section rates in Gauteng had stabilised within central hospitals, the rates should be monitored and evaluated as they could be indicative of changes in the burden of disease profile or the complexity of maternal cases and access to maternal health care. Since 2000, only two countries Finland and Iceland, have slightly reversed the trend of rising C-sections. According to Zizza, Tinelli, Malvasi, Barbone, Stark, De Donno and Guido (2015), C-sections percentages vary between 0.4% and 42.3%. In only three countries do C-section rates exceed 15%, namely Iran (Middle East), Egypt (North African) and South Africa (sub-Saharan) regions respectively. In Egypt, the C-section rate is 22%, and is affected by factors such as birth weight, mother's age and education, birth order, residence and antenatal visits (Khawaja, Kabakian-Khasholian and Jurdi, 2004).

Khawaja et al, (2004) determined that complications at birth were more significant determinants of C-sections in public facilities whereas demographic characteristics were more important predictors within the private facilities. The study also determined that elective C-sections were more prevalent with the affluent members of society. Countries such Brazil, the Dominican Republic, Iran and Turkey are known to have vast differences in access to public health but they still act to curtail the ever rising C-section rates. In the UK C-section rates have increased to 25% (Dahl and Rosseland, 2015). Boussabaine et al (2012) found higher C-sections in private compared to public facilities in French facilities even though the latter are designed to deal with pregnancies that are more complicated. A 2004 study carried out in 18 Arab countries to investigate the associations between C-sections and selected population parameters, identified female literacy and poor location, that is a lack of access to appropriate obstetrical intervention when required (Jurdi and Khawaja, 2004) as significant determinants. It also established that the patient’s liberty and participation in medical decision making (such as a women rights issue) was a factor behind the surge in C-sections. It has been a trend especially in developing countries, that the rich have more C-sections than actually necessary compared to the poor (Victora and Barros, 2006).

In January 2015, Brazil unveiled new rules that would affect nearly 24 million Brazilian women who have private health plans that cover obstetric services. The rules were promulgated after it was noted that 84% of births covered by private health plans were C-sections compared with 40% of total births in Brazil's public hospitals. The rules aimed at stemming a perceived epidemic of C-sections. According to the new rules, health insurance companies were required to provide users with information about the percentage of C-sections performed by individual doctors and hospitals. In South Africa, there is anecdotal evidence that C-section rates are significantly higher within the private compared to the public sector.

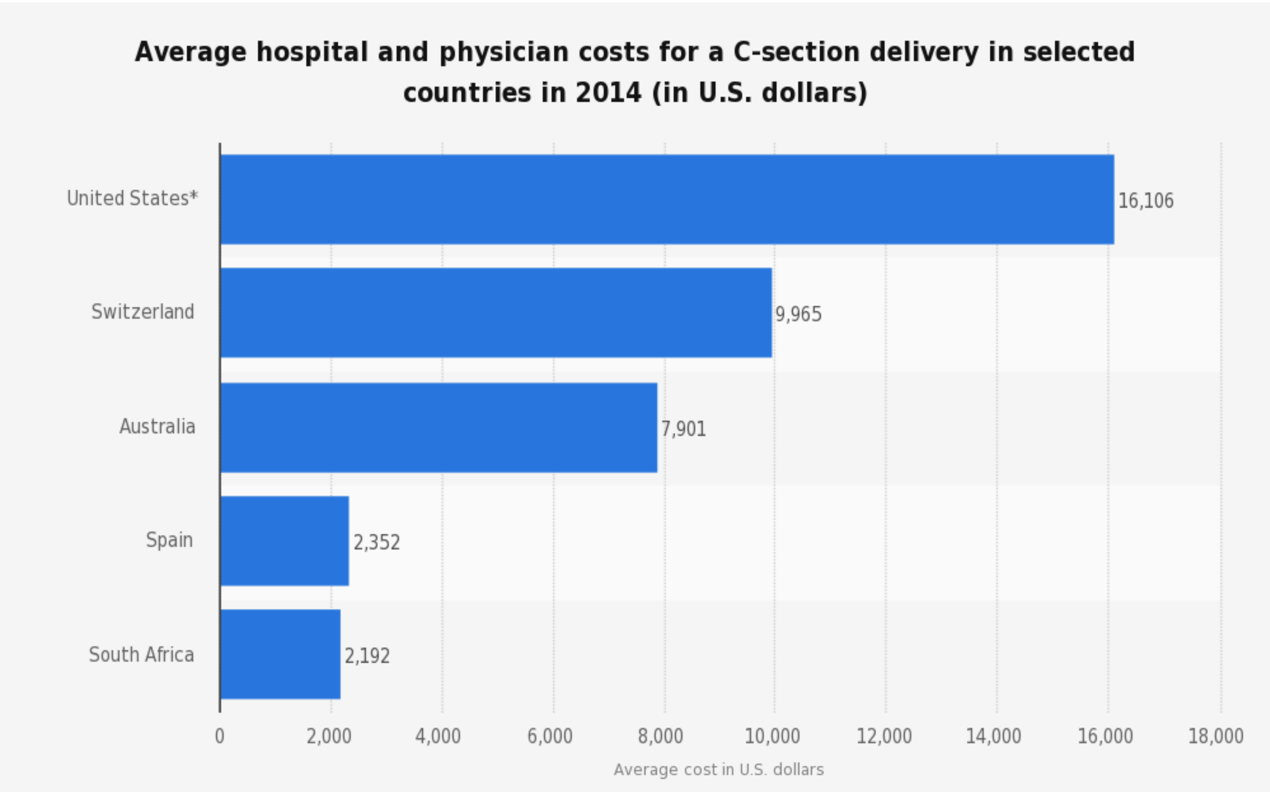
Nathan and Rautenbachet (2014) determined that in Gauteng, the highest average C-section rate occurred at central hospital level (42%) with SBAH having the highest rate (55.5%), followed by CMAH (43%). DGMAH (34.5%) and CHBAH (33.3%) had the lower rates (see also page 146 for 2012 / 2013 C-section rates). It must be noted that in a functional hospital referral system, only the complicated cases (that is high-risk pregnancies) should be referred to central hospitals. This is because from primary level to secondary or tertiary level hospitals, the scale of costs increases and so only a few normal deliveries should occur at central hospitals for the purpose of teaching. If that is adhered to, then by implication almost all deliveries should be C-sections at central hospitals and the facility based C-section rate should be as close as possible to 100% for a facility based indicator, whereas the rate ideally could be considered positive if low for a population based indicator. Figures 2.4 and 2.5 below compare costs of normal vs. C-section deliveries, South Africa vs. selected countries based on 2014 prices.

Figure 2.4: *Costs for normal deliveries for selected countries.*



Source: IFHP; HCCI © Statista 2016

Figure 2.5: *Costs for C-section deliveries for selected countries.*



Source: IFHP; HCCI © Statista 2016

From Figures 2.4 and 2.5 above, one can infer that in South Africa, a delivery by C-section costs 72.5% more compared to a normal delivery. That percentage is 20.6% in Spain, 48.7% in Australia, 28.6% in Switzerland and 49% in the USA. The differential cost between a normal and a C-section delivery is useful in decision-making; but is often made by-passing clinical imperatives for instance the more affluent women often opt for C-section as it's more predictable and manageable on the part of the physician. That however creates several problems in that firstly, it makes the indicator no longer a measure of obstetric issues and trends in the underlying community resulting in the over-estimation of true obstetric effects. Secondly, in the case of South Africa, given the high levels of health care inequality mentioned in chapter 1 and the fact that the vast majority of the population depend on the state; the state picks up a heavier than necessary price tag. For instance, in 2010 South Africa spent US$12 241 688 on unnecessary C-sections (Gibbons et al, 2010).

Factors that impact on and influence the choice for C-section delivery are many and varied; foetal distress in advanced maternal age (AMA) is among the more common cause of C-sections (Benli et al, 2015). Other factors include age and nutritional status which, broadly speaking are a case-mix issues (Chu et al, 2015). In India, researchers such as Singh and Ladusingh (2010), Narzary et al (2015) have shown that the number of C-sections within the private sector tended to be markedly higher owing to the poorly equipped public health institutions in a very populous nation. In Nigeria, areas that serve as a nucleus of the referral patterns in regions are likely to receive high risk cases including repeat C-section cases (Hilekaan et al, 2015), as a result, distinct positive relationship between socio-economic conditions and C-sections has been established in certain communities including positive association to the household wealth index (Narzary et al, 2015). Other associations determined included:

- A positive relationship between educational level and the number of C-section cases.
- Low age at marriage or at first birth, this resulted in a greater likelihood for a C-section.
- A history of previous birth(s) through C-sections was also a predominant factor.

For a population based indicator (such as the baseline of 1000 live births); too high a C-section rate may be indicative of problems with the hospital referral system but inferences are far from being straight forward for a facility based indicator, as is the case with South Africa. In view of the improvements in clinical obstetric care and in the methodology to assess evidence, the need to revisit the recommended C-section rates, apportion causality and model the relationship to efficiency and effectiveness has always been an area of interest. In 1985, World Health Organisation experts recommended C-section rate of 10-15%. That range was criticised as lacking in empirical evidence (Betran et al, 2015) and has recently been revoked; and so the debate on the ideal C-section rate is still a matter of on-going research.

Therefore, there is a need and gap in determining what the ideal C-section rate should be in the case of South Africa by level of care. As a result, a need arises for further research to determine the norms for acceptable C-section rates ranges across all levels of health care (Nathan and Rautenbachet, 2014). What is nevertheless clear is that apart from pregnancy complications, C-sections will always have a technical demand from both patients and doctors. Patients believe C-sections are faster and more controlled. As for the doctors, C-sections come with a lower workload compared to the aftercare required after normal vaginal delivery, as well as the easy of predictability. However, whilst C-sections are required in some circumstances, their benefits in comparison to normal deliveries, especially for uncomplicated deliveries, is still a matter of debate in view of cost differentials for poor resource settings (Chu et al, 2015) and as evidenced by Figures 2.4 and 2.5. The key questions researchers should seek to address include reasons and causes as to why C-sections are the increase, profiling the non-clinical determinants of C-sections as well as determining the appropriateness of C-sections that are not medically necessary. Koechlin et al (OECD 2011b) highlighted some of these challenges.

Generally, the provision of uncomplicated deliveries at central hospitals must always be monitored as there are unintended consequences of distorting the cost structure of service provision at that level as the true adjustment factors become masked. However, through appropriate modelling, analyses can enable better resource allocation and management of the budget through assessing how many patients will require theatre treatment and how long they might stay in care or theatre. In so doing, the number of theatres required can be calculated and so on (Mustafee et al, 2013). Such considerations for instance, require BUR and ALOS and C-sections to be modelled and causality determined in respect of local environment and context. In the USA, the Department of Health and Human Services at some point set a target to reduce the rate of C-sections to 15% in an attempt to reduce expenditure. In South Africa, a reduction in uncomplicated C-sections at central hospitals would free specialists to attend to other areas given the skewed distribution of HRH (specialists included) against state hospitals as earlier on indicated in chapter 1.

The use of hospital efficiency indicators for decision-making and apportioning appropriate interventions in public hospitals is currently constrained. Even though efficiency information is being regularly collected, inferences and patterns are seldomly understood. In fact, as earlier on indicated, not much is known about the applicability of efficiency information in hospital settings (De Korne et al, 2012). Also within the body of literature, many areas of indicator synthesis remain unaddressed. For instance, in October 2014, WHO admitted that the association between C-section rates and other health outcomes could not be determined and that clinicians and administrators struggle to monitor C-section rates in a meaningful, reliable and action-oriented manner (Betran et al, 2015).

2.4 HOSPITAL EFFICIENCY AND PERFORMANCE ACCOUNTABILITY MODELS

The link between hospital efficiency designs and associated gains has long been a grey area and one that has not been thoroughly researched on (Arah, Klazinga, Delnoij, Ten Asbroek and Custers, 2003). In fact, the existence and the effectiveness of any linkages is often assumed rather than investigated, and several barriers are cited in literature for that:

- Problems intrinsic to the indicator.
- Problems with the nature and quality of data that is collected.
- Problems with the use and interpretation of the data.
- The confounding influence of organisational and contextual factors.

Indicator attributes such as efficiency and effectiveness do not occur in isolation, but usually forms part of a suite of levers of hospital performance of 'formative' and 'reflective' indicators (Veillard et al, 2005). The authors regard formative indicators as causative or leading to changes in the value of the latent variable or construct. Reflective indicators are regarded as effect attributes that is, are the results of changes in the latent variable. The cause - effect nature between indicators and performance dimensions constitute a vital link yet it is rarely cited and so arises the need for a body of work, to examine that, as well as the models that respond in a manner that addresses the concerns above. Whilst addressing the above should support the interpretation of indicators and possibly guide intervention strategies, it does little to ascertain attribution.

Hibbert et al (2013) reiterated the support for, and the articulated benefits derived from having a health care system performance framework which aligns to the broader strategic goals and priorities of the health care system, and that it be structured according to a number of domains. Their research laid out key information on criteria underpinning indicator frameworks:

- Being explicit about the target population of published performance data.
- Learning from robust indicator development processes from a wider perspective.
- Enhancing existing PAF's strengths.

In addition to focusing on enhancing the causal relationship which has not been well understood between costs and efficiency (Jha et al, 2009), another possible area of weakness that any indicator performance models must not fail to address is the purpose of the indicator/s. Also, the formulation of efficiency indicator models should avoid the exclusion of measures of governance and policy formulation. This is accommodated in part in this research by grouping and examining indicators in categories provided for by the package of hospital services as per applicable legislative mandate/s.

Developed models must allow users, managers in particular, to identify causes (as opposed to just areas) of poor performance or diminished efficiency and thereafter, to implement process changes. Existing international frameworks developed within the last decade have varied in number, dimensions and intent. The most prominent international frameworks as revealed by Simou and colleagues (2014) include:

- Performance Assessment Tool for Quality Improvement in Hospitals (PATH).
- International Quality Indicator Project (IQIP).
- European Public Health Outcome Research and Indicators Collection (EUPHORIC).
- Safety Improvement for Patients in Europe (SImPatIE).
- OECD’s Health Care Quality Indicators (HCQI).

Whilst highly regarded, the above frameworks focus almost exclusively on health outcomes and patient safety in contexts not applicable in some respects, to the South African situation. For example, the funding mechanism in USA from which most existing quality indicator sets originate from, is not wholly tax dependent as is the South African one, which operates on less than 10% cost recovery for patients capable of paying hospital fees. Hence, there is need to adopt an analytical framework most suitable to local dynamics as there could be non-discretionary variables that hinder hospital efficiency; that may not necessarily be under the control of the hospitals (Lobo, Ozcan, Lins, Silva and Fiszman, 2014). Alaba and McIntyre (2012), argue that there are strong benefits in monitoring process measurements within a hospital as close to the point of care as possible. Given that measurement is central to the concept of hospital performance and provides a means to define what hospitals actually do, capturing costs at ward level would enable and enhance efficiencies.

A move towards cost-centres is envisaged but however; the financing model in the South African public health care differs vastly from those of the developed countries in that efficiency in South African public hospitals is not a function of financial gains as highlighted in the section on delimitations on page 40.

A carefully conducted process evaluation is a good scientific way to shed light on outcome evaluation results and explore various interpretations of the findings. Trends and inferences from the DHIS profiles of the big four indicators are to be correlated with questionnaire results at every stage of the analysis plan to ascertain the specific and measurable descriptions of a change initiative that forms the basis for strategic planning and decision-making. The research methodology will build on the work by Nixon and Ulmann (2006), by methodologically evaluating the impact of lagged effects and by making use of large lagged panel data that should increase the validity of results.

2.5 CHAPTER 2 SUMMARY AND CONCLUSION

This chapter of the literature review triangulated information on the importance and influences of performance indicators and was guided by evaluation in Figure 2.1. The indicators should be broadly representative, covering a wide range of strategic and operational issues and should therefore be understood as a group of measures. What is also coming out of the review is that indicator frameworks are complex to design because they are structured according to multiple dimensions and that most dimensions contain a combination of context, process and outcome assessments. Though generally it is better to assess performance using all three; process measures are usually linked to outcomes whilst outcome measures (mostly involve a time lag), gauge impact as a single indicator and that holds little meaning if mutually exclusive to other indicator domains.

There are major differences in the philosophy and number of indicators as far as countries' indicator frameworks are concerned. For some countries, the frameworks are premised around reporting and accountability, whilst for others around formative gains. That may not be a problem, but it implies contradictory inferences over the same indicator. A case in point is when C-sections are thought to minimise the risks that result in catastrophic birth injuries resulting that lead to litigation (Deutchman and Roberts, 2003). Such a notion pushes the C-section rate upwards and when that happens, tracking of obstetric complications in the population is lost, yet that is probably the main reading expected from the indicator. So one gets a high C-section rate that has nothing to do with obstetric complications as a result.

Efficiency or management indicators measure how hospital resources are being spent and are ideal for the PAF designs. ExPDE measures and compares the inputs (total financial resources) with the outputs (volume of patients seen) and provides a means of benchmarking comparisons for hospitals offering similar package of services. It is a composite process indicator in that it links financial data with service-related data from the hospital admissions. The statistic depicts average costs of a hospital stay for an equivalent 24 hour patient in care and reflects the extent to which the hospital is being optimally managed. BUR provides a measure of the proportion of bed-resources available for delivering services and is an important parameter for cost reduction and of immense relevance in effective decision-making. ALOS is also a function of the discharge rate and is regarded as a good measure of hospital performance and a proxy of resource usage. C-section rates in the context of South Africa are a facility-based indicator used to track obstetric performance, appropriateness of care and a proxy for the capacity and availability of resources. Strategies for managing activities measured by efficiency indicators differ across settings with no clear scientific basis for attribution, the following is nevertheless apparent:

- Use of indicators should identify effective administrative activities or otherwise, in hospital management (Mihut, 2013).

- Lagging effects in health outputs and outcomes are known to be difficult to measure, often taking considerable time to manifest (Ludwig et al, 2010). Through understanding causality and attribution in the value chain of the PAF, efficiency indicators can identify opportunities to allocate resources and to improve hospital financial and operational performances.
- In order to strengthen the performance of health care services, managers need information on how well their units are utilising the resources they get (Hernández et al, 2014). To enhance on that, managers will require a deeper understanding of the intervention strategies relevant to operational indicators under the direct control of management.

The greater debate within literature is not about the usefulness of indicators, but rather causality. The application of indicators for management and accountability purposes is hampered by attribution as there is very little if any evidence at all, of causal linkages. As a result, hospital management teams receive voluminous data from a wide variety of sources, but are unable to extract the strategic information they require to make good decisions, a situation which hampers the call for the introduction of evidence-based approaches to health care management. There is therefore a lack of evidence to support the concept of evidence-based management and hence the concern, that application of scientific management principles and emphasis on effectiveness and efficiency in the management of health services permeating systems around the world has not received serious attention in many African countries as raised by Adindu (2013). The more frequent, diligent and appropriate the analyses of efficiency indicators, the more likely that hospital managers could identify the warnings signs of poor performances.

In the absence of the research’s intended objectives, it would be difficult to generate scientific evidence to inform efficient allocation of resources, regulate hospital expenditure patterns or even curb unnecessary expenditure to realise efficiency gains because there would be no control measures scientifically appropriate enough and suitable in addressing the lack of the utilisation of efficiency indicator information. In that context, the literature review makes a case for the development of a comprehensive theoretical model premised on the causality between indicators dimensions and sub-dimensions to determine attribution. Unless some understanding is gained about efficiency measurement and the implications thereof; public health care will continue consuming more and more (financial) resources with sub-optimal outcomes. Contextually and individually evaluated indicators, monitored on a routine basis can serve as the foundation for the strategic planning activities of the public hospitals. Hospital managers would be encouraged in monitoring operations by examining the basic measures of efficiency indicators if they are able to track operational weakness and identify and implement the necessary corrective actions.

CHAPTER 3: METHODOLOGY

3.1 INTRODUCTION

In this chapter, the broader concept of the methodology and the rationale behind the analytical plan are presented, including an elaboration of the attributes and measurement of efficiency in the context of resource management. The associated impact, the unit of analysis as well as the statistical considerations and toolkit are interrogated as components of the research paradigm.

3.2 RESEARCH PARADIGM

Epistemology is the philosophy of knowledge and methodology is concerned with the specific ways in which the knowledge is acquired as well as the accompanying assumptions. The design of a study defines the study type, research question hypotheses, variables, data collection methods as well as the analytical processes to be followed which affects the data type or information that should be collected in order to answer the research question/s. Research designs include descriptive, correlational and experimental designs. The design used in this research is mixed, as both quantitative and qualitative techniques will be used. Johnson and Onwuegbuzie (2004:17) define mixed methods research as "*the class of research where the researcher mixes or combines quantitative and qualitative research techniques, approaches, concepts or language into a single study*". The central element of a mixed approach being the use of both quantitative and qualitative techniques on one or more of the levels of epistemology, methodology and methods; on the logic that methods, methodologies and paradigms are strongly linked.

Quantitative methodology is more relevant when a researcher seeks to study large-scale patterns of a phenomenon with a view to making inferential deductions as with the (quantitative, objective) efficiency data. Qualitative methodology is more effective when dealing with interactions and relationships in an inductive approach, based on empirical evidence such as with the (qualitative, subjective) questionnaire responses of the managers. The continuous nature of efficiency data, the sampling of respondents to a survey questionnaire as well as the statistical analyses in determining causality shall constitute a quantitative orientation. The development of an interpretive PAF that is more descriptive (or narrative) to gain a deeper understanding of the impact of efficiency indicators, shall seek to ascertain attribution as well as the point of view of hospital managers. This shall then be contrasted against scientific phenomena as outlined by Boundless (2014); that is, determining the essence indicator information provides for improving use of resources to improve efficiency in the management of public central hospitals. A major benefit for adopting mixed methodology is that one is able to uncover unexpected patterns and generate new research questions, to refine and gain new knowledge of social processes given that mixed methods are used to enrich understanding of an experience or issue through confirmation of conclusions, extension of knowledge or by initiating new ways of thinking about the subject of the research.

Types of research philosophies (each representing a model otherwise known as a paradigm for the research) include positivism, interpretive and critical (MacKenzie, Kukolja, House, Loehr, Hirsh, Boyle, Sabel and Mehler, 2012). This research follows the mixed methodology approach and Table 3.1 below lists some of the reasons that are applicable and justify the approach.

Table 3.1: *Rationale of mixed research design.*

Reason	Explanation
Initiation	Initial use of qualitative methodology to define the nature and scope of the research as well as give contextual background and to better understand the research problem, helps in drafting research questions, interview questions and questionnaire items
Complementary	Qualitative and quantitative research used together produces more complete knowledge necessary to inform theory and practice
Interpretation	Can provide stronger evidence for a conclusion through convergence and corroboration of findings
Complementary	Qualitative and quantitative research used together produce more complete knowledge necessary to inform theory and practice
Diversity	Can add insights and understanding that might be missed when only a single method is used
Problem solving	Assists in explaining patterns and results that are obtained.
Focus	Qualitative method is useful in focusing on micro aspects of the study whilst quantitative focus on macro issues
Triangulation	A researcher can use the strengths of an additional method to overcome the weaknesses in another method by using both in a research study
Confidence	Can provide stronger evidence for a conclusion through convergence and corroboration of findings

Adapted from: Johnson and Onwuegbuzie, 2004

In addition to the reasons in the table, other reasons include:

- Clarity of purpose, basis and substantive focus, giving direction to the study and a logical basis for explanation.
- Appropriate use and interpretation of quantified coding from qualitative (questionnaire) data elements.
- Awareness of the limitations of traditional methods as they are modified in a mixed methods environment, as well as employing varied methods to model “deviance” or “residuals” that is modelling the distribution of the error term.
- A need to confirm quantitative measures with qualitative experiences, that is the need to correlate trend data and individual perspectives from hospital managers.
- A need to evaluate the impact of efficiency indicator framework given choice of sample and analytical methods.

3.2.1 THEORIES ADOPTED IN THIS RESEARCH STUDY

Positivism is a scientific method that is based on rationale and empirical data (Burke and Minassians, 2002). The various concepts used in positivism paradigm include quantification, hypotheses and objective measures that are answered through observable social reality, rationale and experiences to arrive at the research conclusion. Positivism paradigm is most commonly aligned with quantitative methods of data collection and analyses. The positivist approach accepts that reality is consistent, observable and predictions can be made on inter-relationships and their realities. Moreover, in positivism studies, the researcher is independent from the study and there are no provisions for human interests, thus limiting the role of the researcher to data collection and interpretation through an objective approach. Positivism is a scientific method that is based on rationale and empirical data that give rise to quantifiable observations that lead to statistical analyses (Burke and Minassians, 2002). This implies that positivism dictates that the researcher needs to concentrate on facts for trustworthy “factual” knowledge to be gained through measured observations and offers a mechanistic causality among social objects.

Following the above discussions, the philosophical assumptions underlying this study come mainly from the positivist approach with footprints in interpretive. Justification of the philosophical approach of positivism is quite common with observations to gather numeric data. The positivist ontology believes that the world is external and that there is a single objective reality to any research phenomenon (Crowther and Lancaster, 2008). As a result, the researcher remains emotionally neutral in order to make clear distinctions between reason and feeling. That is, the research seeks to integrate deductive logic with predominantly empirical quantitative methods. On the other hand, interpretive paradigm and critical paradigm are aligned with a mixture of both qualitative and quantitative methods that is known as mixed method (Mackenzie and Knipe, 2006). Interpretive paradigm is appropriate for understanding the world of human experiences, and in such instances, the researcher recognises the impact of the hospital managers’ background and experiences as prescribed by Burke (2007).

The above approach, should allow for the researcher (who by a declaration, is a senior manager within the Gauteng Department of Health) to assume a neutral yet deductive approach. The approach further allows for objectivity and the use of consistently rational and logical approaches to the research. As such, the use of consistently rational and logical approaches and an authoritative inferential deduction on the view that there is a single objective reality to the causality phenomenon will be enhanced. Statistical and mathematical techniques are central to positivist research, which adheres to specifically structured research techniques to uncover single and objective reality. Table 3.2 below shows the rationale behind the adoption of the positivist approach in mixed analyses as advanced by Rubin and Rubin (2011).

***Table 3.2:** Justification for the positivist approach and mixed analyses*

Topic: The Nature of Reality	
Positivist	There is a single, uniform reality that researchers attempt to measure in a precise, objective, and neutral manner.
Postpositivist slant	In some cases, there may not be a single, external truth.
Interpretive Constructionist (Naturalistic)	Meanings and understandings are plural; individuals and groups see and interpret reality through their own lenses. Understanding is subjective.
Feminist slant	Reality is interpreted through gendered lenses, often in ways that reflect existing male/female hierarchies.
Critical slant	Reality has been interpreted in ways that preserve structures of dominance.
Topic: Types of Knowledge Sought	
Positivist	The goal is to obtain theories that are (nearly) universal in their implications. Usually uses quantitative measures to show relationship between a small number of variables abstracted from context. Looking for general tendencies, often ignores the particular.
Postpositivist slant	Since one cannot prove that a theory is absolutely true, postpositivists are more tentative in their conclusions than classical positivists.
Interpretive Constructionist (Naturalistic)	The goal is to describe particular events, processes, or culture from the perspective of the participants, usually using qualitative techniques. Specifies the conditions under which themes seem to hold. Interested in contending and overlapping versions of reality; many truths possible.
Feminist slant	Emphasis is on how gender relations and gender dominance impact social behaviors.
Critical slant	Learns about structures of dominance to work out ways of reducing them.
Topic: The Role of the Researcher	
Positivist	Neutral-objective person with an authoritative voice in write-up.
Postpositivist slant	It is not possible to be absolutely neutral.
Interpretive Constructionist (Naturalistic)	A respectful listener or observer of other peoples' worlds who recognizes that his or her own slant affects what is learned; less authoritative in write-up than positivists, leaves more room for participants' contending or overlapping views.
Feminist slant	A respectful listener or observer who is empathetic toward those being studied.
Critical slant	A social activist seeking information required to repair social inequities.
Topic: Implications of Findings	
Positivist	Data gathering is meant to move toward universal theories and prediction of behavior; information can be used in practice, but that is not the core purpose of research.
Interpretive Constructionist (Naturalistic)	Descriptions and analysis foster understanding of political, social, and cultural processes and practices; may be relevant to theory or may be the basis of proposed action.
Feminist slant	Research is undertaken to increase understanding of gender-based differences and dominance patterns, usually with the goal of reducing gender-based inequalities.
Critical slant	Research is undertaken to describe and explain inequities and injustice and then to provide a guide for social activism.

Source: Adapted from Rubin and Rubin, (2011).

3.3. RESEARCH DESIGN

The design of a research study refers to the analytical plan for defining and selecting data elements, including sources and types of information that will assist in answering the research questions and objectives. The analytical approach presented below defines variables as well as the units and levels of analysis, as well as the methodological concepts such as the sampling and statistical techniques appropriate to the design. It is essential that elements of the research design are appropriately considered right from the start, bearing in mind that there is a postulated interactive structure among research elements. Also, considered are choices relating to units and level of analysis or sampling methods affecting the applicability of analytical techniques, validity and generalisability of research findings (Dolma, 2010).

In the context of this research, the response cannot be expected to be independent and uncorrelated in that expenditure overlaps from month to month and therefore will suffer lagging effects. Also, efficiency measures and managers will be assumed to be influenced by the hospital's structure and systems. Simply put, unlike conventional linear models, each central hospital exert a behavioral attribute owing to factors and management attributes peculiar and specific to that hospital only. If that assumption is not applicable, statistical measures to be derived in that regard will indeed show so. Therefore hospitals are to be treated as random effects representing different management and operational factors. The efficiency indicators (for objective inferences) and the hospital managers (subjective inferences) will be regarded as the fixed effects both nested within the hospitals. Given the autonomous and hierarchical nature of the fixed effects nested within central hospitals, and that hospital expenditure data is known to be correlated (month to month or quarter to quarter) and skewed (or non-normal), ordinary or classical analytical techniques are not suitable to model such data.

Generalised Linear Mixed Models (GLMMs) provide a more flexible approach for analysing non normal data when random effects are present and will be used to quantify the size of the effect of ALOS, BUR, C-sections and PDE on ExPDE and to ascertain the extent ExPDE is manipulated by each of them. By examining the application and utilisation of efficiency information across all central hospitals, the question arises as to whether there are influences due to hospital specific characteristics (that is, random effects). The response to that is best undertaken from a modelling perspective through GLMMs the requirement of independent and uncorrelated indicator values of the response (ExPDE in this case) is overcome. To model such a design, Granger Causality Analysis (GCA) is useful in generating unique effects through stochastic dependences among random variables (using lagged values to determine significance effects on the current value of another variable) to the existence of 'causal mechanisms' underlying the data.

3.3.1 ANALYTICAL APPROACH

Public health performance services is the extent to which set objectives are achieved in the provision of specific packages of health services to solve a need on the part of the patient (efficacy) in the best possible way (quality) and in the most economical manner (efficiency), (Ioan et al, 2012). Measurement becomes central for one to efficiently and effectively manage and control expenditure as a part of managerial obligations within any Organisation, hospitals included. Technical efficiency is producing the maximum amount of output from a given number of inputs, or alternatively producing a given output with minimum quantities of inputs. Allocative efficiency occurs when the combination of inputs is that which minimises cost given input prices. Scale efficiency occurs when the production unit is the best possible size at which the optimal technical efficiency is reached. Cost or price efficiency is achieved when the inputs necessary to the production are purchased at the lowest possible price, without sacrificing quality. Overall or optimal efficiency occurs when all the previous conditions are met. An appropriate PAF indicator system, should cover that broad spectrum of activities as part of hospital performance.

3.3.1.1 VARIABLES

Patient Day Equivalent (PDE) is a measure of the volume of 24-hour (from midnight to midnight) patients. However, because not all patients spend a full 24 hours at the hospital (there are day patients, outpatients and emergency room patients who contribute to the hospital workload), there is a formula used to calculate the equivalent number of 24-hour patients. A common weighting for inpatient and outpatient services is required in order to accurately assess the impact of efficiency on patient care (Vitikainen et al, 2010). That is mathematically achieved and catered for by combining the various types of patient groups in the PDE formulae. PDE therefore, is a weighted data element or useful as a proxy for estimating resources for all types of patients in terms of inpatient days which shall be defined later on.

When total hospital expenditure is divided by the PDE for the corresponding period, the result is a weighted data element, ExPDE, which is the response variable in this research. This is a proxy for estimating resources for all types of patients and for monitoring effective and efficient financial management as well as management of inpatient facilities when related to other efficiency indicators. ExPDE compares the total cost as the input measure (financial resources) with outputs (volumes of patients seen) and is a measure of overall efficiency of a hospital. ExPDE can also be regarded as a proxy for the extent of efficiently managing expenditure (consumption of financial resources) within the facility. When examined jointly with other efficiency variables, a picture of the level of efficiency in the management of resources expenditure gets generated. Total hospital budget equals ExPDE multiplied by the PDE. The adoption of the above set of variables is supported and is in conformity with similar study designs in literature, such as that by Lu, Sajobi, Lucyk, Lorenzetti and Quan (2015).

As earlier indicated the DHIS is the routine health information system for South Africa for pooling information, efficiency data included from various sources used in the public health sector. The system collects 500 data elements monthly which are examined for administrative purposes every quarter. The NIDS and PIDS definitions of all indicators including the auxiliary variables are defined as follows:

- Inpatient – a patient who has been admitted to a hospital or other health care facility (on a doctor's order) for at least an overnight stay. Generally, such a patient:
    - Occupies an available staffed bed in hospital for at least one night in the course of treatment, examination or observation and is discharged by transfer out or death.
    - Is a mother who delivers in hospital and whose admission and discharge occurs between successive bed counts, usually overnight.
    - Is admitted as an emergency or urgent case.
    - Is a psychiatric patient (however, as indicated earlier, this category of patients if at all present in central hospitals, are excluded in this research study).
- Inpatient days (IPD) - the total number of days inpatients spend in hospital. The day before an inpatient is discharged is the last inpatient day. A day is the count of all patients occupying a bed at midnight. This indicator monitors effectiveness and efficiency of inpatient management.
- Day patients - inpatients admitted and separated on the same calendar day.
- Total Head Count (THC) - total number of people accessing health care services in that period (quarter by default) and is a proxy for health care utilisation.
- Outpatient headcount (OPD) - total number of patients attending general or specialist Outpatient posts (total number of patients attended to in the Outpatient Department).
- Casualty headcount (CH) / Emergency headcount (ER) - total of all patients attending the casualty department, which are health care service points for the treatment of patients with conditions requiring emergency treatment.
- Inpatient separations (IPS) - sum of inpatient deaths, inpatient discharges and inpatient transfers out such that:
    - Inpatient deaths (total): an inpatient death is a death recorded against an admitted inpatient, including the death of a patient admitted earlier on the same day.
    - Inpatient discharges (total): an inpatient discharge is a patient admitted to a ward that completes an inpatient stay and is discharged out of hospital care.
    - Inpatient transfers out (total): admitted patients transferred to another hospital for immediate admission there.

Total hospital expenditure is taken from the Basic Accounting System (BAS) which collates all fixed and variable costs, that is both administrative and patient billing platforms such as PERSAL, MEDCOM and PAAB.

Tables 3.3 and 3.4 below shows definitions and formulae of the efficiency variables as provided for within the DHIS.

Table 3.3: *Description of efficiency variables.*

Indicator	Definition
Average Length Of Stay - **(ALOS)**	The average number of days for admissions in hospital, monitors both quality and efficiencies in the hospital.
Bed Occupancy Rate / utilisation Rate - **(BUR)**	Proportion of Inpatient-bed days used versus the maximum available bed capacity. The number of hospital beds provide a measure of the resources available for delivering services to inpatients in hospitals.
Caesarean Sections - **(C-Sections)**	C-section delivery in facility is the removal of the foetus, placenta and membranes by means of an incision through the abdominal and uterine walls. As a rate, it is the proportion to the total deliveries in the hospital and is a proxy for quality management (access, care, cost and so on).
Inpatient days **(IPD)**	Total number of days inpatients spend in hospital. A day is the count of all patients in care occupying a bed at midnight, that is during the midnight census. Monitors effectiveness and efficiency of inpatient management.
Total Head Count **(THC)**	Total number of people accessing health care services in that given period. Proxy for health care utilisation.

Table 3.4: *Derivation of efficiency variables.*

Indicator	Numerator	Denominator
Average Length Of Stay - (ALOS)	Total patient days = Inpatient days + ½ Day patients.	Total separations (Discharges + Deaths + Transfers out) + Day patients.
Bed Occupancy Rate / utilisation Rate - (BUR)	Total patient days = Inpatient days + ½ Day patients.	Total usable bed days = number of beds x unit time.
Caesarean Sections Rate - (C-Section rate = CSR)	Total number C-section deliveries in the facility.	Total deliveries = C-section deliveries + normal deliveries in the facility.
Expenditure per PDE (ExPDE)	Total hospital expenditure = all fixed and variable costs.	PDE = (Inpatients + ½ day patients + 1/3 outpatients headcount + 1/3 emergency headcount.
Hospital Expenditure (utilisation based budget)	Total spend on one 24 hr-based patient x the number of 24 hr-based patients = ExPDE x PDE.	

To quantify the size of the effect of ALOS, BUR, C-sections on ExPDE as well as in order to ascertain the extent ExPDE is manipulated by each variable is not only a contribution to the body of knowledge; but also forms the basis of empirical evidence towards targeted interventions and harnessing appropriate control measures. The objective of the research study is to ascertain causality of and impact of efficiency information, and how that can contribute towards a greater understanding of expenditure patterns to enable appropriate management of resources within central hospitals in Gauteng. In turn, that will inform the budget required premised on utilisation dynamics.

Mathematically, the objective is to test through Granger-causality models, whether ExPDE Granger-causes ALOS, BUR, C-sections, IPD, THC (and vice-versa). Secondly, the lag in each case denotes the pressure on ExPDE as well as determination of the rate of growth in the indicators. As indicated, hospital budget equals ExPDE multiplied by the PDE. Now, hospital budgets have for some time, been historically determined only adjusting for inflation every year but with no recourse to what informed the baseline thresholds or the drivers thereof. As a result, it's not known whether funding for public hospitals is correctly aligned to the services they provide or whether the hospitals are providing services confined to available budgets. Deriving a budget exclusive of Activity Based Costing (ABC) remains a grey area, and has not yet been explored via the use of efficiency indicator modelling.

Simply examining parity (if any) between hospital performance by disregarding unique hospital specific characteristics (random effects) such as differences in the supporting infrastructure or geographical service areas around the central hospitals, hospital support network and so on; is a big drawback in that its inherently implied that all aspects across the hospitals are the same, yet this may not really be so (Nathan and Rautenbachet, 2014). Analysis of empirical data from hospital managers regarding their understanding and utilisation in planning frameworks should enhance on an efficiency indicator framework postulated under three domains, these are equity, effectiveness and efficiency. Equity has to do with expenditure being shared based on need across the different groups or types of patients. The research addresses crucial gaps both in theory and the real problems confronting the public health care system in general.

3.3.1.2 Unit of Observation and Analyses

The unit of observation and analysis has been described in section 1.4.1. The four central hospitals in Gauteng, SBAH, DGMAH, CHBAH and CMAH constitute the units of observations. The four efficiency indicators collected per hospital per quarter and the managers within each central hospital are the units of analyses. Efficiency data will be for the objective and quantitative approach and the managers responses will be for the subjective and qualitative approach.

3.3.1.3 Methods

In the case of taking 2 time-series variables at a time **X** and **Y**, the following are defined **X** = each of ALOS/BUR/C-Sections/IPD/THC and the response **Y** = ExPDE. The determination of **p**, that is the lag length for every efficiency indicator on ExPDE, shall be an original contribution to the body of knowledge in addition to the actual parameter estimates and associated effects being derived. Thereafter, a model testing uniformity (using variability as opposed to equality) of efficiency measures across the different hospitals will be examined as well as assessing subjective understanding and application of efficiency information by the hospital managers, within and across the hospitals.

a) GRANGER CAUSALITY ANALYSIS (GCA)

Granger (1969) proposed a time-series data based approach in determining if **X** is a cause of **Y**, which is useful in forecasting **Y** by implying that **X** is able to increase the accuracy of the prediction of **Y** considering only past values of **Y** (Bressler and Seth, 2011). Simply put, variable **X** Granger-causes **Y** if **Y** can be better predicted using the histories of both **X** and **Y** than it can predict using the history of **Y** alone. As to how far back the history, is a measure of the lag. There are three different types of situation in which a Granger-causality test can be applied:

(i) In a simple Granger-causality test there are two variables and their lags.
(ii) In a multivariate Granger-causality test more than two variables are included, because it is expected that more than one variable can influence the results.
(iii) In a Vector Auto regression (VAR) framework.

In this case, the multivariate model is extended in order to test for the simultaneity of all included variables. Assuming having an information set (Y_t, X_t) with the form ($x_t, \ldots x_{t-j}$; $y_t, \ldots y_{t-i}$), then X_t Granger causes Y_t with respect to the information set if the variance of the optimal linear predictor of Y_{t+h} based on (Y_t, X_t) has smaller variance than the optimal linear predictor of Y_{t+h} based only on lagged values of Y_t. That is, **X** Granger-causes **Y** if and only if:

$$\theta^2_1\,(Y_t : Y_{t-j}, X_{t-i}) < \theta^2_2\,(Y_t : Y_{t-j}) \text{ for } j, i = 1,2,3,\ldots 36;\ \theta^2 = \text{variance of the forecast error.}$$

Analysing the two variables together enables testing for interaction as well as avoiding possible specification bias. Hence, one can test for the absence of Granger causality by estimating a VAR model, where *j, i = 1…p* is the difference or lagged effect corresponding to time points in quarterly time points from $t = 1$ (quarter 1 of 2008/9) to $t = 28$ (quarter 4 of 2014/15). The model is given:

$$Y_t = a_0 + a_1 Y_{t-1} + \cdots + a_p Y_{t-p} + b_1 X_{t-1} + \cdots + b_p X_{t-p} + \mu_t \qquad (1)$$

$$X_t = c_0 + c_1 X_{t-1} + \cdots + c_p X_{t-p} + d_1 Y_{t-1} + \cdots + d_p Y_{t-p} + u_t \qquad (2)$$

In the notation of the above augmented regression, (**t-1**) implies **1** is the shortest lag length and (**t-p**) implies **p** is the longest lag length for which the lagged value of **X** is significant. The following Generalised Linear Mixed Model (GLMM) and Linear Mixed Model (LMM) hypotheses will be tested. The null hypothesis is that **Y** is influenced only by itself, and not by **X** in (1) and vice-versa for (2). Testing $H_0: b_1 = b_2 = \ldots = b_p = 0$ against H_A: **'Not** H_0**'** tests that **X** does not Granger-cause **Y**. Similarly, testing $H_0: d_1 = d_2 = \ldots = d_p = 0$ against H_A: **'Not** H_0**'** tests that **Y** does not Granger-cause **X** and in each case, a rejection of the null implies there is Granger causality. U_t and V_t are residuals assumed uncorrelated and representing the prediction errors, when the history of each time series is separately considered.

In the above, equation (1) represents the fact that variable **Y** is influenced by lagged variable **X** and **Y**. In equation (2), **X** is the dependent variable instead of **Y**. The hypothesis to be tested seeks to ascertain (i) whether the extent ExPDE is manipulated by each efficiency indicator is the same across all hospitals or not and (ii) whether or not, at the management level there is ecological fallacy, that is are all hospital managers' efficiency operations the same or different depending on hospital? In testing for Granger causality, 2 variables are usually analysed together (to enable testing for their interaction) and all possible permutations are:

- Unidirectional Granger causality from variable $\mathbf{Y}_t$ to variable $\mathbf{X}_t$.
- Unidirectional Granger causality from variable $\mathbf{X}_t$ to $\mathbf{Y}_t$.
- Bi-directional causality (jointly tested).
- No Causality, **X** and **Y** are only independent if they both fail to Granger-cause each other.

Test Statistics

Granger causality implies the lagged **X** influences **Y** significantly in equation (i) and the lagged **Y** influences **X** significantly in equation (2) above. Therefore, one can jointly test if the estimated effects or coefficients $\mathbf{b}_1 = \mathbf{b}_2 = ... = \mathbf{b}_p$ and $\mathbf{a}_1 = \mathbf{a}_2 = ... = \mathbf{a}_p$ are significantly different from zero. Then the test statistic is the **F**-statistic:

$$F = \frac{SSR_r - SSR_U}{n} \Big/ \frac{SSR_U}{T - (m + n + 1)}$$

where SSR_r and SSR_u are the two sums of squared residuals related to the restricted and unrestricted form of the equation, the elements that form the degrees of freedom are **T** being the number of observations, while **n** and **m** are the number of lags. The same procedure is used in order to test for the inverse Granger-causality relation in equation (2). The most common criteria of selecting optimal lagged length (order) include Akaike's Information Criterion (AIC), Corrected AIC (AICC), Hannan-Quinn (HQ) Criterion, Final Prediction Error (FPE) and Schwarz Bayesian Criterion (SBC), also known as Bayesian Information Criterion (BIC). The smaller the statistic the better, but in testing Goodness-Of-Fit however, the larger the value the better the fit.

Decision rule

Reject $\mathbf{H}_0$ if the p-value is less than 0.05, where the p-value is the probability of observing a difference due to chance under the null hypothesis of independence (no Granger causality in either direction). Therefore, the smaller the p-value, the less likely that any observed difference was due to chance but rather would be an indication of a significant parameter effect (often when standard errors are very small, resulting in large t-statistics). The 0.05 = 5% level of significance, unless otherwise stated, the 0.05 is the default significance level throughout the research.

Statistical programming

A VAR model defines a regression system of models in which each variable is a function of lags of itself and all other variables under consideration, the lags are useful for relationships between variables which are similar. VAR analysis uses Granger-causality tests, impulse responses and forecast error variance decompositions (Lütkepohl and Reimers, 1992). For a multivariate time series, the procedure in STATA (VARMAX) estimates the model parameters and generates forecasts associated with vector autoregressive moving-average processes with exogenous predictors models. Economic or financial variables such as ExPDE often are not only contemporaneously correlated to each other, but are also correlated to each other's past values. The model parameter estimation methods used are Ordinary Least Squares (OLS) as well as Maximum Likelihood (ML) techniques.

Underlying assumptions

(i) The future cannot cause the past, the past causes the present or future (consistent with the notion that the cause precedes the effects as the 'correlation equals causation' fallacy says that one thing preceding another can't be used as a proof of causation).
(ii) A cause contains unique information about an effect not available elsewhere.
(iii) The data series are covariance stationary (mean and variance are time-independent) for the test statistics to have a standard distribution. That is, the mean and variance or auto-variance are constant over the lag length and these remain the same, irrespective of the time point measured (Thornton and Batten, 1985).

Methodological Limitations

As earlier indicated, Granger-causality may produce misleading results when the true relationship involves three or more variables (if both **X** and **Y** are driven by a common third process with different lags, one might still fail to reject the alternative hypothesis of Granger-causality). Also, a complication can exist with interpretations when the lagged length is too long as is the case in the context of this study, then too many lags compromise the power of the test. Furthermore, it must be noted that a causality test is sensitive to model specification as 'spurious' relationships can set in. Limitations of Granger-causality include:

- Most models are dependent on unit of time and observational interval. The significance of the time period is that expenditure tracking and indicator reports are reviewed quarterly. The assumption of covariance stationary implies in a way, that the stochastic process is constant over the determined lag length (**p**) (time invariant) and should, therefore, mitigate as mean and variance are time-independent.
- Secondly, if the interval is not fine enough, two correlated time series may exhibit bi-directional Granger-causality.

- Standard methods of statistical inference may give misleading results if some variables are highly persistent.
- Without modification, standard VAR's miss non-linearities including conditional heteroscedasticity and drifts or breaks in parameters.
- Small VAR's of two or three variables are often unstable.
- Adding variables increases the number of VAR parameters.

At the primary or individual (indicator and manager) levels, Granger-causality between $\mathbf{Y_t}$ and $\mathbf{X_t}$ will be done disregarding the hospital, implying only one source of variation, that is the random error. At the secondary or aggregate (hospital) level, the same will be done but performing the analyses of the primary units hospital by hospital.

b) LINEAR MIXED MODEL (LMM)

The primary units (the 7-year indicator measurements for the quantitative analysis and managers for the qualitative analysis) are collected within hospitals and each hospital has its own postulated unique system. For instance, unique leadership or management traits, unique geographical service areas around it, unique hospital support network and so on. Statistically, those differences collectively constitute the secondary level "random effects" or more simply, the "hospital specific characteristics". This creates a second source of variability in addition to the random error and the additional variation attributable to the random effects / hospital specific characteristics is called "variance components". The goal is to determine if the variance components have a causal effect on the primary units (indicator measurements or managers) or not. Therefore, in this study (i) hospitals are treated as the higher (secondary) level units of variation or random effects (ii) efficiency indicators are treated as primary level/fixed effects (for the quantitative design) (iii) managers are treated as primary level / fixed effects (for the qualitative design). That setup, satisfies the requirement of hierarchical data modelling (Singer, 1998). GCA is then applied accordingly, and contrasting the results will ascertain if the hospital effect confounds causality.

Linear Mixed Modelling (LMM) is a part of hierarchical modelling (that allows for the assumption of independent observations within and across hospitals to be circumvented by taking the nesting structure of the data into account) that allows for the components of the regression parameters to vary among the hospitals. The major difference with ordinary regression models is that in this instance, the primary units are no longer required to be independent as it is assumed that they are influenced by the secondary units (that is, hospitals) where each hospital can have its own unique effects. The goal becomes to estimate and to model the variance components for each primary unit, and if that is very small; it can be concluded that there are no significant differences emanating from the random effect / hospital specific characteristics, or simply all the hospitals are more or less similar and affect all indicators or managers in exactly the same way without confounding causality.

Simply examining parity between hospital managers or the efficiency indicators disregarding random effects / hospital specific characteristics creates some crucial drawbacks as that would imply (i) the hospital specific characteristics and variability are discarded from the analysis whereas those have provided valuable information in explaining the causality including the parameters for the dependent variable and (ii) independence of assumptions of the observations at the primary level (as each are grouped or clustered from a specific hospital) would be problematic to model. The ordinary regression models / classical approach would assume that the hospital plays no role in the managers' interaction with efficiency indicator and assume an even playing field across all four central hospitals. Yet, different hospitals may have different strategies and operational modalities which impact differently on things such as expenditure and management of resources, a gap identified for some time now (Hofmann, 1997).

LMM implies that within a group, the group and its members both influence and are influenced by the group membership (Albright and Marinova, 2010). It is that aspect, termed group effects, which is a part of the impact the study seeks to investigate. Therefore, variability can be partitioned at the hospital, indicator and manager level. One hospital may for instance be severely affected only in respect of the dynamics around a certain indicator, but this may not be applicable for the same indicator in other hospitals (Suzuki et al, 1999) or one hospital may be doing things better and differently from the others. By computing the intra-class correlation, it will be possible to determine the proportion of variance (between hospitals) explained by hospital specific characteristics, that is estimating the portion of total variance due to hospital grouping (that is the variance components). Using hierarchical modeling and introducing random effects in order to estimate primary level units (indicators and hospital managers) as functions of secondary level grouping (hospitals) means that the variance components will ultimately show effects at the hospital level and will help understand practices, culture or even problems at that level.

Using LMM allows for correlated indicator values or managerial characteristics to be modelled taking into account the influence of hospital specific characteristics. The intercept between **Y** = ExPDE and **X** (for example ALOS) will show the estimated average ExPDE controlling for ALOS, whilst the parameter estimate b_{ALOS} will show the estimated average slope representing the relationship between ExPDE and ALOS, that is the rate of increase in ExPDE for a unit increase in ALOS. Random intercept models will allow for provision of heteroscedasticity of the error covariance matrix (due to unconstrained variability between hospitals). In other words, covariance parameter estimates will show the variation of intercepts and slopes across hospitals as well as covariance component representing the correlation between intercepts and slopes which gives a larger matrix to represent the random effects across hospitals with respect to variability in intercepts, slopes and the co-variation or covariance between intercepts and slopes.

If the intercepts are very variable, it will imply hospitals vary in ExPDE controlling for **X** for each of ALOS/BOR/C-Sections/IPD/THC. Also, the hospitals will differ in relationship between ExPDE and that **X**, that is the rate of increase in ExPDE for a unit increase in that **X** will vary across hospitals for **X** (each of ALOS/BUR and so on).

The hypotheses to be tested are that each estimated parameter for the variance, that is the variance component = 0. Many possible error-covariance structures are possible; however the one of interest is AR(***p***), that is autoregressive with a lag of ***p***. This is because, in theory, in the matrix of such an error structure, variances along the diagonal are fairly similar with off diagonal elements reducing indicative of decreasing covariance between errors further spaced in time, symbolic of lagged autoregressive structure (Singer, 1998). The research interest will be to predict ExPDE as a function of the indicators taking into account hospital-level characteristics. An empty model or unconditional means can be specified (Albright and Marinova, 2010):

$$Y_{ij} = \beta_{0j} + r_{ij}$$

Such that $\mathbf{Y}_{ij}$ is the ExPDE in quarter ***i = 1,2,3,…28*** for central hospital ***j = 1,2,3, 4.*** Since there may also be an effect that is common to all efficiency indicators within the same hospital, it is necessary to add a hospital-level error term and this is achieved by specifying a separate equation for the intercept:

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

where γ_{00} is the average outcome (ExPDE) and μ_{0j} is a hospital-specific effect. Therefore the first equation can be re-written:

$$Y_{ij} = \gamma_{00} + \mu_{0j} + r_{ij}$$

or **ExPDE** $_{\text{quarter i, hospital j}}$ = **Grand mean ExPDE** + **Hospital Effect** $_{\text{hospital j}}$ + **random term** $_{\text{quarter i, hospital j}}$

If the variance of r_{ij} is denoted by σ^2 and the variance of μ_{0j} by τ_{00}, then the percentage of observed variation in the dependent variable attributable to level 2 that is individual and hospital-level characteristics, which is the intra-hospital correlation coefficient can be determined by:

$$\rho = \frac{\tau_{00}}{\tau_{00}+\sigma^2}.$$

and the percentage of variance attributable to level 1 i.e. quarterly traits is easily determined:

$$1 - \rho.$$

The null hypothesis for the random (hospital) effect is that its variance is equal to zero, implying there is no significant difference in efficiency indicator variability between central hospitals:

$$H_0: {\sigma^2}_\beta = 0 \ \ vs \ \ H_1: {\sigma^2}_\beta > 0 \ .$$

This estimated variance is known as variance components as already indicated. It is possible to partition the variance in ExPDE according to the ratio of the hospital level variance components.

The ratio of the variance components to the total variance is in fact the intra-class (hospital) correlation coefficient. This gives an estimate of the percentage of variance that is attributable to hospital characteristics. The random hospital effect b_i can be tested for significance that is $\mathbf{H_0: b_1 = b_2 = ... = b_4 = 0}$ against **H_A: 'Not H_0'** given that the hospitals are treated as random effects. The evolution of time = 28 quarterly time periods will be treated as the longitudinal sequencing variable.

However, when applying the LMM to responses from the questionnaire (as opposed to efficiency data elements from DHIS), the response $\mathbf{Y_{ij}}$ = response of i^{th} manager at j^{th} hospital. The above model will be refitted, to test for differences for instance, in understanding, synthesis and utilisation of efficiency information (qualitative) and the hypotheses for each construct or measure will be:

$$H_0: \mu_1 = \mu_2 = \ ... \ = \mu_j = 0 \ \ vs \ \ H_1: \ \mu_i \neq \mu_j \ \ and \ \ H_0: \sigma^2{}_\beta = 0 \ \ vs \ \ H_1: \ \sigma^2{}_\beta > 0$$

That is, to assess if the mean levels are the same for managers across the four hospitals or not. If the first set of hypotheses is rejected, it will imply that the mean level of understanding and utilisation of efficiency information differ across hospitals. One would want to establish the different dynamics were significant differences exist. Non-parametric post-hoc tests such as the Kruskal-Wallis (KW) test become relevant in that regard. A non-parametric approach helps overcome the underlying requirement for the distribution of the responses to be normal or to follow a Gaussian distribution, given that the questionnaire has categorical responses.

Parameter Estimation

As there are no closed form solutions for GLMMs, one must use some approximation. The three fairly common methods of approximation are:

- Quasi-likelihood approaches, which use a Taylor series expansion to approximate the likelihood. The parameters are estimated to maximise the quasi-likelihood, that is they are not exact maximum likelihood estimates. A Taylor series uses a finite set of differentiations of a function to approximate the function. The power rule integration can be performed. With each additional term used, the approximation error decreases.
- True likelihood can also be approximated using numerical integration. Quadrature methods are common, perhaps the most common among these uses the Gaussian quadrature rule, but the accuracy increases as the number of integration points increase.
- Monte Carlo methods are the third set of methods and are particularly useful for multidimensional integrals. Although Monte Carlo integration can be used in classical statistics, it is more commonly used in Bayesian statistics.

Covariance structure selection

Wald statistics can be used in covariance structure selection, but an alternative to testing hypotheses on covariance parameters uses likelihood ratio tests where statistics are constructed by taking the differences of the -2 Log likelihoods of two nested models. Under the $\mathbf{H_0}$ that the covariance parameters are 0 in the population. The difference follows a chi-squared distribution with degrees of freedom equal to the difference in the number of parameters between the models.

Limitations of LMM

The main methodological limitation with diagnostics is that tests rely on large sample approximations, however variance components are known to have skewed (and bounded) sampling distributions that render normal approximations questionable (Singer, 1998). The test for hospital (random effects) variability assumes that the parameter value lies in the interior of the parameter space, yet the value of zero is a boundary condition complicating such a test (Verbeke and Molenberghs, 2000). Hence the p-value cannot be relied upon to solely determine significance of the variance components. Verbeke and Molenberghs (2010), underscored the unverifiable nature of random-effects assumptions in a mixed-effects model without assuming the other parts of the hierarchical modeling are correct. The other caveat of this approach is that it requires much larger sample sizes hence the reason why data from 2008/9 to 2014/5 had to be used to ensure that the model is not over-fit (this happens when there are too many independent variables included in the model so that the variation is over-specified). However, in the event that the main response variable ExPDE shows no normal continuous outcomes, SAS also provides two macros (GLMMIX and NLINMIX) that can be used for fitting GLMMs if there is a violation.

c) The Mann-Whitney and the Kruskal-Wallis tests

ExPDE is a skewed variable and under the LMM model, the responses are correlated within a particular hospital but probably not so across different hospitals. In assessing significant differences (if obtained) between primary level units (indicators and managers responses); relationships between variables are analysed to detect whether two or more samples come from the same distribution, under the assumption that the distributions are the same (Zhang et al, 2009). Chi-squared tests for categorical variables for all responses on the questionnaire and the non-parametric Mann-Whitney (quantifiable variables) will be used to test for single item scales. The Kruskal-Wallis for responses that are summed up to convert a nominal or ordinal scale to a quantitative sum-score value, or in relation to quantitative efficiency values (when these are treated as outcomes or dependent outcomes). Post hoc methods such as Tukey or Dunn's test help analyse the specific sample pairs for stochastic dominance.

The main assumptions for the Kruskal-Wallis methodology in the context of this research include:

- Patients are not transferred across the different central hospitals, that is there is a disregard of all treatment between hospitals or expenditure at the lower levels of care.
- Service package is the same at all four central hospitals, although for example the burns unit at CHBAH is regarded as a flagship and, therefore, more likely to be more specialised and resourced in comparison to the other three.

The linear Kruskal-Wallis model can be written:

$$y_i = \mu_i + \alpha_i + \epsilon_i$$

Such that **Y**$_i$ is the vector of responses, μ_i is the grand mean, α_i is the difference to the mean of the ith central hospital to ϵ_i the hospital residual error. The non-parametric approach tests the null hypothesis, that each of the k samples belongs to the same population: $H_0: \bar{R}_i = (n+1)/2$. First, the response vector y is transformed into ranks with increasing order. In the presence of sequences with equal values (that is ties), mean ranks are designated to the corresponding realisations. Then, the test statistic can be calculated:

$$\widehat{H} = \left[\frac{12}{n(n+1)}\right]\left[\sum_{i=1}^{k} \frac{R_{i.}{}^2}{n_{i.}}\right] - 3(n+1)$$

where $n = \sum_i^K n_i$for k = 1…4 hospitals, $n_{i.}$ is the number of data of hospital *i* and $R_{i.}{}^2$ is the squared rank sum of the *i-th* group (the dot implies the summation of all managers within hospital i). As the test statistic is approximately 2-distributed, the null hypothesis is withdrawn, if $\widehat{H} > x^2{}_{k-1;\propto}$. If one is interested in identifying which central hospitals differ and to what extent after rejecting the null hypothesis, pairwise contrasts can be performed using the Tukey post-hoc test alongside the Kruskal-Wallis under the null hypothesis: $H_0: \bar{R}_i = \bar{R}_j$

and is rejected, if a critical absolute difference of mean rank sums exceed

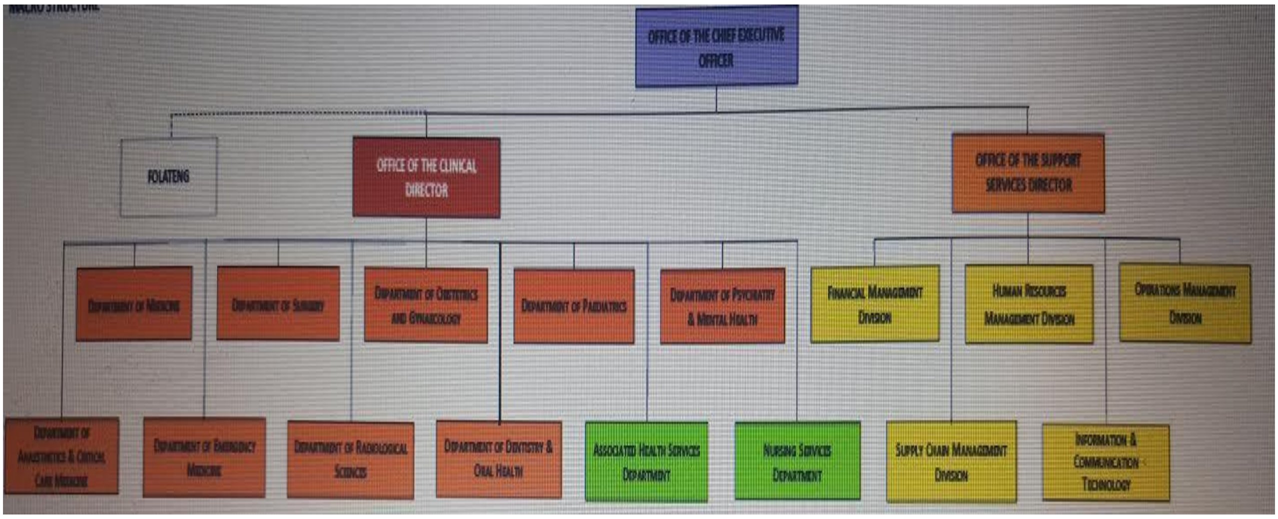
$$\left|\bar{R}_i - \bar{R}_j\right| > \frac{q_{\infty;k;\alpha}}{\sqrt{2}} \sqrt{\left[\frac{n(n+1)}{12}\right]\left[\frac{1}{n_i} + \frac{1}{n_j}\right]}$$

where $q_{\infty;k;\alpha}$ denotes the upper quantile of the studentised range distribution. A limitation of the test is that if one finds no significant difference, it does not imply that the samples are the same, it must rather be taken to mean the test was inconclusive.

3.3.2 SAMPLE SIZE DETERMINATION

There are four observational units and for the qualitative (subjective) responses, managers will be sampled from each observational unit or central hospital. The Central Limit Theorem (CLT) and the Law of Large Numbers (LLN) are two fundamental theorems of probability that help determine the sample size per hospital. In the two theorems above; the z-wald statistics and asymptotic series are among the more common test statistics used in determining limiting convergence for testing parameter estimates and it's the reason statistical procedures work. Figure 3.1 below shows the generic management structure within each hospital, being the target population for the subjective responses. On average, there are 40 senior managers (taking their deputies into account) and this gives a total of 4 x 40 = 160 hospital managers as the target population.

Figure 3.1: *Gauteng Dept. of Health – Central hospital management structure.*



For power and reliability of estimates, the limiting factor is often the sample size at the highest unit of analysis in determining how big the sample needs to be, in order to accurately estimate the population. Table 3.5 below shows the relationship between the (target) population size, the error rate and the sample size to be realised. For example, for a target population of 100 using the 5% level of significance (or 95% level of confidence), the sample size should be 80, had the target population been 500 then the sample size would be 218.

Table 3.5: *Sample size determination using error rate.*

Population	Margin of Error			Confidence Level		
	10%	5%	1%	90%	95%	99%
100	50	80	99	74	80	88
500	81	218	476	176	218	286

It can be inferred by simple linear interpolation that for a target population of 160, a overall target sample size of between 100 and 120 respondents at the 95% level of confidence or 5% level of significance across the four central hospitals is large enough. Therefore, a target sample of 100/4 = **25** to 120/4 = **30** senior manager per hospital responding is adequate. Inorder to avoid bias, one ought to use probability sampling to select the sample of respondents as that ensures that all individuals in the target population have a known chance of responding to the questionnaire. In order to take a probability sample, the generic management structure within each hospital depicted in Figure 3.1 could be used as a sampling frame. However, the complication arises in that not all positions of the management structure are filled in every hospital. The logical choice then, could be to ensure that only a single respondent from each box of Figure 3.1 is selected (as each respondent should individually answer the questionnaire) and ensure as many different boxes as possible are represented.

Such a sampling approach resembles cluster sampling and usually involves at least two stages of selection. The managers are the basic sampling unit (that is, the smallest unit to be sampled) followed by their unit or Deparment in a given hospital as the next level. The final choice of managers is to be made (by the hospital CEO) based on the available warm bodies of the management structure. However; cluster sampling implies that each respondent is not chosen independently of the other respondents. Given that the managers (as respondents) all belong to the same hospital, this may imply correlated responses within the hospital and may also increase the sampling error which can be mitigated by large sample sizes. Larger samples tend to be more precise but are not necessarily less biased. Table 3.6 below shows the total number of questionnaires (see Annexure A) distributed and received by hospital, inferences from Table 3.6 are further elaborated upon in Table 4.15.

Table 3.6: *Distribution of questionnaires received from the 4 central hospitals.*

	SBAH	DGMAH	CHBAH	CMAH	Total
Total number of Questionnaires sent out	40	40	40	40	160
Total number of correctly filled in Questionnaires received	43*	17	30	22	112

**Hospital CEOs were invited to use their discretion and permit respondents whose duties fell into determination of their hospital planning and management frameworks using efficiency data even if such respondents were not senior managers. SBAH had several such respondents, exceeding the number catered for in the generic organogram of senior management, as a result more questionnaires were photocopied and the total exceeded that originally sent to the hospital.*

Datasets

In the first instance, retrospective analysis of hospital quarterly efficiency measures from DHIS were examined for each of the four central hospitals and causality examined longitudinally covering 28 quarterly time points (from quarter 1 (April) of 2008/9 to quarter 4 (March) 2014/15) for the objective and quantitative measures. Next questionnaire responses from the managers were examined for the subjective and qualitative measures. The extent to which hospital managers comprehend efficiency data for planning and initiating control interventions is central to this research study. The questionnaire helped to assess the impact of utilisation, level of understanding and establishing the exact culture of the role such information plays in the management of resources at each hospital (controlling for hospital to determine hospital-specific effects). An effective measurement instrument must gather or measure an accurate counter or indicator of what is being measured. In addition, both respondents and the researcher must find it easy and efficient to use. The questionnaire context, foci and content is premised on findings emerging from literature review and constitutes the basis and rationale to link strategic planning with the extent that management efficiency indicator performance plays a role in managerial planning frameworks such as prescribed by the PAF.

There are three major criteria for evaluating a measurement tool: validity, reliability and practicality. The questionnaire was tested for reliability and validity by means of Cronbach’s alpha (factor analysis) using SPSS. Cronbach alpha is not without its drawbacks, for example, a high alpha will not necessarily inform the researcher of poorly correlating individual items (Brace, Kemp & Snelgar 2012). Therefore, three further techniques were employed to inspect the results of the data further in this test for assurance of reliability; part-whole correlation, the squared multiple correlation and scale Cronbach alpha if value of a particular item is deleted. Brace and colleagues, (2012) define these terms as follows:

- Validity refers to the extent to which a test measures what one actually wants to measure.
- Reliability refers to the accuracy and precision of a measurement procedure – that is, obtaining the same result under the same circumstances.
- Practicality is concerned with a wide range of factors of economy, convenience and interpretability. The research tool should be feasible and usable. It must be of good quality in the sense of being usable in context of the objective to be achieved. It should ease administration, scoring, interpretation and application and must be of low cost to both the respondents and the researcher.

When designing survey questionnaires, one advantage of adopting pre-existing questions is that the validity assessment evidence of the instrument is already established, and so researchers can be fairly confident that the instrument is an effective construct indicator of the concepts of interest.

The problem in this instance as observed in the literature review and Table 1.3 is that the efficiency indicators (and their dimensions) are deliberately chosen, are different and influenced by local environments and context. An illustration for instance, is the C-sections; elsewhere as a population-based indicator, it generated information different with respect to community dynamics than as a facility–based indicator. However, to enhance validity and remove ambiguity, it was necessary that a pilot of the questionnaire be carried out.

The use of questionnaires is one of the most popular methods to obtain information from respondents, as one of their strengths is that they make it possible to collect data designed to answer specific questions, which statistically fall into three main categories:

- Questions of fact (purple section of the questionnaire).
- Questions about opinions, beliefs and judgements (orange and green sections of the questionnaire).
- Questions about behaviour (blue section of the questionnaire).

The constructs listed on the instrument may not have fully reflected the scope of hospital management; however, despite any such limitations, the study has important theoretical and practical relevance for the improvement of health management capacity in the local context. The questionnaire (Annexure A) sought to:

- Establish the use and extent management reviews efficiency data, as well as determine if there is alignment of that usage to operational activities.
- Link managerial background and experience, planning, monitoring and evaluation as well as reporting to trends observable from the efficiency information.
- Infer experiences of impediments as well as the nature of impediments to the use of efficiency information (surrounding infrastructure or geographical service areas).
- Establish aspects that are common throughout and those unique to specific hospitals in respect of all of the above.
- Establish accountability and control measures in line with the PAF framework.

The above approach should address gaps (if any) highlighted in literature, that is, that technical assistance should be provided to hospitals in operations management, data analysis and that hospitals are largely unfamiliar with efficiency methodologies (Litvak and Bisognano, 2011). As indicated, managers perform four activities (i) planning objectives and actions (ii) managing or delivering services (iii) reporting on the performance of services (iv) reviewing and evaluating the outcomes. It is important to declare upfront that responses by managers were not validated in any way, but purely subjective and based on their own self-assessment. Ratings may have been influenced by a respondent's conversance or ignorance on an issue resulting in a lack of confidence to rate the item/s or it may have been based on a self-evident knowledge gap.

3.3.3 DATA QUALITY LIMITATIONS

In the calculation of ExPDE, there are costs attributable to patient care that cannot be allocated accurately to specialities or wards and this may cause inaccuracies in measurement of costs (Vitikainen et al, 2010). It is difficult to rely on expenditure data emanating from inappropriate utilisation as the costs thereof could be masking inefficiencies of which there are potentially five common sources:

(i) The problem with accruals and alignment of expenditure information within the Basic Accounting System (BAS). Payment often reflects as expenditure (Accounts Payable) well after delivery and possibly consumption has taken place. This can in certain instances, run into several months. Therefore, by the time the payment is made and reflected as expenditure, it may not be aligned to activities incurred in the same month as the payment. Moreover when accruals are paid, there is no attempt to align them to the BAS expenditure items. This skews the ExPDE in the month the entry is made.

(ii) Large payments could have been made as settlement in instances of medical malpractice or negligence. The current practice is that such payments are made from the affected hospital's goods and services budget and will reflect in BAS. When the ExPDE for the quarter in which such a payment was made is calculated, this is not separated (as it was a cost incurred and a failure to account for it creates a deficit) yet that payment was essentially not for health care services. This potentially distorts the cost structure of service provision in the modeling of ExPDE.

(iii) ExPDE is confounded by services being offered at central hospital outside of the service package. This is mainly the case when the hospital referral system is not effective and patients end up being treated for conditions which should have been dealt with at lower levels of care, this has the effect of allowing for a distortion of the cost structure at that level of care.

(iv) Operational and financial performance is also not entirely determined by indicators but a multitude of other factors, for example the mixture of public and private hospitals in close proximity and the flow of patients (Chua et al, 2011).

(v) The DHIS is considered the single verified data management system for service delivery and the gold standard in South Africa. However, as indicated in a growing body of literature, in some instances DHIS does not reflect the reality on the ground, this problem is acknowledged and is an area where efforts are being made to improve the system as well as the skills level to ensure better data integrity.

District Health Expenditure Review (DHER) tracks health care service delivery in relation to expenditure in South Africa. For purposes of this research, expenditure data was extracted from BAS (reconciliations between the hospitals and Head Office). DHER is more integral for costs at lower levels (District hospitals).

3.4 CHAPTER 3 SUMMARY AND CONCLUSION

In this chapter, the research design and analytical methodology for the study were described in detail and justified. That includes the mixed and philosophical approach of positivism in integrating deductive logic with predominantly empirical quantitative methods. A major incentive for using mixed methods being to uncover unexpected patterns and generate new research insights. In that sense, the challenge is to keep garnering new insights to allow refinement of existing knowledge of social processes. The rationale of the central hospitals being the observational units and the motivation for treating them as secondary level units hosting random effects, whilst the managers and efficiency measurements within each hospital as primary level units is elaborated upon. The focus on variability across hospitals is to determine if there are significant hospital effects, that by implication, would indicate different management configurations, practices and guidelines between the hospitals.

The rationale behind the analytical tools in a mixed methodology setup to deal with a combination of data that is quantitative (objective) and qualitative (subjective) and why they are suitable to answer the study objectives is presented. Granger Causality analysis (GCA), Linear Mixed Model (LMM) and Kruskal-Wallis (KW) methods are elaborated upon; the basis of each methodology, assumptions, parameter estimation techniques as well as limitations are also presented. Apart from the need to determine attribution through causality; data from an individual hospital is correlated as it is under the same system. That postulation violates the independence assumption between observations as required by the classical approach. In essence, hospital data exhibits correlation in a multi-level (hierarchical) structure in that the data is supposedly correlated at one level (within the same central hospital) but not necessarily at another level (across different central hospitals). This marks a departure from standard regression models and hence the LMM is better equipped to handle such data once causality is modelled by way of the GCA analyses. The KW method is relevant in capturing the differences between hospitals in instances where differences are realised. It was shown that a sample size of between 25 – 30 managers per central hospital using the 5% error rate / confidence level is sufficient.

The questionnaire which was structured along the context of effectiveness of efficiency by Simou et al (2014) examines a number of domains within indicator frameworks. The justification of the questionnaire as a data gathering tool for the qualitative component is discussed and reasons advanced as to why that is an appropriate way of assessing the institutional challenges faced by managers, as well as factors or gaps that influence managerial operational activities in response to efficiency data utilisation. Responses would also inform the development of strategies or interventions to enable a better understanding of efficiency information. The chapter concludes with a discussion on limitations in terms of data quality.

CHAPTER 4: RESULTS

4.1 INTRODUCTION AND EXPLORATORY DESCRIPTIVES

This chapter presents results of statistical analyses done in relation to the research questions, beginning with an overview of the exploratory objective and quantitative results followed by the subjective and qualitative results. The exploratory inferences are followed by causality results and associations. As earlier indicated, 5% level of significance is assumed unless otherwise stated. The hospitals are coded throughout as 1 = SBAH, 2 = DGMAH, 3 = CHBAH and 4 = CMAH.

The primary purpose of using seven year time series methodology sequentially (from 1 to 28 quarters) is to learn something about the longitudinal nature generating the data over time. However, where hospitals have varying attributes that is the hospital specific characteristics or random effects (if present). This variability can confound results and must be isolated in order to see a true undistorted effect exclusive of the variations emanating from agents of differing attributes (Von Holdt and Murphy, 2007). Ignoring this effect causes the underlying assumption inherent in the modelling (that is that there is homogeneity of the effect) to be violated, thus inflating the parameter estimates resulting in larger standard errors and poorer forecasts, Singer (1998). In the context of the study objectives, it becomes necessary to generate scientific evidence to inform efficient forecasting that can enable allocation of resources more effectively, regulate hospital expenditure patterns or even to curb unnecessary expenditure. When that cannot be accomplished, there would be no control measures scientifically appropriate enough to address the problem. For both clinical and administrative staff, it is essential to link hospital operations to efficient resource utilisation as part of ensuring an effective delivery of public health care system and to react to such information with appropriate evidence based intervention strategies. Unless some understanding is gained about efficiency measurement and the implications thereof, public health care will continue consuming more and more (financial) resources with sub-optimal outcomes.

Table 4.1 below shows the Pearson's correlation coefficients with the significant ones highlighted in color. ExPDE is positively correlated to C-sections rate (CSR) and three other auxiliary variables, but not to BUR and ALOS. CSR is linearly correlated to all efficiency indicators and auxiliary variables except only for one. Inpatient separations (IPS) and Casualty headcount (CH) are correlated to the next highest number of variables after CSR. The correlations could suggest that expenditure in hospitals is not a linear functions of the other efficiency indicators (with the exception of C-sections). The literature review cautioned against the limitations of individual metrics in indicator dimensions being read in isolation, and so the rationale in examining the correlation matrix at this stage is to later on, compare and contrast the same after controlling for hospital effects. If there are no significant random effects then the two correlation matrices should not differ as it would imply very little if any influence from hospital specific characteristics.

Table 4.1: *Efficiency indicators' correlation matrix.*

Pearson Correlations										
		ExPDE	ALOS	BUR	CSR	PDE	IPD	IPS	OPD	CH
ExPDE	Pearson Correlation	1	.051	.114	.388**	-.147	-.229*	-.229*	-.156	-.250**
	P-value		.593	.231	.000	.123	.015	.015	.101	.008
ALOS	Pearson Correlation	.051	1	-.093	-.246**	-.184	-.061	-.458**	-.252**	-.260**
	P-value	.593		.329	.009	.052	.523	.000	.007	.006
BUR	Pearson Correlation	.114	-.093	1	.315**	.188*	.113	.140	.527**	.148
	P-value	.231	.329		.001	.047	.236	.140	.000	.120
PDE	Pearson Correlation	-.147	-.184	.188*	-.175	1	.382**	.394**	.191*	.300**
	P-value	.123	.052	.047	.066		.000	.000	.043	.001
CSR	Pearson Correlation	.388**	-.246**	.315**	1	-.175	-.744**	-.571**	.387**	-.618**
	P-value	.000	.009	.001		.066	.000	.000	.000	.000
IPD	Pearson Correlation	-.229*	-.061	.113	-.744**	.382**	1	.898**	-.108	.790**
	P-value	.015	.523	.236	.000	.000		.000	.256	.000
IPS	Pearson Correlation	-.229*	-.458**	.140	-.571**	.394**	.898**	1	.006	.837**
	P-value	.015	.000	.140	.000	.000	.000		.951	.000
OPD	Pearson Correlation	-.156	-.252**	.527**	.387**	.191*	-.108	.006	1	-.156
	P-value	.101	.007	.000	.000	.043	.256	.951		.101
CH	Pearson Correlation	-.250**	-.260**	.148	-.618**	.300**	.790**	.837**	-.156	1
	P-value	.008	.006	.120	.000	.001	.000	.000	.101	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

More discussion will follow in section 4.2.2 under triangulation. Figures 4.1 and 4.2 below represent the longitudinal profile of mean ExPDE by hospital against the target ExPDE (as prescribed by NDoH). The 28 quarterly time points over 7 years are measured sequentially from 1 to 28, that is quarter 1 (2008/09) to quarter 4 (2014/15).

Figure 4.1: *Distribution of ExPDE.*

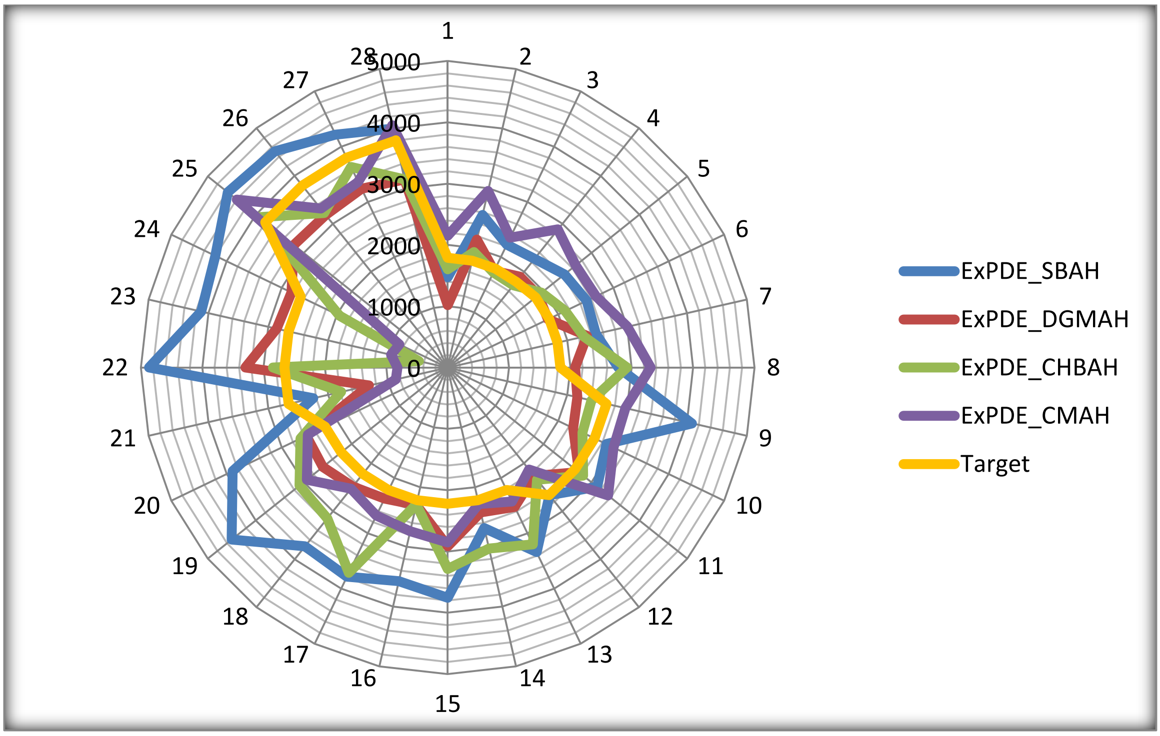
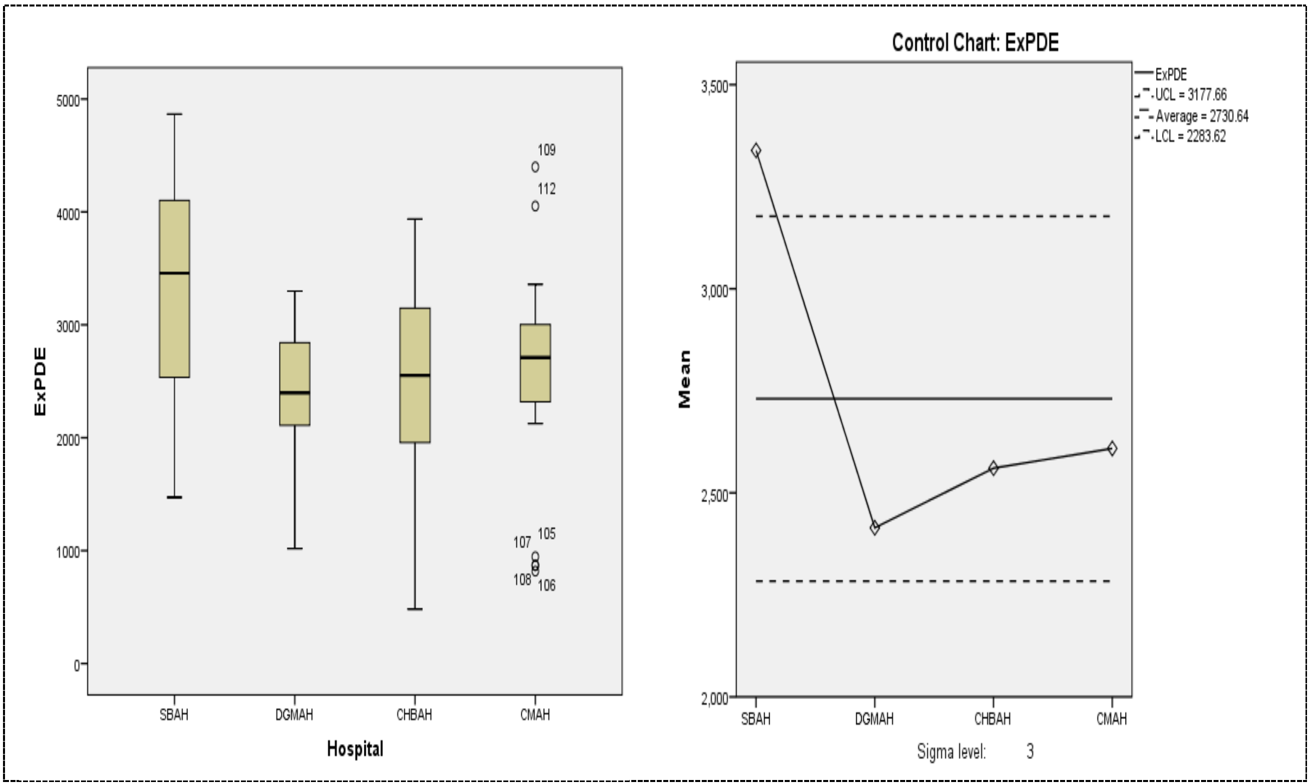


Figure 4.1 shows that, generally there is poor resemblance of the target ExPDE at the central hospitals with the exception of DGMAH. SBAH expenditure has consistently remained above target ExPDE levels with mean levels outside the 95% confidence bounds of the average of all four central hospitals. SBAH also exhibits a high level of variability across the seven years. DGMAH and CMAH are the more consistent ones, though mean ExPDE levels at CMAH are higher (but more consistent) in comparison to DGMAH. There is not only a lack of a realisable expenditure pattern, but also wide variations across the hospitals. The challenge is to identify a cause - effect generating mechanism capable of ensuring that expenditure stays on track. Figure 4.2 shows a contrast of the ExPDE boxplot and mean distributions across the four hospitals.

Figure 4.2: *Distribution of the mean ExPDE.*

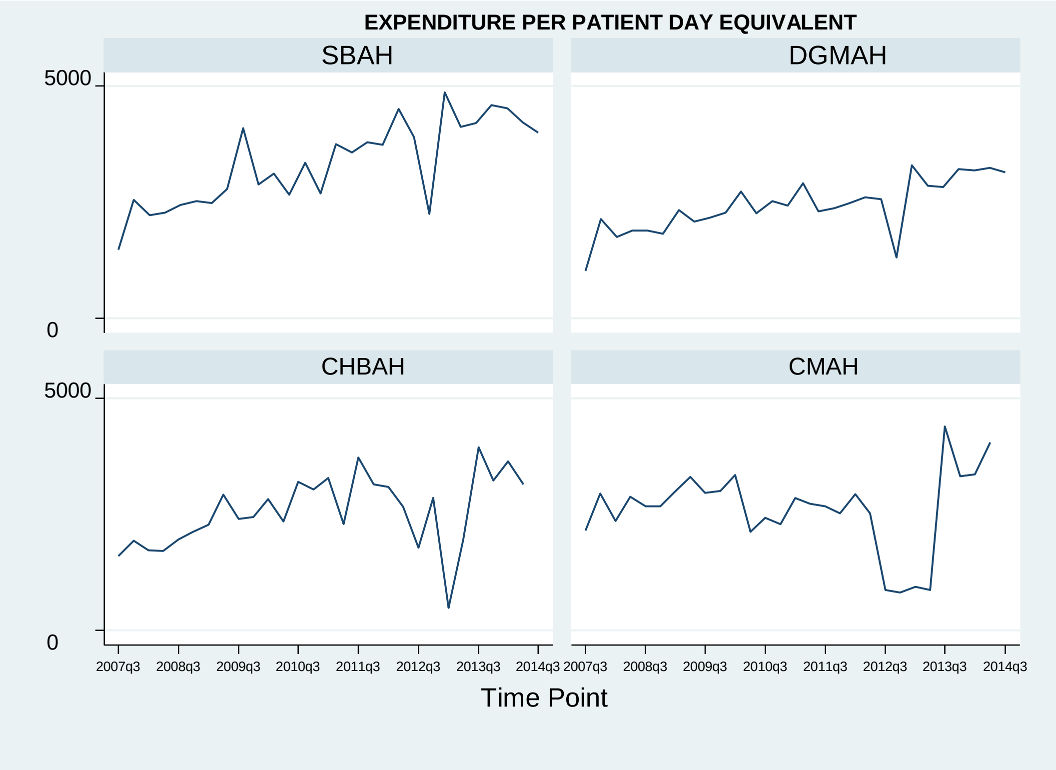


The nature of the cause - effect system generating the expenditure trends appears out of sync even within the confines of the set targets. The rationale for quarterly measurements as opposed to monthly, is due to:

- (i) Processing of the DHIS data takes between 45 - 60 days at which point it is cleaned, verified and ready for use.
- (ii) Management reviews and reporting frameworks of efficiency information are done on a quarterly basis.
- (iii) Quarterly benchmarking enables sufficient proactivity and implementation of appropriate control measures without overlap.

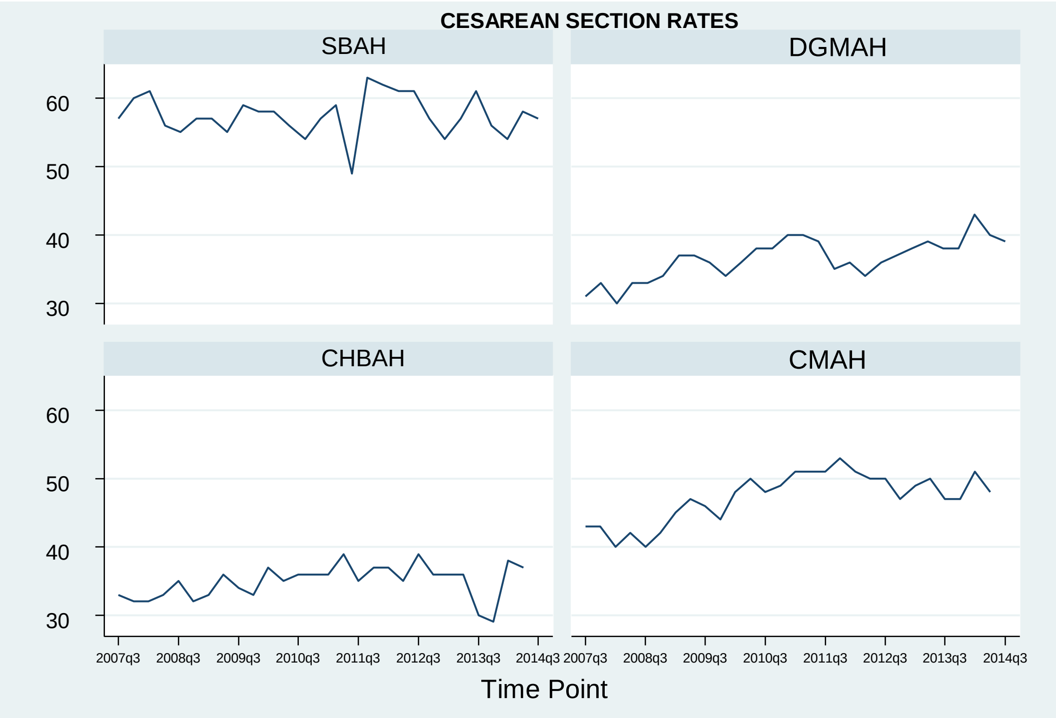
Figures 4.3 to 4.6 below show the longitudinal evolution and variations of the four efficiency indicators over the seven years by hospital.

Figure 4.3: *Variation of ExPDE across the 4 hospitals.*



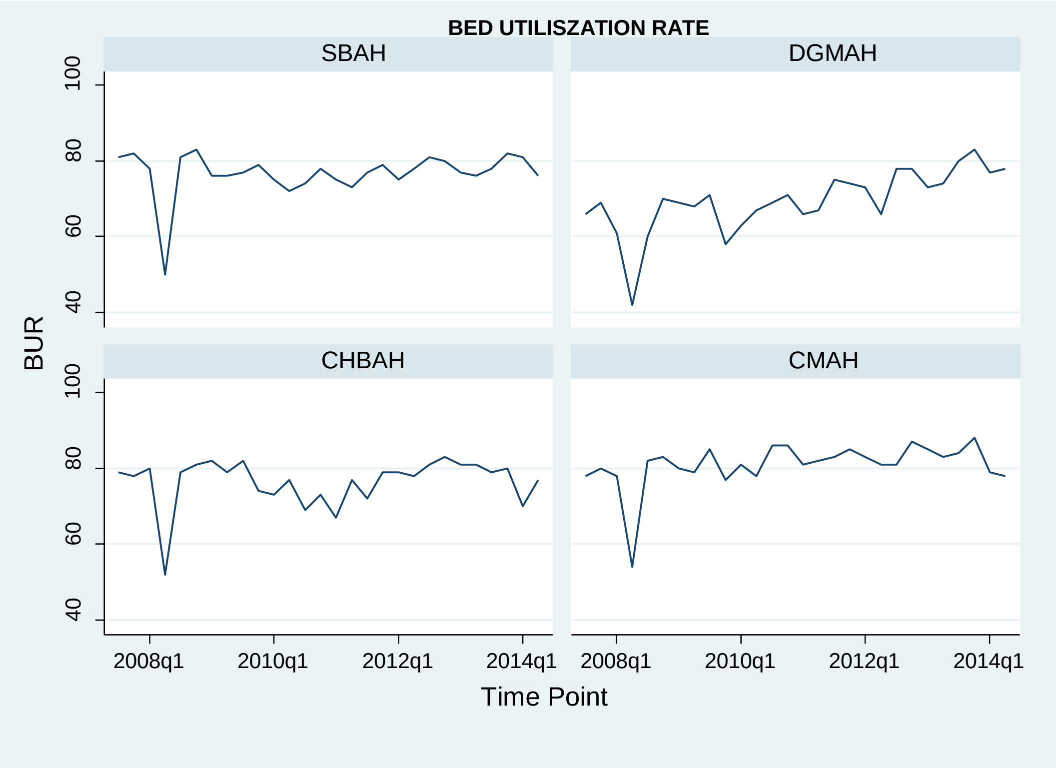
SBAH is far ahead.

Figure 4.4: *Variation of C-sections across the 4 hospitals.*



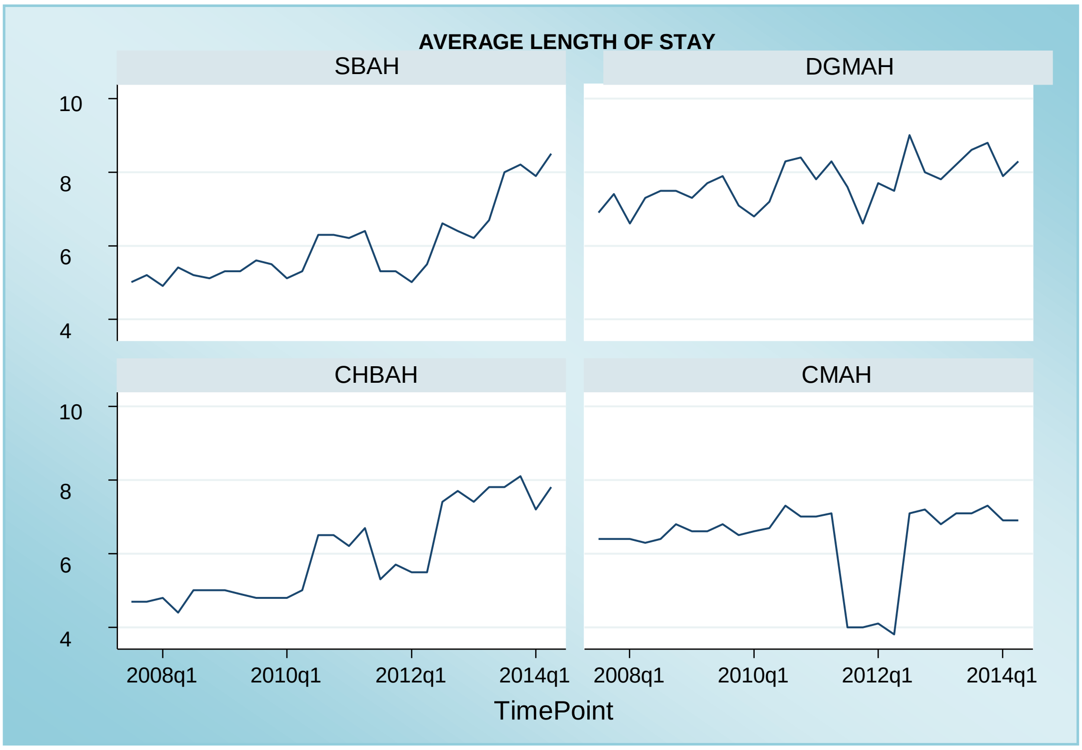
SBAH is still far ahead; it would appear CHBAH has the lowest of the four.

***Figure 4.5**: Variation of BUR across the 4 hospitals.*



A steady but gradual incline in BUR is evident.

***Figure 4.6**: Variation of ALOS across the 4 hospitals.*



CMAH appears to have the least of variability with the exception for the period around 2012q1.

4.2 GRANGER CAUSALITY AND LINEAR MIXED MODEL ANALYSES

4.2.1 MODEL BUILD UP USING THE RESULTS

Figures 4.3 to 4.6 suggest from a glance that the greatest variability is in C-section rates across the four indicators. The variation between hospitals for the same indicator distorts the visibility or detection of any causal patterns possibly resulting in ecological fallacy (a phenomenon that occurs when parity between hospitals is not accounted for or the hospital specific characteristics / random effects are ignored). The fallacy often results in conflicting or inconclusive inferences being between primary and higher levels analytically. Treating the hospitals as random effects allows for different dynamics to be modelled, for example heterogeneous variability using variance components models in which the Vector Auto-Regression (VAR) is specified (Verbeke and Molenberghs, 1997).

A VAR model is one in which each variable is a function of lags of itself and all other variables under consideration. This is useful for relationships between variables which are similar or postulated to influence one another. The following questions are crucial in a VAR modelling scenario:

- Can a value at the present time be predicted from values at past times?
- Is there a trend or a regularly repeating pattern of highs and lows related, for example, to quarterly time periods?
- Are there long-run cycles or periods unrelated to seasonal factors?
- Is there constant variance over time, or is the variance non-constant?
- Are there any abrupt changes to either the level of the series or the variance?

In running regressions on time-dependent data, as with quarterly intervals which are the longitudinal time points in this research; it is often necessary to include lagged values of the dependent variable (ExPDE) as independent variables for reasons stated earlier on. That is, financial variables such as ExPDE often are not only contemporaneously correlated to each other, but are also correlated to each other's past values. The logic being that for instance, current spending may not immediately affect outcomes until after some time later. In the context of the research, that time is the lag and the shorter it is, the greater the pressure on ExPDE.

Determining the Order

The order of the (VAR) model indicates how many previous times we use to predict the present time. To determine the error structure or variance components of lagged autoregressive structure of the AR(**p**), differencing (or lagged effect by quarter) is performed. Results on the determination of the autoregressive order (**p**) are presented as obtained through Generalised Estimating Equations (GEE) technique as shown in Table 4.2 below.

***Table 4.2:** Results of the autoregressive order (**p**).*

p = 1

GEE population-averaged model Number of obs = 112
Group and time vars: hospital Quarter Number of groups = 4
Link: identity Obs per group: min = 28
Family: Gaussian avg = 28.0
Correlation: AR(1) max = 28
Wald chi2(7) = 26.65
Scale parameter: 507160.9 Prob > chi2 = 0.0004

expde	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
alos	-17.62753	85.35567	-0.21	0.836	-184.9216	149.6665
bur	6.696148	12.25131	0.55	0.585	-17.31599	30.70828
pde	-.0003317	.000667	-0.50	0.619	-.0016389	.0009756
ipd	.0058226	.0040349	1.44	0.149	-.0020857	.013731
csr	52.15711	18.20775	2.86	0.004	16.47057	87.84365
opd	-.0056035	.0015506	-3.61	0.000	-.0086426	-.0025644
opd	0 (omitted)					
ch	-.0282467	.0236914	-1.19	0.233	-.0746809	.0181876
_cons	582.7407	1185.876	0.49	0.623	-1741.534	2907.016

p = 2

GEE population-averaged model Number of obs = 112
Group and time vars: hospital Quarter Number of groups = 4
Link: identity Obs per group: min = 28
Family: Gaussian avg = 28.0
Correlation: AR(2) max = 28
Wald chi2(7) = 19.26
Scale parameter: 552342.2 Prob > chi2 = 0.0074

expde	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
alos	-100.468	87.94524	-1.14	0.253	-272.8376	71.90147
bur	11.10912	11.63415	0.95	0.340	-11.6934	33.91163
pde	-.0001263	.0006403	-0.20	0.844	-.0013812	.0011287
ipd	.0033091	.0048391	0.68	0.494	-.0061754	.0127935
csr	32.4433	19.66596	1.65	0.099	-6.101281	70.98787
opd	-.0065827	.0017813	-3.70	0.000	-.0100741	-.0030914
opd	0 (omitted)					
ch	-.0372561	.0252524	-1.48	0.140	-.0867498	.0122377
_cons	2116.356	1246.644	1.70	0.090	-327.0199	4559.733

p =3

GEE population-averaged model Number of obs = 112
Group and time vars: hospital Quarter Number of groups = 4
Link: identity Obs per group: min = 28
Family: Gaussian avg = 28.0
Correlation: AR(3) max = 28
Wald chi2(7) = 22.04
Scale parameter: 585866.2 Prob > chi2 = 0.0025

expde	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
alos	-139.09	86.83062	-1.60	0.109	-309.2749	31.0949
bur	6.768694	11.88306	0.57	0.569	-16.52168	30.05907
pde	-.0001277	.0006344	-0.20	0.840	-.0013711	.0011156
ipd	.004496	.0053175	0.85	0.398	-.0059261	.0149181
csr	33.84131	20.70598	1.63	0.102	-6.741672	74.4243
opd	-.0074291	.0018605	-3.99	0.000	-.0110756	-.0037825
opd	0 (omitted)					
ch	-.0454493	.0256111	-1.77	0.076	-.0956462	.0047475
_cons	2728.435	1266.486	2.15	0.031	246.1676	5210.702

Since the data is per quarter, it is only logical to consider **p** = 1, 2, 3 or 4. The covariance parameter **p**, will depict variation of intercepts and slopes across hospitals as well as the covariance component representing the correlation between intercepts, slopes and the co-variation or covariance between intercepts and slopes. Goodness-of-fit criteria include Akaike's Information Criterion (AIC), Corrected AIC (AICC), Hannan-Quinn (HQ) Criterion, Final Prediction Error (FPE) and Schwarz Bayesian criterion (SBC), also known as Bayesian Information Criterion (BIC). In the above results, the smaller the scale parameter, the better the fit.

GEE autoregressive analyses results above indicate **p** = 1 as more plausible and also has the smallest standard errors. Note that, by implication:

- AR(1) yields better and more significant parameter estimates.
- AR(1) means a linear model predicted the value at a particular quarter from the value at the previous quarter.
- VAR(1) constituted good candidature for the error distribution of both the LMM and GCA.
- VAR(1) model is fitted with only **p** = 1 time lag (mean of series or variance components remaining constant over time = covariance stationarity), hence, the stochastic process is implied constant over the determined lag length (**p**=1).

As a result, all analysis of efficiency and auxiliary data (variables) were run using VAR models to estimate Granger Causality in Stata by way of the ‘vargranger’ command using the above error/ variance-covariance structure, order of stationarity = 1.

Vector Auto regression (VAR) - Lag selection

The lag length has the interpretation, how many quarters down the AR process can serial correlation be significantly determined? Simply put, how far back are past values (lags) still affecting today's values or, alternatively, after how long does current spending (ExPDE) begin to show up in ALOS, BUR or CSR and vice-versa. Too many lags could increase the error in the forecasts; too few could leave out relevant information. The above elements are all important as inferences are dependent on the correct model specification and the model’s parameter stability.

Three commonly used selection procedures are Schwarz's Bayesian Information Criterion (SBIC), Akaike's Information Criterion (AIC) and Hannan - Quinn Information Criterion (HQIC). The three measures do not always agree but Ventzislav and Lutz (2005), showed that for VAR models with quarterly data, HQIC appears to be more accurate except when sample sizes are smaller than 120, in which case SIC is more accurate. However, AIC and Final Prediction Error (FPE) tend to be superior when the sample is 60 observations and below in that they minimise any chance of under-estimating while maximising the chance of recovering the true lag length. AIC and FPE are recommended for the estimation of the autoregressive lag length in such instances (Liew, 2004). The results in Table 4.3 below are obtained for lag length between ExPDE and ALOS.

Table 4.3: *ExPDE and ALOS Lag selection.*

Hospital 1 = SBAH

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-169.239				628474	19.0266	19.0402	19.1255
1	-156.146	26.186	4	0.000	230215	18.0162	18.0572	18.313
2	-154.956	2.3807	4	0.666	322110	18.3284	18.3966	18.8231
3	-152.655	4.6016	4	0.331	411630	18.5172	18.6127	19.2097
4	-151.355	2.6009	4	0.627	620727	18.8172	18.9399	19.7075
5	-148.185	6.3384	4	0.175	832394	18.9095	19.0595	19.9977
6	-144.249	7.8731	4	0.096	1.2e+06	18.9165	19.0939	20.2026
7	-126.453	35.591	4	0.000	524602	17.3837	17.5883	18.8676

Hospital 2 = DGMAH

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-153.365				107711	17.2627	17.2764	17.3617
1	-147.266	12.198	4	0.016	85821.8	17.0295	17.0704	17.3263
2	-145.224	4.0822	4	0.395	109249	17.2472	17.3154	17.7418
3	-141.238	7.9733	4	0.093	115762	17.2486	17.3441	17.9412
4	-140.005	2.4653	4	0.651	175888	17.5561	17.6789	18.4465
5	-138.592	2.8259	4	0.587	286689	17.8436	17.9936	18.9318
6	-127.107	22.97	4	0.000	179220	17.0119	17.1892	18.298
7	-117.302	19.611	4	0.001	189772	16.3669	16.5715	17.8508

Hospital 3 = CHBAH

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-172.239				877134	19.3599	19.3736	19.4589
1	-163.034	18.411	4	0.001	494872	18.7815	18.8225	19.0783
2	-162.44	1.1872	4	0.880	739880	19.16	19.2282	19.6547
3	-159.293	6.2946	4	0.178	860627	19.2548	19.3503	19.9473
4	-156.337	5.9117	4	0.206	1.1e+06	19.3708	19.4936	20.2612
5	-146.682	19.31	4	0.001	704340	18.7424	18.8925	19.8307
6	-143.216	6.9327	4	0.139	1.1e+06	18.8017	18.9791	20.0878
7	-126.132	34.168	4	0.000	506188	17.348	17.5526	18.8319

Hospital 4 = CMAH

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-180.318				2.2e+06	20.2576	20.2712	20.3565
1	-172.353	15.931	4	0.003	1.4e+06	19.817	19.8579	20.1137
2	-171.653	1.3993	4	0.844	2.1e+06	20.1837	20.2519	20.6783
3	-169.032	5.2419	4	0.263	2.5e+06	20.3369	20.4324	21.0294
4	-150.235	37.594	4	0.000	548113	18.6928	18.8155	19.5831
5	-144.82	10.829	4	0.029	572734	18.5356	18.6857	19.6238
6	-142.939	3.7625	4	0.439	1.0e+06	18.771	18.9484	20.0571
7	-141.143	3.5932	4	0.464	2.7e+06	19.0158	19.2205	20.4998

Using the ‘varsoc’ command in Stata, the results in Table 4.3 above are obtained. The results show a plausible length of **p** = 1 between ExPDE and ALOS across all four hospitals. Repeating the same procedure for all variables yields Table 4.4 below. Full procedures leading to the results are attached in Annexure E under ‘lag selection’.

Table 4.4: *ExPDE pressure* due to differencing by hospital.*

	SBAH	DGMAH	CHBAH	CMAH	Possible inferences
ALOS	1	1	1	1	It is normal to have different lag lengths in a Granger-causal analysis for the same indicator across the hospitals. This could in part, be a result of difference in sample sizes, hospital specific characteristics or simply due to the dynamics embodied in the quarterly VAR models differ necessitating controlling for the hospital (random) effect, Comincioli, (1996).
BUR	3	1	0	2	
C-sections	1	1	0	1	
PDE	1	1	0	1	
IPD	4	3	0	0	
IPS	1	0	1	1	
OPD	1	2	1	1	
CH/EH	2	1	1	1	

* How far back are the past indicator values are still affecting today's ExPDE values (proxy for pressure or need)

The use of lagged values of ExPDE to quantify the pressure on other variables has the advantage of pulling more expenditure information in accounting for the effects of ExPDE on that very variable rather than just concentrating on the current levels for both ExPDE and the variable of concern and constitutes the basis of GCA. A comprehensive analysis of the implication of the above table is presented in the chapter on discussion.

The above results must be analysed in conjunction with GCA results after causality is established (still to be presented). However, across all four central hospitals for instance, current spending in ExPDE will be picked up in ALOS within the next quarter or more simply, current patterns in ALOS are in response to ExPDE from the last quarter. Converse associations and interpretations will depend on whether or not the causality is bi-directional and significant. Lag length = 0 ultimately implies that the pressure or manifestation of effect is immediate but that is only if there is Granger-causality. The pressure on expenditure based on the above table, is greatest on CHBAH and least on SBAH (yet SBAH tends to spend much more and above the target ExPDE as presented earlier). If one is restricted to efficiency indicators (the first three rows) only then:

- CHBAH has 2 zeros and a 1, confirming extreme pressure on ExPDE. This makes the hospital the most stressed and begins to confirm findings by Von Holdt and Murphy (2007).
- DGMAH has three ones confirming the consistence highlighted earlier.
- BUR at SBAH = 3; BUR exerts the least pressure on ExPDE need at SBAH.

CMAH has pressure in relation to Inpatient days and DGMAH has pressure in relation to Inpatient separations. This shall also be further examined on in section 5.1 (in relation to Figure 5.1).

Looking at the results more holistically so far, some hospital specific characteristics are beginning to show and must be isolated, for example:

- From Figure 4.5, BUR at SBAH is almost constant and is not a source of pressure from Table 4.4. When the number of patients (by type of patient) are examined, and given the high IPD, it will become apparent that SBAH is in fact over the seven years seeing fewer and fewer patients but keeping them longer in care, hence the increase trend-wise in ALOS in Figure 4.6. In terms of efficiency, the implication would be that patients are being kept in care on the basis of bed capacity being available.
- CHBAH is under strain, but one attribute that is of interest is the lower C-section rate. It is the lowest of all four hospitals which could suggest that the cost implication of C-sections at CHBAH is probably the lowest across the four hospitals. However, in Table 4.4, C-section rates have a zero indicating extreme pressure. The research investigated that conflicting phenomenon and addressed the issue as will be presented later on in Section 5.1.

Having determined the possible influence and presence of hospital specific characteristics from the lag differences in Table 4.4; then examining causality should reveal the different dynamics affecting the indicators. Table 4.4 clearly shows that pressure on ExPDE is affected differently across the central hospitals. Comincioli (1996) attributes this to random effects or differences in sample sizes. Traditionally, the tendency in assessing factors around ExPDE, has been to look at the volume of patients (whose proxy is the Patient Day Equivalent) but in isolation of type and / or cost of services being utilised. However, what is now apparent from Table 4.4 is that the volume of patients is only an issue at CHBAH and CMAH and not at SBAH and DGMAH. This could possibly be a result of the wide spectrum of primary and subspecialised services on offer at the former (Nathan and Rautenbachet, 2014), that matter will be discussed in more detail in the discussion section. The implication of efficiency indicators and their direct effect on expenditure has often been deemed difficult to isolate or quantify over time, and that has actually created a lack of their adoption for purposes of planning. The above results and analyses begin to show how they in fact, can and should be integrated in hospital management and planning frameworks.

Auto-correlation (ACF)

In GCA, the assumption of stationarity of the series as explained in the methodology is a necessary condition. The ACF gives correlations between the series at current time and lagged values of the series, and is postulated to depend on lag alone; whereas cross-correlations examine the correlational manner between series of two distinct variables. A desirable result is that the correlation is 0 between residuals separated by any given time span, meaning that residuals should be unrelated to each other.

In a stationary time series, the ACF will drop to 0 relatively quickly, while the ACF of non-stationary data decreases slowly. Also, for non-stationary data, the value of the correlation coefficient is often large and positive. To explore autocorrelation, a correlogram is generated (using the command 'corrgram' in Stata). Results on number of pre-determined lags are shown in Table 4.5 below. It can be inferred that on average, the ACF is dropping to 0 relatively quickly in all hospitals and therefore the assumption of stationarity is reasonable.

Table 4.5: *Auto-correlation of ExPDE.*

Corrgram of ExPDE in hospital 1 = SBAH:

```
                                    -1       0       1 -1       0       1
 LAG     AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.4938  0.5062  7.5854  0.0059         |---            |----
2      0.5001  0.3953  15.665  0.0004         |----           |---
3      0.4518  0.3397  22.523  0.0001         |---            |--
4      0.3523  0.2558  26.868  0.0000         |--             |--
5      0.2116  0.0358  28.503  0.0000         |-              |
6      0.2295  0.2089  30.514  0.0000         |-              |-
```

Corrgram of ExPDE in hospital 2 = DGMAH:

```
                                    -1       0       1    -1       0       1
 LAG     AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.3621  0.3911  4.0785  0.0434         |--             |---
2      0.4225  0.4165  9.8456  0.0073         |---            |---
3      0.3572  0.3486  14.132  0.0027         |--             |--
4      0.2624  0.2692  16.543  0.0024         |--             |--
5      0.1769  0.1433  17.686  0.0034         |-              |-
6     -0.0431 -0.2764  17.757  0.0069         |             --|
```

Corrgram of ExPDE in hospital 3 = CHBAH:

```
                                    -1       0       1 -1       0       1
 LAG     AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.3314  0.3402  3.4159  0.0646         |--             |--
2      0.2265  0.1731  5.0733  0.0791         |-              |-
3      0.0992  0.0368  5.4041  0.1445         |               |
4     -0.1938 -0.2782  6.7184  0.1515        -|             --|
5     -0.0868  0.0428  6.9935  0.2211         |               |
6     -0.1614 -0.1600  7.9885  0.2389        -|              -|
```

Corrgram of ExPDE in hospital 4 = CMAH:

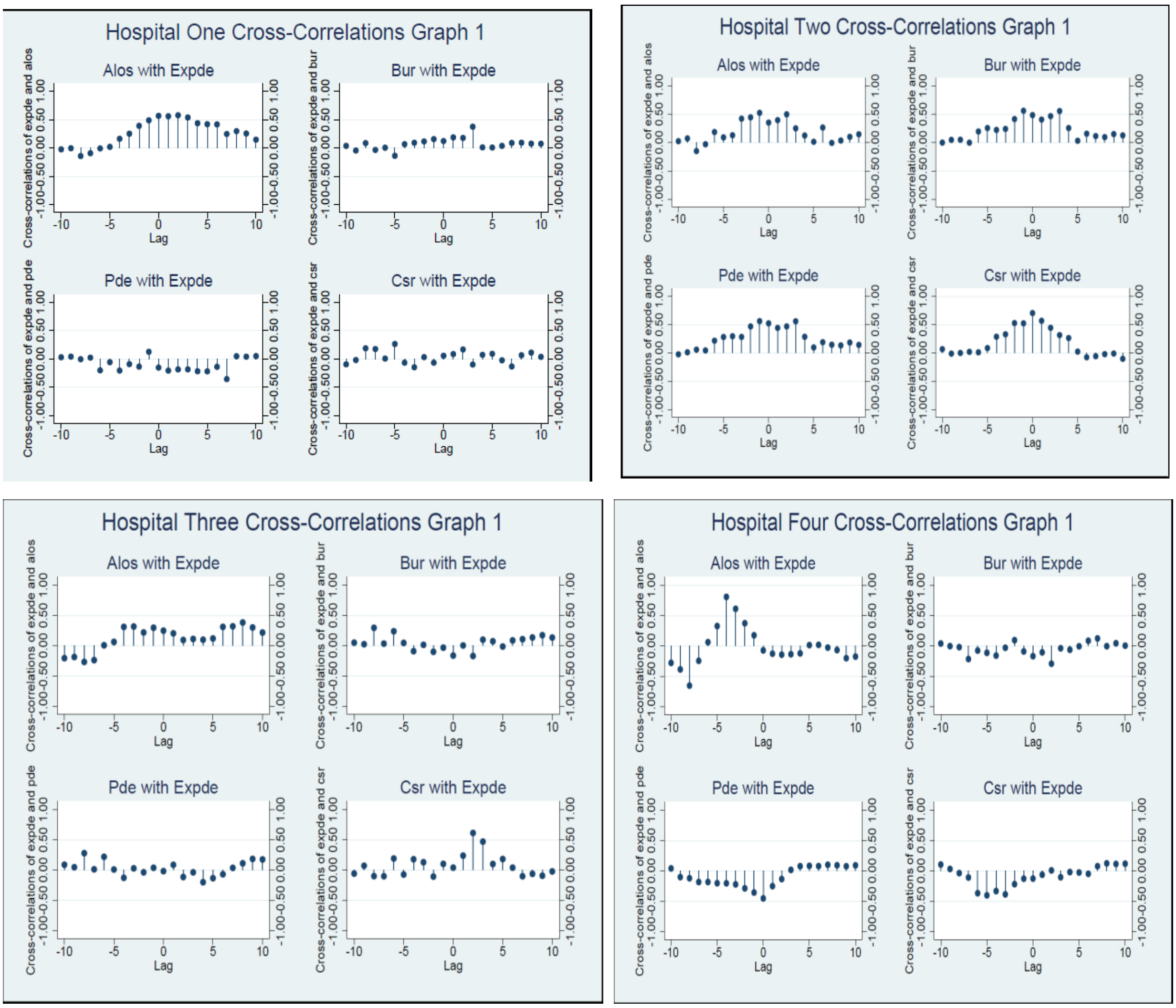
```
                     -1       0       1 -1       0       1
 LAG     AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.4441  0.4966  6.1358  0.0132         |---            |---
2      0.2153  0.0263  7.634  0.0220         |-              |
3     -0.0136 -0.1410  7.6402  0.0541         |              -|
4     -0.4028 -0.5789  13.319  0.0098      ---|           ----|
5     -0.2962  0.2927  16.523  0.0055       --|               |--
6     -0.1918  0.2712  17.928  0.0064        -|               |--
```

Looking at the first set of results for hospital 1 = SBAH in Table 4.5 above, ACF shows that the correlation between the current value of ExPDE and its value 2 quarters ago to be 0.5 and 3 quarters ago to be 0.4518. Note that ACF drastically reduces after quarter 3. PAC shows that the correlation between the current value of ExPDE and its value 2 quarters ago to be 0.395 and 3 quarters ago to be 0.339 (without the effect of the two previous lags). PAC is optimal at t = 1 and this is important, given that it can be used to define the p in AR(**p**) only in the stationary VAR series (mean and variance are time-independent).

Cross-correlations:

Cross-correlations (between ExPDE and each indicator) examine the correlational manner two variables move in time (at times where one is possibly not the cause of the other) despite seemingly moving in the same direction. The cross-correlations results are presented below:

Figure 4.7: *ExPDE cross-correlations.*



The important results from ACF and cross-correlations are:

- Box-Pierce Q statistic tests the null hypothesis that all correlation up to lag *k* are equal to 0 and the series shows significant autocorrelation as shown in by the p-values (Prob>Q) which at any lag or *k*, are less than the level of significance 0.05. This, therefore, rejects the null that all lags are not auto correlated.
- The graphic views are of ACF and show a quick decay in the trend, suggesting stationarity, whereas that of PAC (Partial Autocor) does not show spikes after the fourth lag which suggests that all other successive lags are mirror lags.
- Combining all hospitals, the results suggest a lag of 1 in three hospitals and a lag of 2 in one hospital. Therefore, taking a maximum lag of 3 in Granger-Causality is statistically plausible and logically reasonable.

To avoid the pitfall of too many or too few lags for GCA (as too many lags could increase the error in the forecasts and too few could leave out relevant information) a maximum lag of 3 for causality in the GCA is therefore established. From the cross-correlations, the evolution of ExPDE in time is influenced differently across the four central hospitals and this further confirms the presence of hospital specific characteristics (random effect). In practice, significant hospital specific characteristics suggests the absence of a standardised efficiency indicator framework leaving each hospital to devise its own. If however there is one, then there would be serious departures from it by the hospitals. Also, the cross-correlations between ExPDE and the 3 other indicators most closely resemble one another at DGMAH (again confirms the consistence observed in Table 4.4) and least resemble each other at hospital 4 = CMAH.

The fact that ExPDE is influenced differently across the four central hospitals cannot be ignored. Any modelling should therefore, allow for different hospital effects. As stated previously, simply examining parity between hospital managers by disregarding the specific hospital they operate in creates some crucial drawbacks as that ignores hospital specific dynamics. In literature, membership to a particular grouping influences the group, much as the grouping itself also influences individual members (Singer, 1998; Suzuki and Sheu, 1999; Albright and Marinova, 2010). The practical implication of the influences above being that members of a group are held together by the grouping itself and therefore, statistically, the grouping effect should always be tested for (to see if indeed the members who do not have the same trait as the grouping variable or effect would, in fact, not be within the group) and vice-versa, something achieved by LMM. To compliment that, GCA employs formal time series analysis methods on sequential data to make inferences about the nature of the cause-effect system generating the data. The causality results are presented and explained below, using GCA and a maximum lag of 3 as outlined.

Granger Causality Analysis (GCA) - contrasts using VAR model:

To understand the nature of the cause-effect system generating the data through GCA, lagged values of ExPDE are regressed on each variable (and vice-versa). If the coefficients of the lagged variable are significantly different from 0, then that variable Granger-causes ExPDE, that is to say the variable (including its lagged values) can be useful in predicting ExPDE. The null hypothesis of the Granger-causality test is that ExPDE (as variable 1) is influenced by itself only and not by a second variable (that is, each of the other efficiency and auxiliary indicators) up to a maximum of 3 lags as determined earlier. Table 4.6 below is an illustration of the output for DGMAH.

Table 4.6: *Granger – causality of ExPDE vs. ALOS at DGMAH.*

Hospital = 2 (DGMAH):

```
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
alos         |
        alos |
         L1. |   .2629104   .1844551     1.43   0.154    -.0986149    .6244357
         L2. |  -.1816676   .1906944    -0.95   0.341    -.5554218    .1920867
         L3. |  -.4153477    .188705    -2.20   0.028    -.7852028   -.0454927
             |
       expde |
         L1. |   .0006037   .0002471     2.44   0.015     .0001194    .0010879
         L2. |   .0005768   .0002375     2.43   0.015     .0001114    .0010422
         L3. |  -.0000366   .0002158    -0.17   0.865    -.0004597    .0003864
             |
       _cons |   7.561248   1.576615     4.80   0.000     4.471138    10.65136
-------------+----------------------------------------------------------------
expde        |
        alos |
         L1. |   312.1939    136.643     2.28   0.022     44.37843    580.0093
         L2. |   68.59699   141.2651     0.49   0.627    -208.2776    345.4716
         L3. |   357.9142   139.7914     2.56   0.010     83.92812    631.9003
             |
       expde |
         L1. |  -.0345378   .1830217    -0.19   0.850    -.3932538    .3241781
         L2. |   .0114018   .1759029     0.06   0.948    -.3333615    .3561651
         L3. |   .1757204   .1598984     1.10   0.272    -.1376748    .4891156
             |
       _cons |  -3521.753   1167.946    -3.02   0.003    -5810.885   -1232.621
------------------------------------------------------------------------------
Granger Causality Wald tests (hosp=2)
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |              alos              expde |  15.973     3    0.001    |
  |              alos                ALL |  15.973     3    0.001    |
  |--------------------------------------+---------------------------|
  |             expde               alos |  14.472     3    0.002    |
  |             expde                ALL |  14.472     3    0.002    |
  +------------------------------------------------------------------.-+
```

The area shaded yellow in Table 4.6 above tests ‘ExPDE does not Granger-Cause ALOS’ whereas that shaded grey tests the converse, ‘ALOS does not Granger-cause ExPDE’. The above results retained p-values of 0.001 and 0.002, which are less than the 0.05 = 5% level of significance. Hence in both cases, the null hypothesis that each variable does not Granger-cause the other is rejected at the 5% level of significance. Technically, it implies that not all the contrasts (L1-L3) are insignificant, which is evidence that shows that the cause – effect generating mechanism is not random. Also, there is bi-directional causality as in both instances (yellow and grey), the null hypothesis of ‘no causality’ gets rejected.

Goodness-Of-Fit:

In instances where causality has been established, it is prudent to test the goodness-of-fit. The goodness-of-fit looks at how good the model fitted is. In particular, model fit is useful in determining the precision in forecasts as well as model perturbation; that is to what extent does the model capture changes in one variable if there are changes in the other variable as per the causal relationship?

Table 4.7: *Goodness-of-fit statistics.*

Vector auto regression

Sample: 6344q1 - 6350q1		No. of obs =	25
Log likelihood = -191.9459		AIC =	16.47567
FPE =	50546.39	HQIC =	16.66499
Det(Sigma_ml) =	15993.19	SBIC =	17.15824

Equation	Parms	RMSE	R-sq	chi2	P>chi2
alos	7	.49034	0.4926	24.27214	0.0005
expde	7	363.241	0.6135	39.67651	0.0000

Note the following from Table 4.7 above:

- The causal model is a better fit as compared to the one presented in Table 4.3 under VAR - Lag selection for hospital 2 = DGMAH as evidenced by the smaller information criterion values throughout (50546.39 vs. 85821.8 (FPE); 16.47567 vs. 17.0295 (AIC); 16.66499 vs.17.0704 (HQIC) as well as 17.15824 vs. 17.3263 (SBIC). Hospital 2 was selected from Table 4.3 so as to compare with the statistics in Tables 4.6 and 4.7 above.
- This is evidence that the above model set at a maximum of 3 lag lengths is superior to the one in Table 4.3 (with more than 3). As mentioned earlier, too many lags could increase the error in the forecasts and too few could leave out relevant information. Therefore, the model in Table 4.3 resulted in increased forecast errors and thus poorer in fit, hence the larger goodness-of-fit statistics (in comparison to Tables 4.6 and 4.7).

The Granger-causality procedure is repeated for ExPDE and all variables pair-wise and Table 4.8 below shows the results across all hospitals (Annexure E has more results). The findings summarise causal relationships to the expenditure (ExPDE) at each hospital. It is clear that the nature of associations is not the same across the hospitals even for the same indicator, association in one direction does not guarantee converse associations in the opposite direction.

Table 4.8: *Causality attribution.*

Key:

Dark green	Bi-directional causality (jointly confirmed both directions)
Light green	Unidirectional Granger Causality from only one variable to the other.
Red	No causality (Variables are independent, both fail to Granger-Cause each other)

Hospital = 1 (SBAH):

	ALOS	BUR	C-section	PDE	IPD	IPS	OPD	CH
P - value **ExPDE** as Y or 'var 1'	0.576	0.765	0.116	0.148	0.903	0.647	0.611	0.696
P - value **ExPDE** as X or 'var 2'	0.456	0.000	0.035	0.501	0.093	0.455	0.379	0.793

Hospital = 2 (DGMAH):

	ALOS	BUR	C-section	PDE	IPD	IPS	OPD	CH
P - value **ExPDE** as Y or 'var 1'	0.002	0.028	0.449	0.033	0.034	0.239	0.114	0.002
P - value **ExPDE** as X or 'var 2'	0.001	0.004	0.114	0.024	0.003	0.000	0.161	0.009

Hospital = 3 (CHBAH):

	ALOS	BUR	C-section	PDE	IPD	IPS	OPD	CH
P - value **ExPDE** as Y or 'var 1'	0.020	0.948	0.331	0.972	0.978	0.430	0.875	0.843
P - value **ExPDE** as X or 'var 2'	0.785	0.724	0.000	0.793	0.792	0.784	0.784	0.794

Hospital = 4 (CMAH):

	ALOS	BUR	C-section	PDE	IPD	IPS	OPD	CH
P - value **ExPDE** as Y or 'var 1'	0.008	0.834	0.065	0.820	0.716	0.013	0.536	0.951
P - value **ExPDE** as X or 'var 2'	0.981	0.297	0.497	0.088	0.191	0.784	0.112	0.438

The results show that:

- The causal associations impacting on ExPDE differ across all four central hospitals, further testimony of significant hospital specific characteristics.
- DGMAH has the most significant indicators not only in number but directions as most (except for IPS) exhibit bi-directional causality. ALOS and BUR both Granger-cause ExPDE. This may explain why it is the more consistent central hospital, even by different approaches
- At SBAH, BUR and C-sections Granger-cause ExPDE.
- At CHBAH, C-sections Granger-cause ExPDE.
- ALOS has the most forward associations. That means ExPDE can be better predicted using the histories of both ALOS and ExPDE than by just using the history of ExPDE alone, and this is significant in all hospitals except SBAH. This possibly explains why expenditure at SBAH is persistently high; it is uncontrolled and does not get detected in all variables at that hospital (in forward causal associations).

- No efficiency indicator or auxiliary variable Granger-causes ExPDE at CMAH. That suggests that the mechanism generating expenditure is likely to be erratic / undetermined.
- BUR, C-sections and IPS have the most converse causal associations (two each) albeit at different hospitals. For example, at CHBAH, C-sections can better be predicted using the histories of both ExPDE and C-sections than just using the history of C-sections alone. That possibly suggests either a high number of C-sections or, alternatively, a higher expenditure towards the C-sections. This seems strange as the C-section rate is lowest at CHBAH. As already indicated, the research further investigated this issue with very interesting results and valuable insight gained as presented later on in the discussion, in Chapter 5.
- Two causal associations are BUR at SBAH and IPS at DGMAH possibly suggesting either (i) at SBAH a higher BUR or, alternatively a higher expenditure towards BUR (ii) at DGMAH a higher IPS or, alternatively a cost saving as a result of IPS discharges.

By comparing results from Table 4.8, four issues are apparent:

- ExPDE is affected differently at each hospital. Table 4.8 suggests the efficiency indicators are best assessed within the context of the individual hospital. Reasons for the variations would require further research but in the context of this research, hospital specific characteristics are a proxy for different management practices between the four hospitals.
- Examining the consistence of ExPDE against the other three efficiency indicators as in Figures 4.1, 4.7 and Table 4.4; it is clear that DGMAH has the least variability and therefore greater consistence. DGMAH according to Table 4.8 above has the highest number of variables Granger-causing ExPDE. In addition, its the only hospital were causality associations were established in both directions.
- Table 4.8 suggests that, and perhaps most importantly, a need to recognise the limitations of individual indicator metrics as there is no one indicator that is applied equally to all four hospitals. This may be indicative of factors outside of the hospital, such as those raised by Nathan and Rautenbachet (2014), that is, package of services rendered the supporting infrastructure around the hospital, differences in the geographical service area, transportation routes and level of affluence in the population as well as the hospital referral system and to some extent policy. However, more research would be required before concluding that but the evidence suggests in all likelihood, a random variation which is not common or shared across all four hospitals to the same extent.
- Variation of ExPDE in three of the four hospitals would require more indicators than currently provided for in order to be satisfactorily ascertained and modelled (DGMAH being the exception) to yield a standardised set of indicators whose effects are common across all hospitals.

4.2.2 KRUSKAL WALLIS AND LINEAR MIXED MODEL (QUANTITATIVE)

The Kruskal-Wallis (KW) test is useful in showing differences between efficiency data as well as management differences between the central hospitals. According to Von Holdt and Murphy (2007), a primary factor indicative of differentials in resource allocation and workload between institutions is the varying capacity and depth of management between them. The KW approach uses the means (quantitative) or medians (qualitative) in testing hypotheses shown in the second column. If the p-value (= *Sig*) is less than the 0.05, the null hypothesis is rejected implying that significant differences in the construct measured between the hospitals exist.

Figure 4.8: *Kruskal Wallis contrasts.*

Hypothesis Test Summary

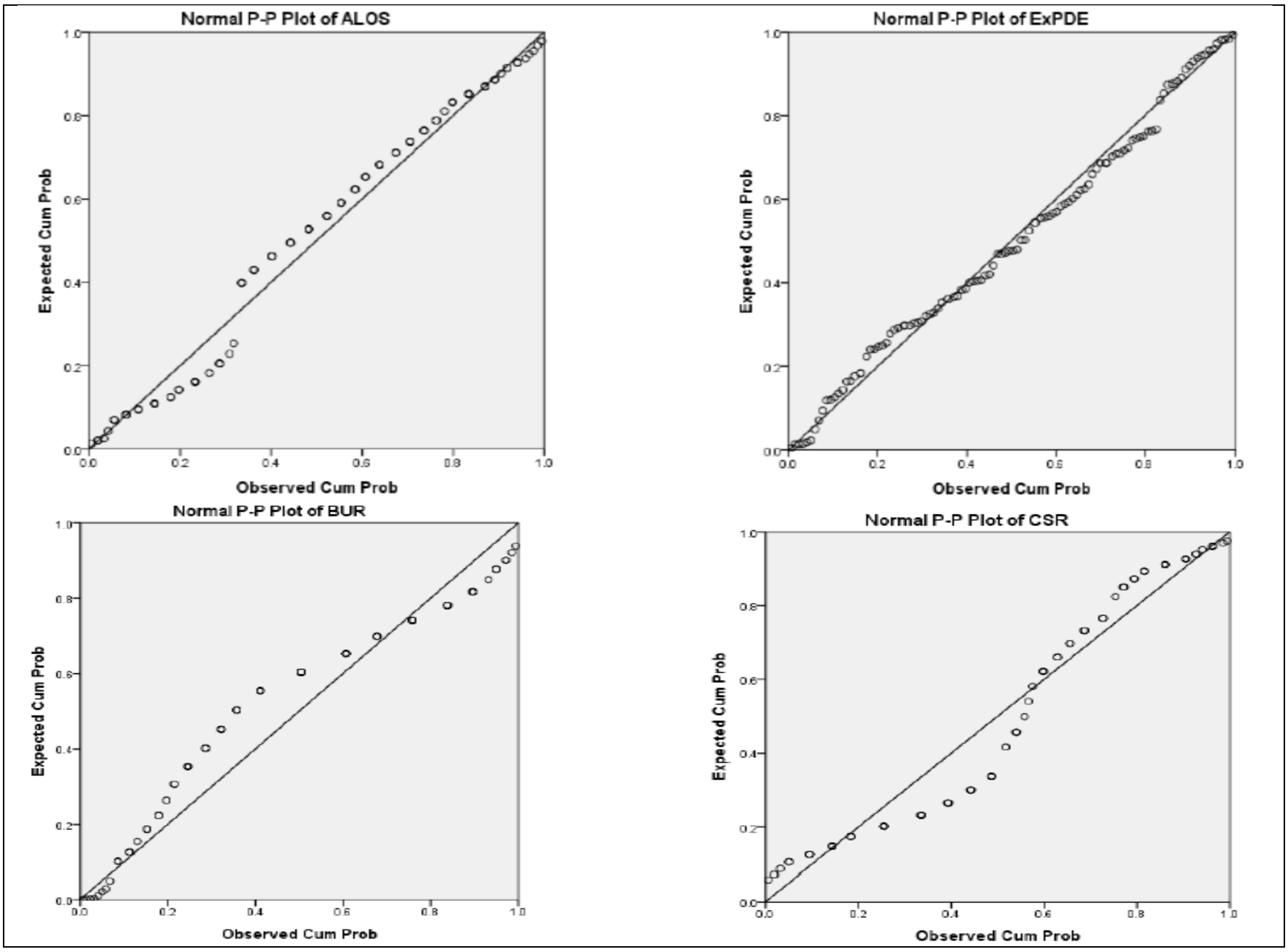
	Null Hypothesis	Test	Sig.	Decision
1	The distribution of ExPDE is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.001	Reject the null hypothesis.
2	The distribution of ALOS is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
3	The distribution of BUR is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
4	The distribution of PDE is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
5	The distribution of CSR is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
6	The distribution of IPD is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
7	The distribution of IPS is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
8	The distribution of OPD is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
9	The distribution of CH is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Figure 4.8 above shows results from the Kruskal-Wallis (KW) which confirms results from section 4.2.1 obtained by way of Granger-Causality Analysis (GCA); that is, the impact of efficiency indicators is not the same across the four central hospitals, as all p-values are significant. This implies there is a variation specific to individual hospitals or hospital specific characteristics influence the indicator cause - effect generating mechanism across the hospitals. That confirms the results from Figures 4.1, 4.7 and Table 4.4. There is scientific grounds and evidence for hospitals are to be treated as random effects.

To determine the magnitude of the hospital / random effect on the efficiency indicators across the hospitals and subsequent association to resource expenditure, Linear Mixed Model (LMM) is used. A pre-requisite and requirement of the LMM methodology is that the response, ExPDE, must be normally distributed. P-P plots compare the empirical cumulative distribution function of a measure with the cumulative distribution function of the normal distribution and Q-Q plots comparing the quantiles of a data distribution with the quantiles of a standardised normal distribution to assess for departures from normality. The P-P plots magnify deviations from the normal distribution in the middle whereas the Q-Q plots magnify deviations from the tails of the normal distribution. An advantage of the the P-P plots distribution is that they clean out all the statistical fluctuation, the P-P plots for the four efficiency indicators are as shown below.

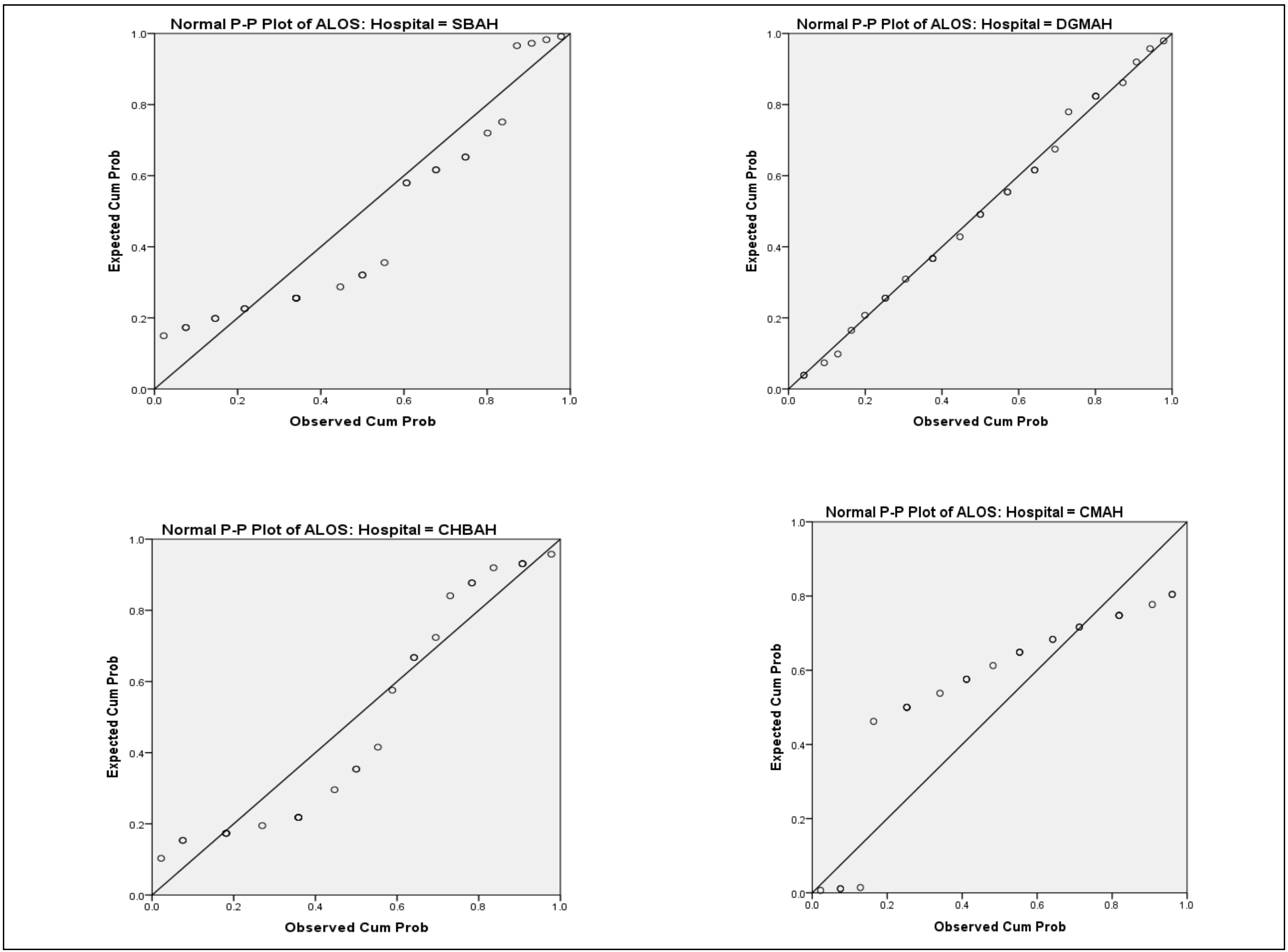
Figure 4.9: *P-P plots testing for normality of ALOS, ExPDE, BUR and C-sections rate (CSR).*



No serious departures from normality are apparent for the response ExPDE. The P-P plots show heavy tails for C-section rates and BUR, implying that although the probability of percentage values at the tails is small, the frequency is nevertheless large. These small tail values become vital in that they impact greatly on cause - effect association to ExPDE and are to be modelled and not discarded as what often happens to outliers. From above, C-sections have the most robust random effect influence (impact already known to be mainly at two hospitals CHBAH and SBAH) followed by BUR (impact already known to be mainly at SBAH).

One of the issues mentioned in literature by Zemencuk and colleagues (2006), is that ALOS can be positively skewed. This is indeed confirmed, as there are more observations above the median line in the first quadrant. The absence of heavy tails suggest the possibility that there are no big variations in case-mix or that there are not many patients who stay fewer or much longer days than the median. If there were, then fewer patients would have longer stays and even less severe cases extending way beyond the median. Using that analytical technique as a proxy for case-mix, Figure 4.10 below shows the P-P plots per hospital for ALOS to address the problem highlighted in literature, that is data on case-mix is not readily available.

Figure 4.10: *P-P plots of ALOS (as a proxy for case-mix) by hospital.*



At SBAH, the extreme average effect balances out with equal numbers above and below the median. It is clear that case-mix is not an issue at DGMAH and the consistence is once again evident. At CMAH, there are a few patients who stay much shorter and much longer (heavy tails both sides), but generally there is an erratic surge and as shall be seen in Figure 5.1, this is from OPD - a type of day patients. That pronounced deviation from normality at CMAH indicates a conundrum in determining case-mix. CHBAH has pronounced heavy tails and deviations from the median throughout, implying there is substantial case-mix at all times.

When hospital specific characteristics or random effect are significant, it is logical to quantify the magnitude of the variation of that hospital random effect, that is the variance component. That magnitude is computationally equivalent to the intra-class correlation coefficient in regression settings involving a blocking or class effect. The null hypothesis for LMM is that the random effect is not present or more equivalently, that its variance component is equal to zero. The null, hypothesizes that all variation is attributable to primary units (error variance) irrespective of hospital specific characteristics or the affiliation of the primary units to specific hospitals. The LMM results are shown below in Table 4.9.

***Table 4.9**: Linear Mixed Model - covariance parameter estimates.*

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		500878.204284	68478.658320	7.314	.000	383140.670193	654795.992815
Hospital [subject = Hospital]	Variance	153403.894915	139881.042273	1.097	.273	25684.429287	916226.508772

a. Dependent Variable: ExPDE.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		500878.204284	68478.658320	7.314	.000	383140.670193	654795.992815
Hospital [subject = Hospital]	AR1 diagonal	153403.894915	139881.042273	1.097	.273	25684.429287	916226.508772
	AR1 rho	.000000[b]	.000000	.	.	.	.

a. Dependent Variable: ExPDE.

b. This covariance parameter is redundant. The test statistic and confidence interval cannot be computed.

Specifying the 1st-order autoregressive AR(1) as determined earlier on yields the above results. However, since only a single hospital-level variance component is estimated, dealing with the specification of the covariance structure yields very little change and so the variance component (VC) covariance structure can also be specified, as in the upper part of table 20.

The variance component (variance of the hospital specific characteristics or random effect) is calculated as the intra-class correlation coefficient; which equals to {153403.894915 / (153403.894915 + 500878.204284)} x 100 = **23.4%**. This has the interpretation that **23.4**% of the total variation in ExPDE is attributable to factors that differ across the 4 central hospitals. Simply put, of the total variation in ExPDE, **23.4**% emanates from differences in characteristics across the different hospitals. The remaining variation of **76.6**%, is the percentage of total variance attributable to the progression of ExPDE across the 28 quarterly time points. However, the estimate is still more than the size of its standard error, suggesting that there remains a significant amount of unexplained hospital-level variance of approximately {(153403-139881) / 139881)} x 100 = **10**%. This constitutes a basis for further research in that regard. Estimates for the variance components parameter estimates in Table 4.9 have a p-value of 0.273, possibly suggesting a failure to reject the null hypothesis.

The p-value for testing of variance components is still a matter of on-going research as highlighted earlier on (under Limitations of LMM), as the main methodological limitation with diagnostics of variance components is that tests rely on large sample approximations and variance components are known to have skewed (and bounded) sampling distributions that render normal approximations questionable. Significance is generally assumed if the value exceeds 10% (Singer, 1998) though research is on-going (Xu, Guo and Yu, 2016). Therefore, the test for random variance component assumes that the parameter value lies in the interior of the parameter space (Verbeke and Molenberghs, 2010); yet the value of zero is a boundary condition complicating such a test, hence the complication of significance. Suggestions have been to rather test through bootstrap methods and score tests. The variance components are for the random effects, estimates for the fixed parameter estimates (coefficient of ExPDE with time) are shown.

Table 4.10*: Linear Mixed Model - fixed parameter estimates.*

Estimates of Fixed Effects[a]							
						95% Confidence Interval	
Parameter	Estimate	Std. Error	df	t	Sig.	Lower Bound	Upper Bound
Intercept	2092.398810	239.234795	5.342	8.746	.000	1489.074571	2695.723048
time	44.016831	8.278789	107	5.317	.000	27.605098	60.428564
a. Dependent Variable: ExPDE.							

The slope or intercept is statistically significant (p-value = 0.000) and has the interpretation that the average expenditure levels (ExPDE) are not zero. On a practical basis, this is indicative of levels in fixed costs (at a mean level of **R**2092.398810) before considering the evolution of ExPDE across time (that is, the value of ExPDE when time = 0). The parameter estimate for time = **R**44.016831 and represents the magnitude of change in ExPDE between any two consecutive quarters (that is between time = *t* and *t+1*). Repeating the above for all efficiency indicators, the summary in Table 4.11 below is obtained.

Table 4.11*: Linear Mixed Model – combined results for all 4 indicators.*

	ExPDE	**ALOS**	**BUR**	**C-section**
Intercept = GEE Mean value (p-value)	**2092.398810** (0.000)	**5.493056** (0.000)	**71.414683** (0.000)	**41.595238** (0.004)
Time (quarter parameter) (p – value)	**44.016831** (0.000)	**0.070614** (0.000)	**0.311918** (0.000)	**0.167693** (0.000)
Hospital / Random effect (variance component) (p – value)	**23.4%** (0.273)	**48.2%** (0.238)	**35.3%** (0.250)	**93.6%** (0.222)

Time parameter estimates for all indicators are statistically significant (p-values less than 0.05) as shown in the middle row in the table above. The significance of variance components has been discussed and despite the large p-values, they all exceed 10%, set by Singer (1998).

The following can be inferred from Table 4.11:

- The random effect measuring the variance components (attribution of the hospital specific characteristics) is scientifically quantified, that is 23.4% in ExPDE, 48.2% in ALOS, 35.3% in BUR and 93.6% in C-section rates.
- ExPDE has a rate of change of **R**44.016831 per quarter (from a mean level of **R**2092.398810 before the start of quarter 1, 2008/09).
- ALOS has a rate of change of 0.07 days per quarter (from a mean level of 5.49 days before the start of quarter 1, 2008/09).
- BUR has a rate of change of 0.31% per quarter (from a mean level of 71.4% before the start of quarter 1, 2008/09).
- C-sections rate has a rate of change of 0.17% per quarter (from a mean level of 41.6% before the start of quarter 1, 2008/09).

Based on the LMM, the hospital specific characteristics most confound the C-section rate and least confound the ExPDE across the hospitals. That is, different hospital attributes significantly affect C-section rates the most and ExPDE the least, the magnitude being the percentages highlighted above. As all four percentages are above 10%, theory concludes that the variations are significant and not attributable to chance or a mere statistical error emanating from sampling variation. This is a contribution in addressing a gap in theory and literature, where the effect of efficiency indicators has been deemed difficult to measure and quantify over time.

Evidence that LMM parameters are better estimates:

Parameter estimates from a classical approach that is, simply fitting an ordinary trend line using Ordinary Least Squares (OLS) regression are compared to results derived from the Linear Mixed Method (LMM). The OLS quarterly increment is obtained by dividing the range by one less the number of time points (that is, the degrees of freedom). Results are as shown in Table 4.12 below.

Table 4.12: *Contrasting OLS vs. LMM outputs.*

	CLASSICAL APPROACH **(OLS)**			LINEAR MIXED MODEL **(LMM)**		
	Arithmetic Mean	Standard Error	Increment per Quarter	GEE Intercept Mean	Standard Error	Increment per Quarter
ExPDE	2730.64	860.241	162.370370	2092.398810	239.234795	44.016831
ALOS	6.517	1.2317	0.1925925	5.493056	0.435261	0.070614
BOR	75.94	7.807	1.7037037	71.414683	2.600600	0.311918
CSR	44.03	9.621	1.2592592	41.595238	5.272722	0.167693

The more reliable and better parameter estimates on the right hand side (with lower standard errors) are because the variance components (random effect variability) have largely been accounted for and separated from the error variability. It follows therefore that LMM forecasts will (because of smaller standard errors), be more pointed and show less error variability when forecasting. The mean values are also smaller, this is because the random effects model with varying intercepts was permitted for to allow for unrestricted model specification. In a practical sense, this implies efficiency measurements across the four central hospitals are generated independently.

Triangulation (hospital effect)

Triangulation refers to the use of different data collection techniques within one study in order to validate findings from different methods (Aristovnik 2014; Saunders, Lewis & Thornhill 2012); that is, its purpose as indicated in Table 3.1, is to ascertain for convergence, corroboration, and correspondence of results across the different methods. This section discusses how by triangulating the results, the hospital (random) effect is also apparent:

- Granger-causality analysis (GCA) shows that the influence of the indicators differ (i) by hospital and (ii) within hospital. The use of lagged values to quantify the pressure on ExPDE by the other three efficiency indicators shows consistence only for DGMAH only (Table 4.4) which had the most variables bi-causal to ExPDE (Table 4.8). Also in Figures 4.7 and 4.10, hospital 2 (=DGMAH)'s consistence is further supported.
- The preceding bullet points to the notion that indicators 'behave' differently across hospitals. This is apparent in the causal generating mechanism differing by hospital (Table 4.8) and within hospital (Table 4.4) as pointed above. In Table 4.11, the variance components are derived and these differ substantially from another. If the hospital effect is accounted for in a modelling context, the output as shown in Table 4.12, is more pointed and reliable owing to the smaller standard errors and thus more precise.

The existence of the random effect is furthermore confirmed by calculating correlation between original values and contrasted against those obtained from the LMM predicted values (Tables 4.13 and 4.14). Changes can be observed before and after controlling for the hospital effect, for example, the correlation between ExPDE and BUR adjusts from being insignificant (before) to being significant (after). Now from Table 4.8, BUR Granger-causes ExPDE in only two hospitals which are SBAH and DGMAH and if no profiling is done by hospital, BUR values from CHBAH and CMAH dilute and mask the dynamics at the former two hospitals. Magnitudes of the variance components (Table 4.11) closely resemble the number of variables each efficiency indicators significantly correlates to, after controlling for the hospital effect. C-section rates have the highest variability followed by ALOS, BUR and ExPDE.

***Table 4.13:** Pearson correlation coefficients (before and after correcting for hospital effect, that is original vs. LMM predicted values.*

		ExPDE	ExPDE#	ALOS	ALOS#	BUR	BUR#	C-section	C-section#
ExPDE	coefficient	1	1	.051	.040	.114	.204	.388**	.322
	p-value		.	.593	.677	.231	.031	.000	.001
ALOS	coefficient	.051	.040	1	1	-.093	-.083	-.246**	-.285
	p-value	.593	.677		.	.329	.385	.009	.002
BUR	coefficient	.114	.204	-.093	-.083	1	1	.315**	.473
	p-value	.231	.031	.329	.385		.	.001	.000
CSR	coefficient	.388**	.322	-.246**	-.285	.315**	.473	1	1
	p-value	.000	.001	.009	.002	.001	.000		.
PDE	coefficient	-.147	-.098	-.184	-.178	.188*	.140	-.175	-.109
	p-value	.123	.304	.052	.061	.047	.142	.066	.254
IPD	coefficient	-.229*	-.141	-.061	-.046	.113	.004	-.744**	-.700
	p-value	.015	.141	.523	.630	.236	.970	.000	.000
IPS	coefficient	-.229*	-.144	-.458**	-.475	.140	.039	-.571**	-.500
	p-value	.015	.133	.000	.000	.140	.685	.000	.000
OPD	coefficient	-.156	-.033	-.252**	-.261	.527**	.466	.387**	.697
	p-value	.101	.729	.007	.006	.000	.000	.000	.000
CH	coefficient	-.250**	-.146	-.260**	-.270	.148	.019	-.618**	-.539
	p-value	.008	.125	.006	.004	.120	.845	.000	.000

# denotes correlation after controlling for the hospital / random effect.

Table 4.14: *Pearson correlation coefficients (before and after correcting for hospital effect, that is original vs. LMM predicted values.*

		PDE	PDE#	IPD	IPD #	IPS	IPS#	OPD	OPD #	CH #	CH#
ExPDE	coefficient	-.147	-.098	-.229*	-.141	-.229*	-.144	-.156	-.033	-.250**	-.146
	p-value	.123	.304	.015	.141	.015	.133	.101	.729	.008	.125
ALOS	coefficient	-.184	-.178	-.061	-.046	-.458**	-.475	-.252**	-.261	-.260**	-.270
	p-value	.052	.061	.523	.630	.000	.000	.007	.006	.006	.004
BUR	coefficient	.188*	.140	.113	.004	.140	.039	.527**	.466	.148	.019
	p-value	.047	.142	.236	.970	.140	.685	.000	.000	.120	.845
C-section	coefficient	-.175	-.109	-.744**	-.700	-.571**	-.500	.387**	.697	-.618**	-.539
	p-value	.066	.254	.000	.000	.000	.000	.000	.000	.000	.000
PDE	coefficient	1	1.000	.382**	.337	.394**	.351	.191*	.111	.300**	.237
	p-value		.	.000	.000	.000	.000	.043	.248	.001	.012
IPD	coefficient	.382**	.337	1	1.000	.898**	.880	-.108	-.364	.790**	.747
	p-value	.000	.000		.	.000	.000	.256	.000	.000	.000
IPS	coefficient	.394**	.351	.898**	.880	1	1.000	.006	-.214	.837**	.807
	p-value	.000	.000	.000	.000		.	.951	.024	.000	.000
OPD	coefficient	.191*	.111	-.108	-.364	.006	-.214	1	1.000	-.156	-.489
	p-value	.043	.248	.256	.000	.951	.024		.	.101	.000
CH	coefficient	.300**	.237	.790**	.747	.837**	.807	-.156	-.489	1	1.000
	p-value	.001	.012	.000	.000	.000	.000	.101	.000		.

# denotes correlation after controlling for the hospital / random effect.

4.2.3. KRUSKAL WALLIS AND LINEAR MIXED MODEL (QUALITATIVE)

Questionnaire responses from the hospital managers at the four central hospitals were analysed and the response rate is shown below. In line with the sample size determination methodology presented in the earlier chapter, a target of at least 25 of the 40 senior managers per hospital was set. Table 4.15 below shows the response rate realised by hospital.

Table 4.15: *Distribution of responses received from the 4 central hospitals.*

	SBAH	DGMAH	CHBAH	CMAH	Total
Target poln. size	40	40	40	40	160
Realised sample	43*	17	30	22	112
% Response rate	107.5%*	42.50%	75%	55%	70%

**Hospital CEOs were invited to use their discretion and permit respondents whose duties fell into determination of their hospital planning and management frameworks using efficiency data even if such respondents were not senior managers. SBAH had several such respondents, exceeding the number catered for in the generic organogram of senior management.*

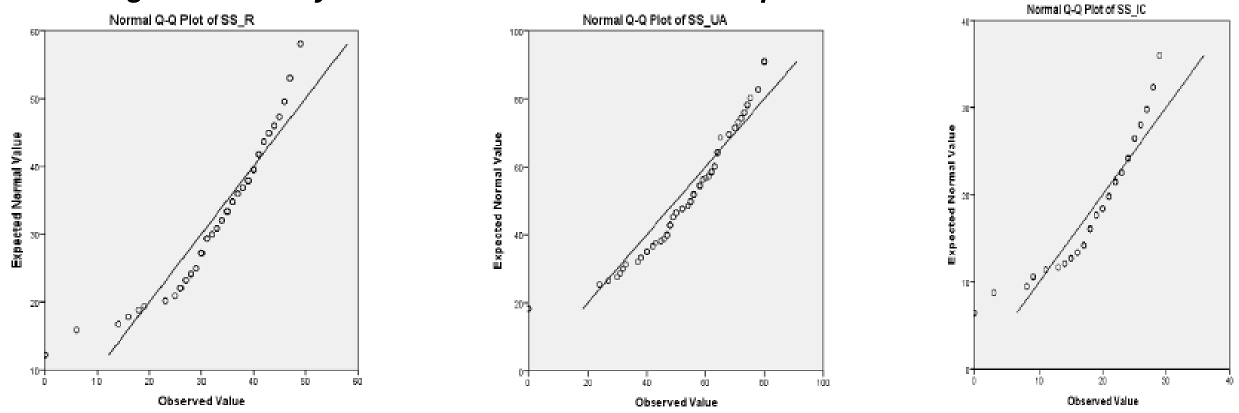
4.2.3.1 SUM SCORE ANALYSES (KW)

The rationale and context of the questionnaire was premised on elements raised mainly in sections 2.1 and 3.3.2. Questions 13 to 22 sought to measure the senior managers rationale of the efficiency indicators; questions 23 to 38 sought to measure their understanding and application, whilst questions 39 to 44 sought to capture institutional challenges inhibiting utilisation of efficiency information as perceived by the managers.

For each question, a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) option had to be selected. By summing questions in each of the 3 categories above, different ordinal items are transformed from ordinal into a single interval value known as "sum-score" and, upon checking for normality, can be used for parametric (or non-parametric if non-normal) as a combined continuous measure. Hence sum-score_rationale (SS_R) is a value between 10 and 50 for each respondent, the higher the value, the more understood the rationale behind the efficiency data in planning and management. Sum-score_understanding_and_application (SS_{UA}) ranges between 16 – 80, the higher the value, the more those efficiency measures are understood and applied in planning and decision making. Sum-score_institutional_challenges (SS_{IC}) ranges between 6 – 30 and the higher the value, the more they act as a deterrent to efficiency indicator utilisation. In the last instance, this is so because the questions are negatively presented and sum score is direction sensitive. In each case, as 3 is halfway between 1 and 5 so the midpoint of each sum score domain represents the transition point. Table 4.16 below shows the distributions of sum-score attributes.

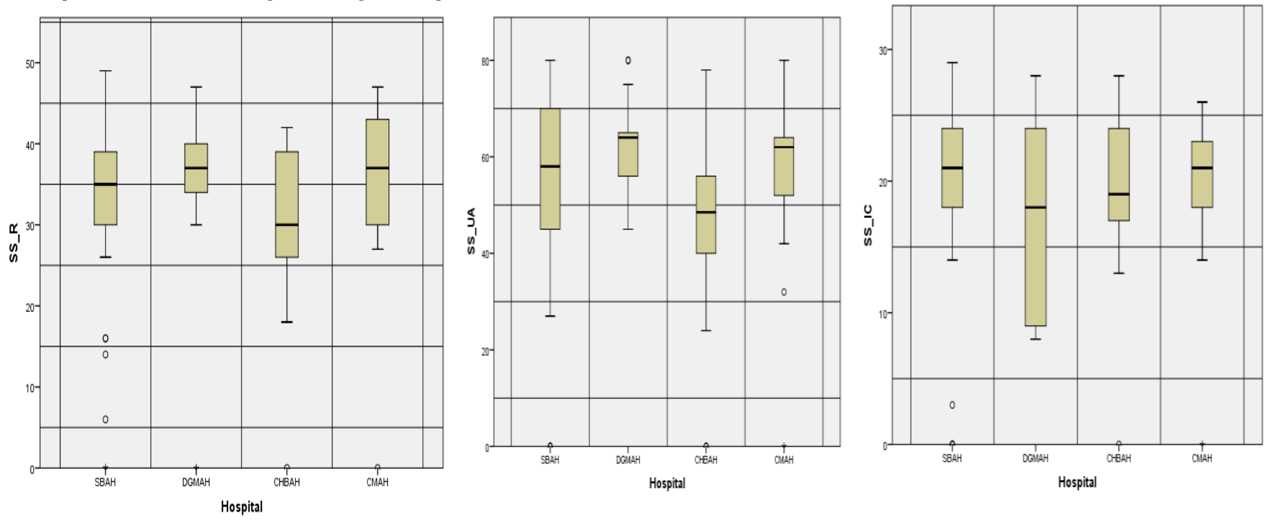
Table 4.16: *Distributions of sum-score attributes.*

Assessing for normality of sum-scores and calculated parameters:



Estimated Distribution Parameters				
		SS_R	SS_{UA}	SS_{IC}
Normal Distribution	Location = mean	33.34	53.39	19.13
	Scale = sigma	10.629	19.628	6.635
The cases are unweighted.				

Box-plot mean analyses by hospital:



Kruskal-Wallis Test:

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of SS_R is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.056	Retain the null hypothesis.
2	The distribution of SS_UA is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.009	Reject the null hypothesis.
3	The distribution of SS_IC is the same across categories of Hospital.	Independent-Samples Kruskal-Wallis Test	.695	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Linear Mixed Model - fixed parameter estimates:

	SS_R	**SS_{UA}**	**SS_{IC}**
Intercept (p-value)	33.403032 (0.010)	54.034966 (0.003)	18.780888 (0.000)
Manager_id Parameter (p – value)	0.002299 (0.961)	0.003933 (0.972)	0.006249 (0.749)
variance component (p – value)	2.94% (0.661)	10.9% (0.405)	undefined (Hessian)

Results from Table 4.16 show the following:

- There are no serious departures from normality on all three domains namely SS_R, SS_{UA} and SS_{IC}.
- There are heavy tails for SS_R and SS_{IC} meaning there are few but significant number of managers who virtually do not believe there is any rationale at all behind the efficiency measurements and a few who rate highly the rationale of efficiency data in planning and management with the majority being between. The same explanation holds for SS_{IC} in respect of views on institutional challenges being a deterrent to efficiency indicator utilisation.
- Both the Kruskal Wallis test and Linear Mixed Model pick up differences in SS_{UA} but not in the other two domains. The former generates a significant p-value (highlighted in yellow) and the later has a variance component greater than the traditional 10%.
- Box–plot analyses (if plotted on the same scale) reveal no significant differences between hospitals in SS_R and SS_{IC}; a result confirmed by the Kruskal-Wallis test. Significant differences are present in SS_{UA}, implying the efficiency indicators are understood and applied in planning and decision making differently based on hospital. This begins to suggest the root-cause of the hospital / random effect. A closer examination of the SS_{UA} box-plot further confirms (i) that DGMAH has the highest mean value (ii) is more consistent with the smallest inter-quartile range and smallest range (iii) CHBAH has the lowest mean and largest range, indicative of a wide range of diverse understanding and application methodology. The latter would in the context of the study, suggest a weak or total absence of a standardised framework with respect to indicator designs and management.

The above inferences, begin to address issues raised in literature such as in section 2.1 and section 3.3.2 on the questionnaire. That is (i) purpose of indicators (ii) barriers of indicator usage and (iii) evidence of impact of performance indicators raised by Hibbert et al (2013) must be aspects clear enough. In South Africa, a rudimentary understanding of health information is an obstacle to effective health care management (Dlamini et al, 2008; Pillay et al, 2008). More importantly, it was mentioned that although the comprehension of performance measures largely relied on the specification of the output, the extent managers at public hospitals decipher efficiency information or are familiar with indicator methodology remained undetermined. The essence of the subjective inferences talks to the gap identified by Dlamini et al (2008), when they noted that if efforts to ensure the transformation of efficiency data into standard indicators fit for making rational decisions are to bear fruit in public hospitals, then hospital managers should be encouraged and capacitated to interact with key hospital indicators.

In that regard, notable observations that can be made include:

- The rationale SS_R of efficiency indicators is more highly rated at DGMAH and CMAH. DGMAH also rates understanding and application SS_{UA} more highly than any other hospital. This could suggest that these hospitals are more inclined to understand and apply efficiency information in planning and decision making compared to the other hospitals and explain the consistency of DGMAH, as evidenced by its lowest variability in SS_{UA} also.
- CMAH tended to identify more with institutional challenges SS_{IC} compared to the other hospitals, this could possibly relate to its central location within the Johannesburg CBD.
- CHBAH has a smaller proportion of senior managers (in comparison to the proportion in other hospitals) who appreciate and understand the rationale behind the use of efficiency data in planning and management SS_R.
- Understanding and application SS_{UA} presents the most effect across different hospitals (in line with the investigation of the research), followed by how the rationale behind the efficiency indicators is regarded. Institutional challenges are viewed as having the least impact on the utilisation of efficiency information in management, except at CMAH.

Differences (relative to the questions on the questionnaire) realised include:

- A difference in SS_R (the rationale behind the efficiency data planning and management) based on the extent and ability one is able to synthesize technical information (Q7).
- A difference in SS_R (the rationale behind the efficiency data planning and management) and SS_{UA} (understanding and application of efficiency information in planning and decision making) based on the extent one's work requires the use of, or interaction with, efficiency information (Q9).
- A difference in SS_R (the rationale behind the efficiency data planning and management) and SS_{UA} (understanding and application of efficiency information in planning and decision making) based on one's views on whether efficiency indicators provide benefit to one's current work (Q10).
- A difference in SS_{UA} (understanding and application of efficiency information in planning and decision making) based on one's ability to use efficiency information if and when required to do so (Q11).
- A difference in SS_R (the rationale behind the efficiency data planning and management) and SS_{UA} (understanding and application of efficiency information in planning and decision making) based on one's knowledge of the DHMIS policy (Q12).

It was noted in literature that the utilisation of indicator information in hospital settings is largely influenced by background with most hospital managers in the public health care sector more likely to have a health or medical background whereas those in the private sector being more inclined to emanate from a commerce or management background (Pillay, 2008). Table 4.17 below shows cross tabulation of professional background with current role.

Table 4.17: *Cross tabulation of professional background by current role.*

Current role:	**Professional background**		**% Total**
	Clinical / Medical	Management / Business	
Clinical / Patient care	39.4%	3.2%	**42.6%**
Administration / Support	17.0%	40.4%	**57.4%**
% Total	**56.4%**	**43.6%**	**100%**

The majority of hospital managers are from a medical background but in terms of current role, the majority are currently in administration/support, which is expected as the survey targeted senior hospital managers entrusted with administrative obligations. The majority of those with medical backgrounds are mostly deployed in clinical patient care, whilst the majority of those with a business background are mostly in administration/support roles. Table 4.18 below shows the inclination to utilisation of efficiency information by professional background and by current role in a 2x2 contingency table in which the relative risk (RR) and risk difference (RD) are computed with the 95% confidence intervals.

Table 4.18: *Contingency table of professional background by current role.*

Professional background		*Clinical / Medical*	*Management / Buss*	Risk measures	conf. intervals
Understanding Efficiency Indicators	Yes	46	32	R/R = 1.14	[0.9336 1.3900]
	No	7	10	RD = 0.106	[-0.0518 0.2638]
Current interaction with Efficiency Indicators	Yes	44	37	R/R = 0.942	[0.7991 1.1113]
	No	9	5	RD = -0.051	[-0.1915 0.0899]
Current Role		*Clinical / Patient care*	*Admin / Support*		
Understanding Efficiency Indicators	Yes	34	52	R/R = 1.14	[0.9537 1.3628]
	No	5	16	RD = 0.11	[-0.0384 0.2526]
Current interaction with Efficiency Indicators	Yes	34	53	R/R = 1.11	[0.9278 1.3091]
	No	5	14	RD = 0.081	[-0.0624 0.2239]

It can be inferred from the risk measures in yellow above, that a manager with a medical background or currently within patient care is 1.14 times more likely to comprehend efficiency data than one with a business management background. Interaction with efficiency information in current role is 1.14 times more likely for those in patient care than for those in Administration / Support. Eleven more managers from 100 with a clinical medical background can be expected to understand efficiency information than from 100 with a management/business background.

Descriptive frequencies and cross tabulations (see Annexure E) show that, even though 82% of hospital senior managers indicate a positive understanding of hospital efficiency indicators, only 73% of the managers regard hospital efficiency indicators as relevant and vital in planning and resource management. About two in every five (39.8%) hospital managers believe they have an acceptable grasp and understanding of the DHMIS policy that sets out the framework for the measurement and reporting of the hospital indicators. Other findings include:

- Slightly more than 85% of hospital senior managers see their work as requiring the use of, or interaction with, efficiency-indicator information.
- Of the senior managers, 89.7% would want to be more proficient in the use and synthesis of efficiency data.
- Managers mostly agree to the appropriateness of the 4 efficiency indicators, followed by their adoption in strategy and implementation.
- ExPDE is the least used when planning and making decisions.
- ALOS and BUR are rated the most understood and applied as well as the most used in planning and resource management.
- The widest gap between having knowledge of the indicator and its being applied in planning and management decision making is with BUR, followed by C-sections.
- The least gap between having knowledge of the indicator and its being applied in planning and management decision making is with hospital expenditure.
- A greater proportion of the crosstabulation between administration / support with current role; had little understanding, application or interaction with hospital efficiency indicators.
- Dynamism (if the indicators have become redundant over time), workload, behavioral and cultural norms at workplace are issues that the managers do not regard as hindering the utilisation of efficiency information.

In literature, Zizza et al (2015) alluded to the fact that the determinants of, as well as the impact of C-section rates world-wide are often questioned. Bullet 6 above resonates with that issue. Literature also suggested that hospital managers could be too overwhelmed to concentrate on synthesis of indicator information. However, the last bullet does not confirm that as a matter of fact in this research. The above findings suggests that the hospital managers are well aware of the obligations of data-driven decision-making, but that experiences in both using and taking ownership of the data could be lacking, a fact in line with observations made by Dlamini et al (2008). Therefore, and as highlighted within the body of literature; there are grounds for technical assistance to be provided to hospitals in order to address the gap identified, that is hospitals are largely unfamiliar with efficiency methodologies (Litvak and Bisognano, 2011).

4.3: CHAPTER 4 SUMMARY AND CONCLUSION

In chapter 4, research results pertinent to the research problem and question are presented. The main research problem sought not only to describe the change, but how changes in indicator constructs and expenditure are attributable one to the other, as that would ultimately guide resource interventions strategies. In that regard, the main research question sought to establish cause-effect relationships between the hospital efficiency indicators with a particular focus on hospital expenditure (as a dimension of performance) in and across the hospitals. Across the hospitals, longitudinal profiles of the indicators differed substantially almost being random between hospitals. That variation between hospitals distorts the visibility or detection of any causal patterns but through GCA, LMM and KW; the hospital effect (that distorts the detection of patterns) was modelled, determined and quantified for each efficiency indicator. Appropriate parameter estimates leading to empirical model specification were presented, from the lag selection necessary for the VAR model, the order of the (VAR) model, the ACF necessary for the assumption of stationarity of the series and then determining Granger-causality impacting on the efficiency indicators. The focus on variability across hospitals is to determine if there are significant hospital effects that would indicate different practices and guidelines between the hospitals, and the results do confirm this to be indeed the case.

The results showed the limitations of individual indicator metrics, as there is not a single indicator that applied significantly across all four hospitals. This implies that indicators should cover a broad basis of dimensions. In fact the four indicators employed as management indicators in South Africa could very well be too few, compared to other countries in Table 2.1 for instance. It would appear that the indicators are best assessed within the context of the individual hospital, with the exception of DGMAH, apart from having most of the efficiency and auxiliary indicators as significant; the ExPDE P-P plot and ALOS P-P plot are normally distributed. This suggests a symmetrical balance in expenditure and slight variability in case-mix of patients. Managers from DGMAH had higher mean values in appraising the rationale as well as in understanding and comprehending hospital efficiency indicators and with the least variability in both instances. They also report the lowest score in terms of institutional challenges or deterrence’s to indicator utilisation, results from DGMAH show consistence throughout.

Finally, it is imperative to note that the rankings and assessments by managers were purely subjective and based on self-evaluations, and not externally validated. These may have been influenced by the respondents’ lack of knowledge resulting in an inability to rate the items, or may have been based on a self-evident knowledge gaps. The competencies listed may also not have fully reflected the scope of indicator measurements and management to some’s expectation. However, despite such limitations, the research achieved important theoretical, practical and relevant aspects necessary for the improvement of hospital indicators and the subsequent health resources management in public central hospitals.

CHAPTER 5: DISCUSSION - HOSPITAL / RANDOM EFFECT AND EIMT

5.1: THE HOSPITAL / RANDOM EFFECT

Central hospitals are at the top end of the referral chain, and should always be managed as an integral part of the health care system as a whole. The question of whether indicators can guide the configuration of such services in a public setting has been a matter of debate. That is so because hospital have traditionally been viewed as providers of clinical care services disregarding resource management accountability. Until the value of the indicators and their linkages to managerial strategies that inform hospital operations (forecasting included) can be determined; opportunities to improve on hospital operational activities would always be suspect. This is because public hospitals cannot be assessed on the same basis as private health care providers who are inclined to profit related performances.

Given that there are major disparities between financing of the public and private health sectors as articulated in chapter 1, there have been suggestions that the public health care system is more inadequately funded than it is inefficient. The implication being that only when resources are known not to be lacking, can a determination on efficiency be certain. Therefore and unless some understanding is gained about efficiency measurement and the implications thereof; public health care will continue to increasingly consume financial resources with sub-optimal outcomes. Christian and Crisp (2012), pointed out that if increased revenue marked for redistribution to the public health system is to have optimal impact on health outcomes, then management inefficiencies within the public health care system must be addressed. Inferences in this regard contribute towards policy decisions regarding hospital indicator measurements and designs, elements vested with the National Minister of Health advised by relevant structures established for this purpose, for example the National Health Council and its technical committee.

This research sought to evaluate and explore causal relationships between hospital efficiency indicators as dimensions of performance, their linkages to hospital operations across the hospitals and subsequent association to resource expenditure. A major focus was to also determine factors or gaps that influence managerial operational activities in response to indicator constructs and thereafter develop or recommend an implementational strategy for efficiency indicators that is optimal and best suited to enhance evidence-based management within public hospitals based on the research findings. The latter is presented towards the end of this chapter, after consolidating the main findings of the research study. One of the key findings emanating from the study is the significant hospital specific characteristics or random effect. That essentially implies that the cause - effect relationships are contextual and specific by hospital, and may not be applicable to a different hospital as illustrated in Table 4.8, and it’s more pronounced at DGMAH. It is apparent that there is no one-size fits all metric of indicators that is applicable equally to all hospitals.

The above finding is significant as it is unexpected for hospitals offering the same service of packages. Significant hospital specific characteristics distort both the cost structure and funding model for service provision by packages of services as outlined in section 1.1.1, as hospitals are funded based on the category of services (standardised) they are designated to offer. The magnitude of the variance components as shown in Table 4.11, that is, 93.6% in C-section rates, 48.2% in ALOS, 35.3% in BUR and 23.4% in ExPDE attest to serious deviations from the set levels.

Whilst DGMAH is the more consistent in terms of indicator framework (Table 4.8, Figures 4.7 and 4.10), in terms of individual indicators only ALOS (Table 4.4) is consistent in lag selection across all four hospitals, that is ExPDE is showing up in ALOS' levels in the following quarter after the expenditure is made. Table 4.4 suggests pressure on expenditure emanating from BUR not being an issue at SBAH nor at CMAH. CHBAH is under pressure in every respect except from ALOS. BUR, C-sections, PDE and IPD exert financial pressure at CHBAH. IPS exerts pressure at DGMAH and IPD exerts pressure at CMAH. SBAH suffers virtually no pressure at all.

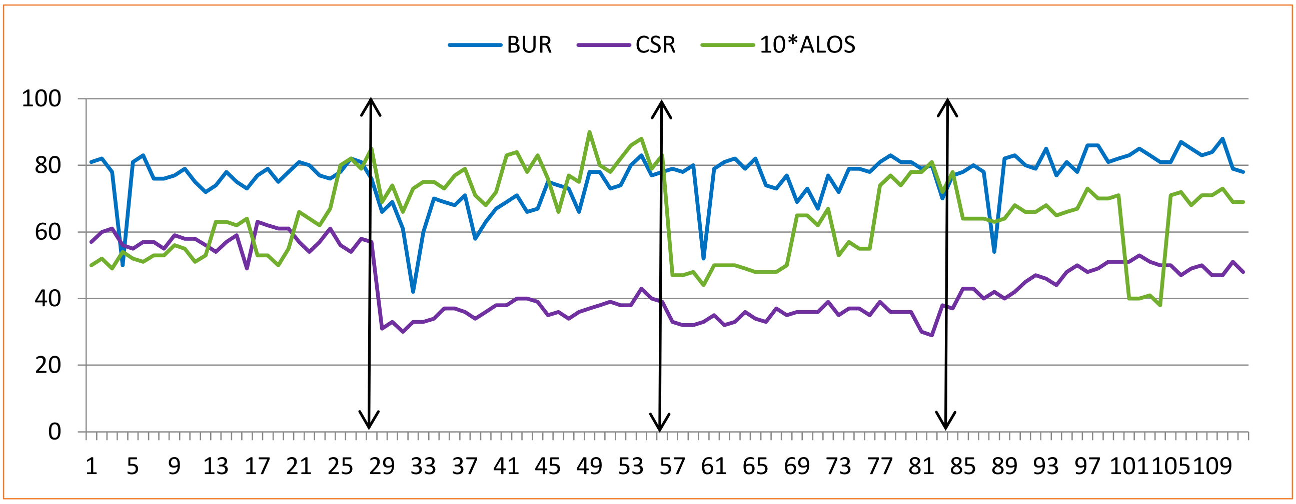
The above findings can be corroborated by literature presented earlier on, where it was mentioned that quality of hospital care varied widely across different indicators. Nathan and Rautenbach (2014) concluded that unlike other central hospitals in Gauteng, SBAH benefits immensely from a supportive infrastructure around the hospital, and that could be the reason as to why there is no pressure picked up in this research there. That is, there is a District hospital (Tshwane District Hospital) within its premises, it is situated in a better geographical and more affluent service area with easily accessible transportation routes and subsequently, a better performing hospital referral network. This possibly explains why there is no pressure of any sort at SBAH. When one examines Figures 4.3 to 4.6 and Figure 5.1 below (showing the 28 quarterly time points from quarter 1 2008/9 to quarter 4 2014/15 in chronological order such that 1-28 =SBAH; 29-56 =DGMAH; 57-84 = CHBAH and 85-112 = CMAH). It can be concluded:

- IPS requires attention at DGMAH and CHBAH (as implied in Table 4.4). Clearly this relates to the underlying densely populated geographical areas where the hospitals are, unlike CHBAH which has 2888 beds, DGMAH only has 1652 (Table 2.3) and as such, the demand on bedding is much higher for DGMAH than for CHBAH (Figure 4.5). The implication is that there is more severity on the need to discharge patients at DGMAH and more frequently as depicted in the 3rd graph of Figure 5.1.
- Figures 4.5 and 4.6 show that for CMAH, there is no spike in BUR or ALOS and so the pressure from IPD in Table 4.4 is a ratio of demand of beds to OPD patients (day patients). This can be confirmed by a slight gradual increase in BUR over time and it is clear that CMAH is seeing an unusually high number of OPD, possibly by virtue of its location and accessibility.

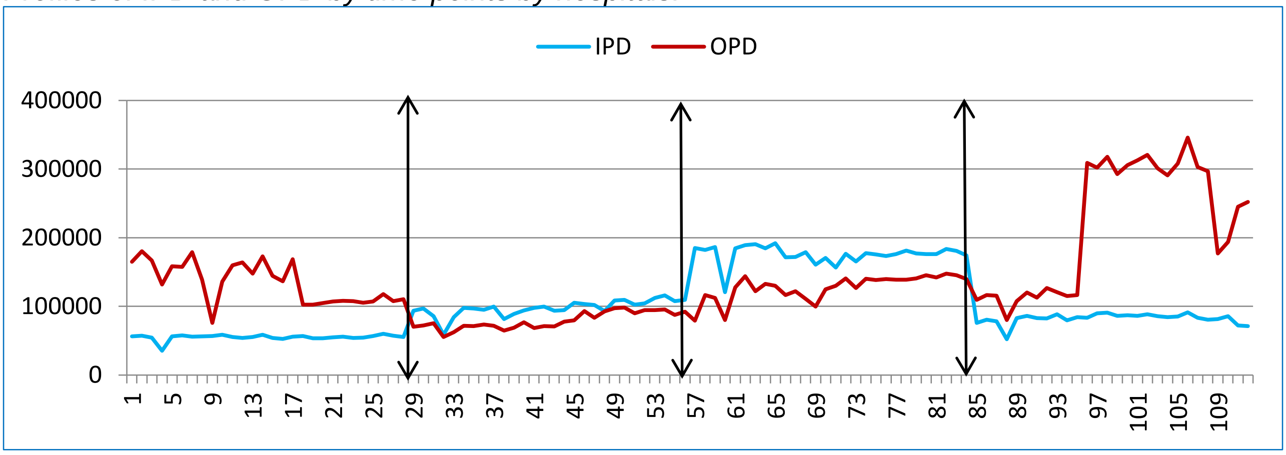
***Figure 5.1:** Profiles of selected indicators (28 time points by hospital).*

In chronological order: 1-28 =SBAH; 29-56 =DGMAH; 57-84 = CHBAH and 85-112 = CMAH.

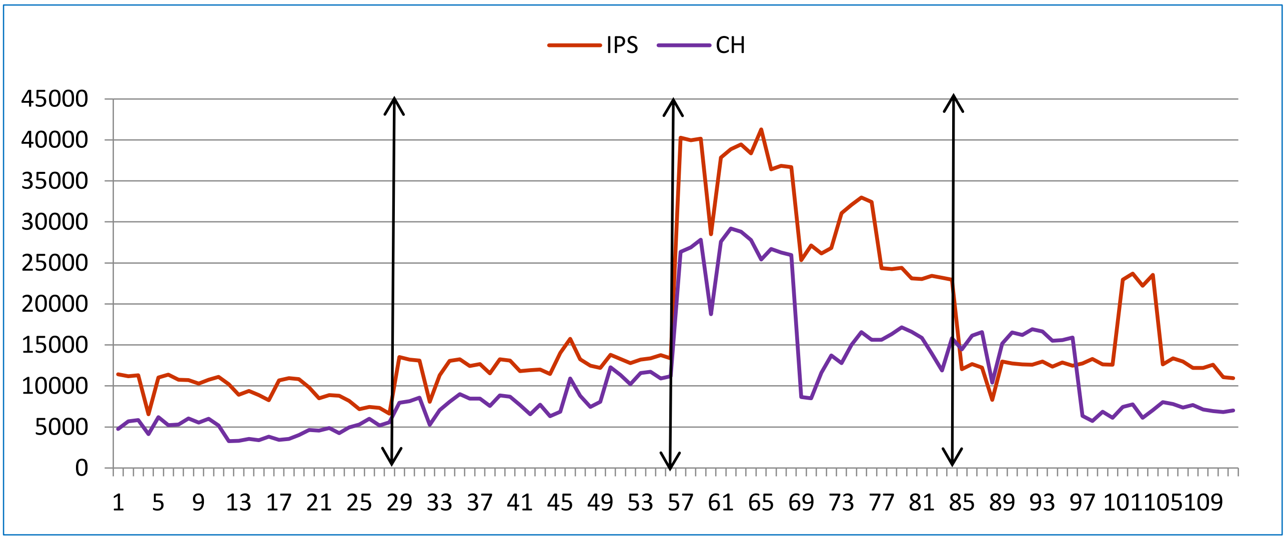
Profiles of BUR, C-Section and ALOS by time points by hospitals.



Profiles of IPD and OPD by time points by hospitals.



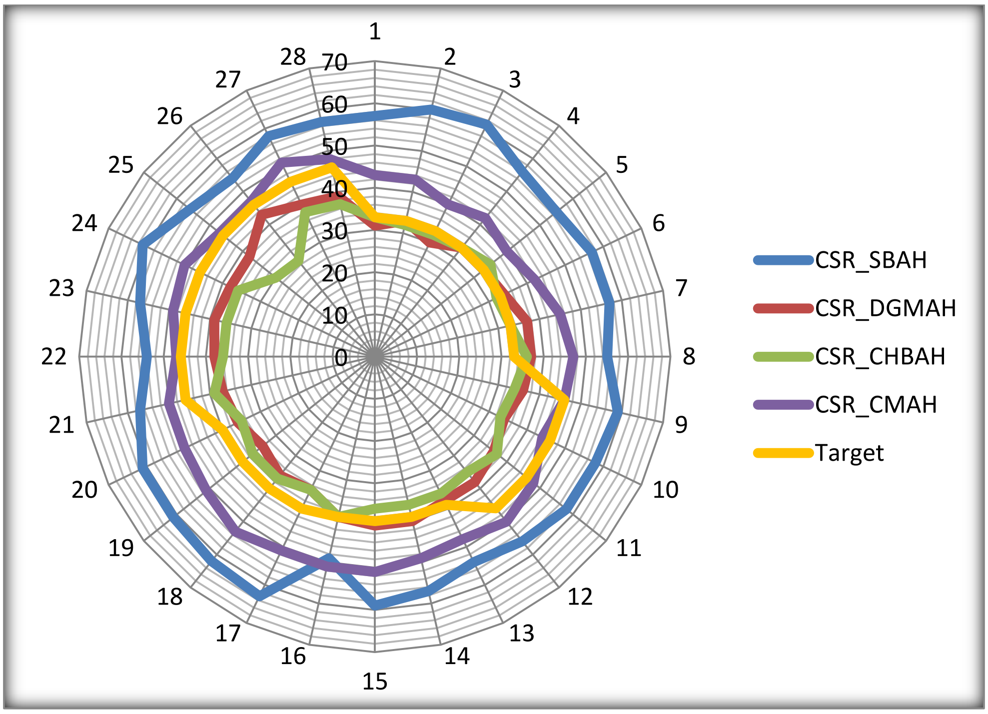
Profiles of IPS and CH/ER by time points by hospitals.



- At SBAH, ALOS has increased but not necessarily BUR suggesting SBAH could possibly be keeping patients for longer than necessary as there are no serious case-mix situations. Whilst ExPDE increase steeply C-section rate does not and therefore, higher (ExPDE) costs are possibly attributable to high numbers of day patients. At SBAH, as indicated earlier, BUR is higher than ALOS (which has gradually been increasing) and OPD is greater than IPD. That suggests more day patients are being seen. IPS does not increase suggesting inpatients are being kept longer, and note that SBAH enjoys a much lower CH.
- At CHBAH, ALOS is much lower than BUR, possibly indicative of pressure emanating from high utilisation. BUR is unusually above target and increasing C-sections at CMAH, suggesting better utilisation / access. At DGMAH, trends in ExPDE, BUR and ALOS are consistent to one another. BUR is less than ALOS, suggesting faster discharges or high IPS. CHBAH recorded high levels of IPD, possibly due to high levels of utilisation and the unusually high IPS and CH confirm high utilisation levels and hence the pressure.

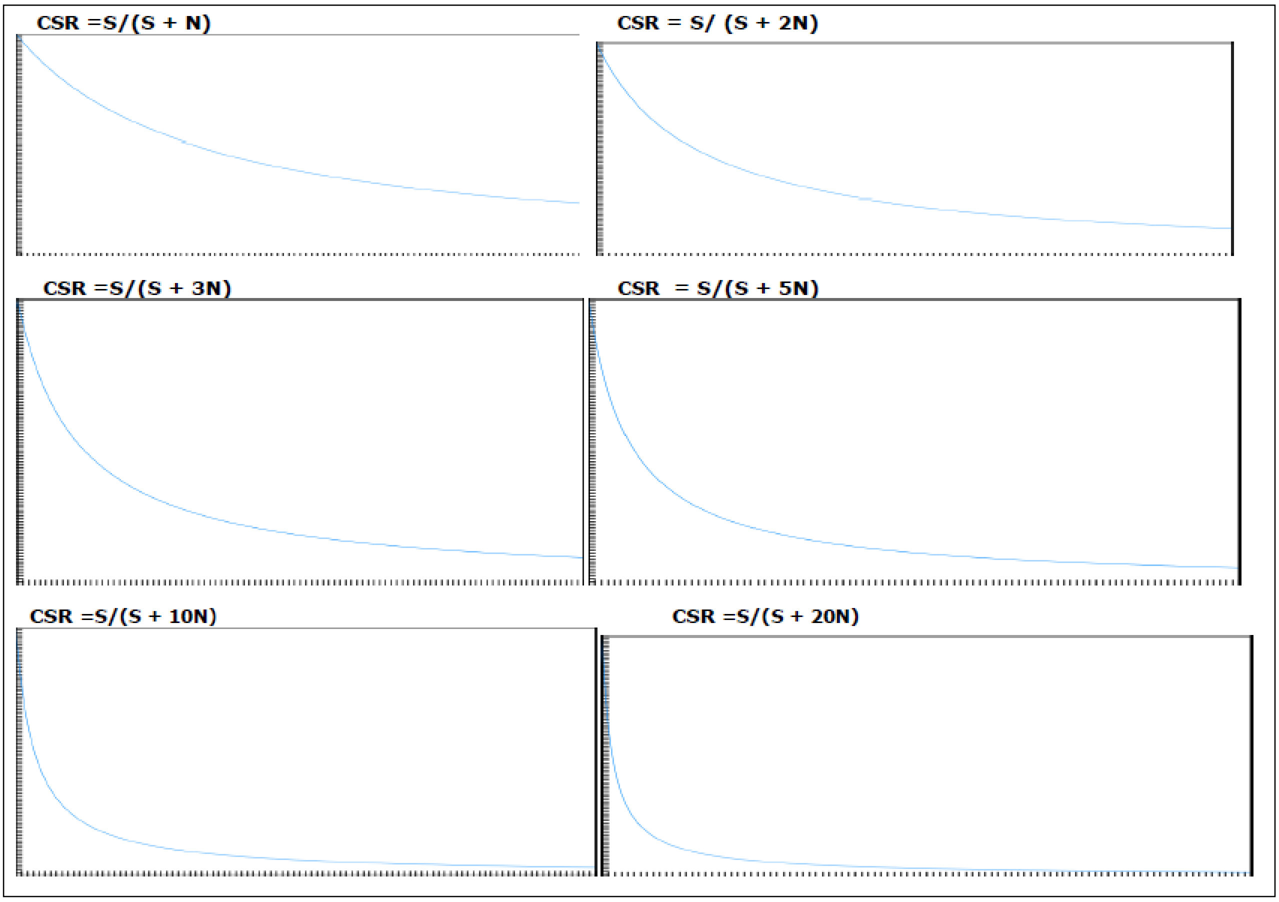
Based on Figure 5.1, the second and third diagrams show the pressure on CHBAH. This is also confirmed by Table 4.4, were CHBAH virtually has four zeros and the remainder are all 1's. It's the only hospital not to have a lag greater than 1. Tables 4.8 and 4.11 provided some insight as to what the root-cause could be. According to Table 4.8, at CHBAH only ALOS and C-sections show causality attribution. In Table 22, the variance component for ALOS is 48.2% whilst its 93.6% for C-sections rates. This suggests that C-sections at CHBAH are masking certain information with a very huge impact and completely different to the other three hospitals. Figure 30 below shows the distribution of C-section rates over the 28 time points.

Figure 5.2: *Distribution of C-sections.*



The inferences raise some concern about a general lack of transparency over C-section rates as a cost driver, for example, in the case of SBAH vs. CHBAH. Such concerns are also highlighted in the body of literature (Boussabaine et al, 2012). Upon further investigation, at CHBAH, the indicator is presenting an incorrect picture and, that can be presented mathematically. The manner C-section rates are defined (as a facility indicator) is CSR = [S / (S + N)] * 100, where S = number of deliveries by Caesarean and N = number of normal deliveries and CSR = C-sections rate. Two elements to recall are (i) the service package at central hospital level is such that only complicated deliveries should be taking place at tertiary level. That is, N should be minimised as possible (not exceeding S) and ideally N = 0 (meaning no normal or uncomplicated deliveries took place in a central hospital), and in an ideal case CSR = 1 (implying all the deliveries were complicated and therefore by Caesarean). However for purposes of teaching, N cannot be strictly = 0 (ii) when the rate of increase in N supersedes that of S, that is if N increases much more dramatically, the effect is to dilute CSR and make it appear as if caesarean complications are under control when nothing could be further from the truth. Figure 5.3 below shows what happens when N is increased to a value much larger than S, the value of S is kept constant whilst N increases from N to 20N and as that happens, the indicator becomes diluted and lowered.

Figure 5.3: *Simulating the effect of increased normal deliveries on C-sections rate.*



The problem emanating from the figure above is:

- Too many normal births confound this indicator, in that as normal deliveries increase from N to 20N, the denominator increases lowering the index. This is testimony to the disadvantage of adopting a facility based indicator whereas elsewhere the indicator is population based (Dahl and Rosseland, 2015).
- The facility based indicator is robust, and can move across the different graphs in response to hospital specific (random) effects generating higher outcomes than in the true population and extreme variation, whereas a population based indicator moves towards the right of a particular one constant graph only and not between different graphs.
- Table 5.1 below shows that in the case of CHBAH, there are far too many normal deliveries and this pulls down the CSR ratio. The hospital finds itself in an environment where it caters for **high cost and high volume** due to its geographical service area/s, poor clustering network affecting supporting infrastructure and a need to provide for a range of lower level package of services. Table 5.1 below also confirms using 2012/13 deliveries, the masking of the C-section rates emanating from a large number of normal births.

Table 5.1: *Normal vs C-sections deliveries (2008 – 2013).*

	Total Deliveries						CSR
	2008/2009	2009/2010	2010/2011	2011/2012	2012/13 (S+N)	2012/13 (S)	2012/13 = S/(S+N)
SBAH	3882	3393	2778	2825	3009	1856	61.7
DGMAH	10112	9489	9289	9027	10106	3563	35.3
CHBAH	22887	21998	22763	22555	22001	7858	35.7
CMAH	7555	8030	9295	9453	9121	4643	50.9

Source: In-depth analysis of the Gauteng Province Hospital Efficiency indicators (2008/09 to 2012/13)

The effect and cost of the high total deliveries (that is S+N) at CHBAH gets offset by a lower CSR rate, suggesting that if there are obstetric complications around the populations, preference might go towards SBAH (based on CSR) yet it should be on CHBAH. In addition to the case mix of the level 1 patients, CHBAH services a larger than usual obstetric population and is without immediate recourse to nearby health care facilities in contrast to SBAH and CMAH, and is therefore more prone to capacity and budgetary constraints. The huge drag of Level 1 patients and, more specifically, the high number of natural births at CHBAH mean the CSR indicator in its current form is confounded and offers no real credible information. Table 5.1 also confirms similar observations by Naidoo et al (2013), Nathan et al (2014) and Van Schaik et al (2014), who observed that DGMAH and CHBAH are providing antenatal care to low risk patients who could be serviced at lower levels of care where costs are lower (efficiency) to reduce unnecessary C-sections and that interventions have shown limited effectiveness to date (Betran et al, 2015).

Gebhardt et al (2015) suggested that more intensive skills training in C-sections should be intensified at the undergraduate medical curriculum. It can very well be that the above computations would be better understood at that entry level and effect a change in the current methodology and manner of doing things. A high number of C-sections trigger a corresponding increase in IPD and BUR as the patients are kept in care. Critical aspects of over-crowded public hospitals have been well documented, and findings include high re-admission rates for medical outlier patients when assigned to inappropriate wards with bed shortages more pronounced in medicine and geriatrics (Serafini et al, 2015). However, the above issues clearly make a case for further investigation of factors, both within and outside of the hospitals that impact on efficiency indicators and is therefore a strong recommendation emanating from this research. Furthermore, the study recommends that the C-section rate target at all central hospital levels be reconfigured as suggested (CSR = 1; implying all the deliveries should have been complicated and therefore by Caesarean) and only then will the true picture and value for information emerge. The target of one as earlier on indicated, may be too strict as some tolerance levels must be made for teaching purposes as presented in the literature, but an acceptable tolerance from one can be agreed upon inorder to correlate deviances thereafter to obstetric or burden-of-disease challenges and so on.

In other countries, the denominator is set and calculated differently (that is per 1000 deliveries as a population based index) as pointed out in the literature. Alternatively, the indicator could be more regarded as a measure of efficacy or effectiveness (focusing instead on quality of clinical care in relation to departmental obstetric care service goals) as opposed to efficiency. From a management perspective, this is concerned with minimising wastages in achieving organisational goals and penalising higher scales of costs, notwithstanding the effectiveness thereof (normal deliveries). The above findings confirm issues raised by Ioan et al (2012), who found that indicators for hospital performance management should allow useful interpretations and analyses as a basis of administrative decisions, which affect the functioning of the system in a hospital. The alternative to above is to then have it classified as a quality / clinical care proxy. The downside remains that, in its current form, the indicator will generate inferences higher than the true population effect, further compounding the bias of estimating the actual population (birth complications) due to the way the denominator is premised, that is it is not a population but facility oriented base.

The different dynamics at each hospital as outlined since the beginning of this chapter, give rise to the hospital / random effect. Figure 4.10 showed varying degrees of case-mix within the hospitals, suggesting that the hospitals are seeing patients of varying levels of severity and acuity; this too gives rise to the hospital specific characteristics resulting in large variability in similar indicators or dimensions and inequalities in performances. Another issue could be, in comparison to Table 2.1, the adequacy of only four indicators in such environments.

The above section outlined consequences of the hospital specific characteristics / random effects. It is clear that if the random effect is not accounted for (where it exists and is significant); then the extent efficiency indicators purport to be measuring what they are intended to measure is far from being straight forward as the measurements then encompasses large standard errors as shown in Table 4.12 and become less precise and less valid. Large standard errors imply the estimating models are less pointed and less consistent and subsequently any information generated for management purposes could be low in construct validity, sensitivity and reliability.

Methodologically, variability is evident in all sets of results Granger Causality Analysis (GCA), Linear Mixed Modelling (LMM), Generalised Estimating Equations (GEE) and the Kruskal-Wallis (KW) approaches. All the results showed for instance, that a significant effect of one indicator in the expenditure pattern at one hospital is not necessarily reproduced at another hospital (Tables 4.4 and 4.8). There is always the possibility that the cause-effect may be instantaneous and non-linear or a confounding between the indicators. Tables 4.13 and 4.14 show for instance that ExPDE and BUR are uncorrelated disregarding the random effect, but significant when the random effect is controlled for. This is easy to see why using Table 4.8; the attribution between ExPDE and BUR is uni-directional at SBAH and bi-directional at DGMAH. There is no attribution at CHBAH and at CMAH, and so when all is examined as a single dataset disregarding the hospital effect, the attribution in the other two hospitals is neutralised by the non-attribution in the other two hospitals. When hospital is controlled for, the associations (one weak and one strong) are then picked up. The ExPDE and CSR correlation are significant before and after controlling for the random effect because almost all the modelled variability (93.6%) resides with CHBAH as explained in the preceding section, and that attribution is significant at CHBAH in Table 4.8.

The problem of attribution is especially pertinent to indicator measurement because there are commonly many determinants of health care outcomes, some of which are spurious. In a practical sense, one can only try to gauge the varying dynamics giving rise to the hospital specific characteristics / random effect by further research. In discussions with hospital CEOs, some of the hospital managers as well as input from research and other literature, possible reasons giving rise to the hospital specific variation (random effect) include:

- ALOS and BUR are susceptible to the random fluctuations of dwindling patient numbers during the festive seasons (half of quarter 4 and half of quarter 1), that is the period November to February annually. The hospitals are affected differently and, as discussed in the literature review, are akin to the cycle of “peaks and valleys”, (Mustafee et al, 2013).
- A large component of services offered in three of the four central hospitals have a large L1 (lower level of care) services workload.

- In the absence of a referral network, clinicians find it a problem turning patients away and fear the negativity generated thereafter especially in the media, particularly as public health care services are constitutionally guaranteed to all those within the republic, hence they end up treating L1 conditions anyway.
- At the level of each hospital, the rate and manner in which ward rounds are undertaken is not standardised and will thus affect rate of discharges (inherently linking to ALOS, IPS and BUR)

The above are some of the dynamics that explain sources of hospital specific characteristics / random effect and differ from hospital to hospital. As a result, it is important that managers must recognise the limitations posed by individual metrics in isolation to each hospital. Managers should look at different remedies to ascertain what is causal or correlated to their expenditure patterns given the size of the random effect at 23.4%. Another of variability source can be found in the theory or formulae of the indicators, take the formulae BUR and ALOS for instance:

BUR	**Inpatients + 0.5 Day Patients**
	Usuable Beds X Days in the month

and

ALOS	**Inpatient Days + 0.5 Day Patients**
	Total Separations + Day Patients

Total separation is the sum of inpatient deaths, inpatient discharges and inpatient transfers out. To show linkages or dependency, the above can be re-written (as they both have a common term in the numerator) one as a function of the other. Within one hospital and working on an average of 30 days per month, the number of usable or available beds does not change so the product of (useable beds or bed capacity) x (number of days in the month) can be regarded as a constant.

ALOS	**BUR x (useable Beds X Days in the month) = BUR x Constant**
	Total Separations + Day Patients

and

BUR x Constant	**ALOS x (Total Separations + Day Patients)**

(**note:** when using quarter as time, Days in the month is replaced with days in the quarter)

In traversing across different hospitals, bed capacity changes (but remains again a different constant specific only to that hospital - this is in line with the significant correlation established between ExPDE and BUR only after controlling for the random or hospital effect so that BUR moves together with the random effect across hospitals but remains constant within a particular hospital). This creates a second constant different to that of the one in the first hospital. The random effect is in part, due to the variation all such constants taken together.

Note that, as total separations increase, ALOS decreases due to inverse proportions (this is obviously through timely discharges and enforcement of continuous monitoring of patients well enough to be discharged, deaths are also a part of total separations though). Also if BUR is held constant per month or per quarter, then ALOS is basically a function of total separations and day patients. This is critical in addressing the gap identified by Lu et al (2015), where the recommendation was to employ administrative data to enable accurate prediction of hospital ALOS to improve hospital performance evaluation and performance-based budgeting.

Hospitals should therefore examine the indicator information more regularly to understand the pattern of their day patients. Central hospitals are high cost and low volume and so for example, IPD should not take up most of the ExPDE or resources in general. By seeing more OPD, CMAH actually determined that as a solution, as discussed on the first line of page 161. If there is a significant rise of day patients, there should be an investigation in respect of levels of severity or growth in the burden of disease and such data should be raised as budget bilateral as it will affect the denominator of the PDE = (Inpatient days + 0.5 Day Patients + 0.33 OPD Head count + 0.33 Emergency Head count) and therefore ultimately the budget, since Total expenditure = ExPDE x PDE. Therefore, clearly ALOS is the easiest of all efficiency indicators to ethically manage and the effect filters to the other indicators. Next to manage would be the adherence to service package, that in turn should lower at least in theory, the volume of day patients.

According to Veillard et al (2003), the optimal use of (available) resources, utilisation and staffing ratios and financial management all impact on the measurement of efficiency. Gaspar and colleagues (2012) noted that hospitals are complex organisations as quality of care, efficiency and the hospital assessment performance are features far from being straight forward to measure and estimate. Therefore, the design of hospital indicator systems should be such that service and funding platforms are efficiently configured to optimise available resources and aim to manage and improve hospital functions in the provision of health care services. Two of the gaps identified in literature in that regard pertain (i) indicator benchmarking, increasingly held in high esteem as a management tool but, little is known about its applicability in hospital settings (De Korne et al, 2012) (ii) the challenge of strengthening linkages between resource shifts and outcomes in an efficient, effective and, above all, sustainable manner (Van and Moses, 2012).

Policy plays a crucial role. For example, whilst constitutionally public health care facilities cannot turn away patients, more still needs to be done to ensure the correct patients are seen at the appropriate level of care besides just strengthening the hospital referral network. SBAH has a district hospital right across the road, and can refer walk-in patients thereby not treating L1 patients as earlier indicated and is a privilege not enjoyed by other central hospitals. The policy discussion then becomes whether a mixed-service package should be adopted at one hospital or not.

The research study has established as an original contribution, that controlling for hospital variability resulted in better estimates (more forecasting precision) due to lower standard errors compared to the classical approach. It can be inferred in the last 7 years:

- ExPDE grew at the rate of **R**44.016831 per quarter (or **R**176.07 per annum).
- C-section rate grew at the rate of 0.17% per quarter (or 0.68% per annum).
- BUR grew at the rate of 0.31% per quarter (or 1.24% per annum).
- ALOS grew at the rate of 0.07 days per quarter (or 0.28 days per annum).

The above inferences are crucial for both policy makers as well as the people in charge of setting national targets for this level of care. The impact that efficiency indicators can play in forecasting the budgetary pressure is real and plausible. Even though hospitals and the health care sector as a whole face a great deal of pressure to control constantly escalating costs (Vitikainen et al, 2010), quite often budgetary allocations in public hospitals are determined by way of an inflationary consumer price index (CPI) related adjustment. Though the medical inflation index is a part of the CPI weights, its relative contribution is diluted at a national level when mixed with commodities such as fuel and electricity prices. As a result, if the previous budget was inadequate, increasing the budget for the next cycle by a CPI related factor premised on the previous budget simply perpetuates the status quo. The above determined rates would be a more realistic basis of threshold setting that are more reflective of differences within the cost structure. Aside from the cost implications, variables can forecast the implications for each indicator and therefore enable appropriate control measures to address or contain costs such as BUR or ALOS. That is, use the incremental growths to generate target thresholds for future financial years. This research study makes a crucial gap contribution towards addressing that through the EIMT, as presented later in Section 5.4.

Isolating the impact of hospital indicators is far from being straight forward, and isolating this to a particular hospital (as opposed to a community health service for instance) even more troublesome. Whilst methods of measuring efficiency within the health care sector have received attention and developed significantly in recent years, research on the impact of indicator information on the effectiveness of health care systems are rarely carried out. It has been demonstrated that the use of hospital efficiency indicators could allow for the creation and implementation of an efficient system of control and measurement to introduce improvements in hospital performance. A need for training and guidance, on how to incorporate the information into hospital operational and planning frameworks as a strategic function rather than administrative routine exists. That will ensure that efficiency indicator utilisation translates to administrative efficiency gains in synergy with other hospital operations and create ownership of the data and ensure that there is also the necessary buy-in to sustain the necessary interventions.

5.2: QUALITATIVE INFERENCES

Von Holdt and Murphy (2007) indicated that a primary factor influencing differentials in resource allocation and workload between institutions is the varying capacity and quality of managerial competences. Managers were questioned in areas relating to how they see, interact and understand efficiency data in their day to day activities. The areas were, the rationale of efficiency indicators SS_R, their understanding and application of efficiency indicator information SS_{UA} and experiences of institutional challenges SS_{IC} as impediments to efficiency information utilisation. The results were presented in section 4.2.3.

Those results indicated a greater inclination of managers from a medical background to use hospital efficiency information; yet the greater interest could in fact be more to do with clinical management protocols and outcomes as opposed to administrative decision-making. This also explains why ALOS and BUR (collected from the wards) are popular in contrast to ExPDE (collected from the administration office), a weighted proxy for estimating resources for all types of patients in terms of inpatient days by volume of patients. ALOS is the average number of days for admissions in hospital but can be regarded as a proxy for effectiveness and efficiency of healthcare utilisation. BUR being the proportion of inpatient-bed days used as a function of maximum available bedding capacity can also be regarded as a proxy for the measure of supporting infrastructure, package of services, burden of disease profile or complexity of cases, elements which also affect ALOS. Clinicians are, therefore, more likely to identify with ALOS and BUR as both occur in the wards, in contrast to ExPDE which resides in the accounts / administration office. This implies a gap in flair for efficiency data notwithstanding background.

Even though ExPDE is also the least used when planning and making decisions, the fact that the least gap between having knowledge of the indicator and its being applied in planning and management decision-making is with hospital expenditure could possibly be attributed to the fact that senior managers are responsible for and in charge of budgets and have to account for such in line with provisions of the PFMA / Treasury regulations. That process requires keeping track of expenditure (in order to account) but this could be so, not necessarily to proactively react with interventions and control measures but more in response to compliance, with probably limited understanding. Findings from Table 4.17 and 4.18 are in conformity with other observations in literature, such as Pillay (2008)'s observation that the majority of public sector managers had a medical / health related background. Those were found to be more forthcoming in admitting on the need to become more proficient in efficiency and effectiveness development in comparison to those from a commerce or management background. When one transposes current role with professional background, there is an almost equal distribution (39.4% against 40.4%) but there are more managers with a clinical / medical background whose current role is in administration (17%) compared to the converse (3.2%).

If one considers Table 4.16 on the box-plot mean analyses for the more consistent DGMAH, there is wide variability in SS_{IC}. It can be deducted that the reason why institutional challenges hindering efficiency indicator utilisation was not overally significant, could be attributed to that high variability as the other three hospitals are quite moderate. That suggests that DGMAH has managers who strongly believe that there are institutional challenges hindering efficiency indicator utilisation whilst others strongly feel the opposite. Views in all other hospitals can be regarded as moderate. The lowest rating of all the domains was from CHBAH on the rationale behind the efficiency data in planning and management. In fact, the box-plot mean analyses show that across all three domains, DGMAH has the highest of scores whilst CHBAH has the lowest. That may explain the high attributions at DGMAH (Table 4.8) as well as the severity levels at CHBAH (Table 4.4).

Generally, the results presented in section 4.2.3 point to a need for managers to not only interact with efficiency data, but grasp the set of connected processes that can lead to change in desired outcomes premised on how dimensions are developed and intertwined in theory. In that regard, if efficiency data are to translate into standard indicators fit for making rational decisions in public central hospitals, then senior hospital managers ought to be given guidance on the interpretation and relevance of such, including implications for variations, as indicators should not be read in isolation. Hence, if progress is to be made in promoting the utilisation of efficiency data to standard indicators fit for making rational decisions, then managers ought to interact with key indicators from their data portal and ensure this translates to efficiency gains in hospital daily operations. That is necessary and useful for informing decisions at all levels of the public health care system in order to support sustained equitable and efficient use of health resources. Given that results showed a wider variability in understanding and application of efficiency indicator information, SS_{UA}, hospital managers should take ownership and oversee the entire value chain of hospital efficiency data from production to utilisation as a first step. That could also lead into the identification of data quality gaps and possibly begin to see remedial action being taken.

One of the appeals of mixed methods is that it helps “triangulate” the measurement strategy as it allows the use different measures of the same concept in providing a more robust overall picture. The research questions are answered from a number of different perspectives, as triangulation (integrating quantitative and qualitative methodologies) generates new insights and provides a better understanding of the research problem. In the above discussion, there is positive confirmation of quantitative measures with qualitative experiences thus providing for clarity of purpose, and substantive logical basis for explanations. The above contributes in filling the gap highlighted by Bem et al (2014), that managers fail to align measurements of indicator information to activities pertaining hospital performance in a public hospital context.

5.3 COMPARISON AND IMPLICATIONS OF RESULTS

Among some of the reasons outlined in section 5.1. for the existence of hospital specific characteristics / random effect was the case-mix, and this was justified using Table 4.18. It was mentioned that SBAH has a District hospital right across the road, and can refer walk-in patients thereby not treating L1 patients, a privilege not enjoyed by other central hospitals. This causes a distortion of both the cost structure and funding model for service provision by packages of services as outlined in section 1.1.1. The role of the hospital referral network was emphasised and that its lack of effectiveness not only meant that clinicians end up treating L1, but also implies the absence of integration of health care services (Maimela, Van Geertruyden, Alberts, Modjadji, Meulemans, Fraeyman, and Bastiaens, 2015).

In 2012, the National Department of Health (NDoH)'s National Tertiary Health Services Plan and Clinical Teaching and Training of Health Professionals sought to and allocated the proportion of Level 1 (L1) workload as a function of the total budget as part of developing the National Tertiary Services Plan (NTSP). The results on workload were applied to the 2014/15 budgets to quantify the proportion of the overall hospital budget spent on L1 work. The results are shown below in Table 5.2.

Table 5.2: *NTSP's model showing the proportion of L1 workload.*

District	Hospital Category	Hospital Name	Usable Beds	Estimated % L1 work in the hospital	Estimated L1 beds in the hospital	2014/15 Total Budget	% L1 Budget
	Regional	Tambo Memorial Hospital	540	77%	418	583 024 000	451 303 763
	Regional	Far East Rand Hospital	390	85%	333	402 632 000	343 785 785
	Regional	Natalspruit Hospital	800	88%	706	627 061 000	553 381 333
	Regional	Pholosong Hospital	483	87%	419	379 850 000	329 517 909
	Tertiary	Tembisa Hospital	836	89%	748	749 409 000	670 523 842
Ekurhuleni			**3049**		**262**	**2 741 976 000**	**2 348 512 631**
	Central	Charlotte Maxeke Hospital	794	2%	1	2 284 455 000	54 665 800
	Central	Chris Hani Baragwanath	2308	52%	119	2 841 691 000	1 471 326 145
	Regional	Edenvale Hospital	230	83%	192	293 139 000	244 707 339
	Tertiary	Helen Joseph Hospital	576	64%	369	773 663 000	495 627 859
	Tertiary	Rahima Moosa Hospital	310	52%	162	455 617 000	238 096 626
Johannesburg			**4218**		**193**	**6 648 565 000**	**2 504 423 770**
	Regional	Sebokeng Hospital	745	85%	631	559 799 000	474 138 482
Sedibeng			**745**		**631**	**559 799 000**	**474 138 482**
	Central	Dr George Mukhari Hospital	1236	51%	636	1 694 576 000	871 966 291
	Central	Steve Biko Hospital	599	-6%	-35	1 718 939 000	-
	Regional	Mamelodi Hospital	282	63%	179	351 555 000	223 150 160
	Regional	Leratong Hospital	813	85%	691	592 844 000	503 880 940
	Tertiary	Kalafong Hospital	763	73%	558	797 264 000	583 058 076
Tshwane			**3693**		**202**	**5 155 178 000**	**2 182 055 467**
GAUTENG			**11705**		**722**	**15 105 518 000**	**7 509 130 350**

***Source:** Regulations Pertaining to Categories of Hospitals, 2012*

It must be noted that, ideally, L1 services should not even be rendered at central hospital level.

Based on the NTSP report (based on the assumptions and norms that related the number of specialists to L2 and L3 services, the negative sign for SBAH depicts a higher number of specialists than L2 and L3 patients), CMAH and SBAH had lower L1 workload estimates. The report acknowledged that central hospitals are offering district and regional levels of care. Using that approach, the percentage of L1 workload as a function of the 2014/15 (adjusted) budget for regional, tertiary and central hospitals = (**R**7,5 bn / **R**15, 1bn) x 100 = 49.71% and so about half of the hospital beds in such instances do not always reflect the level of care that is provided, confounding the funding model and distorting the cost structure (and allocative efficiency).

Offering a lower level of care L1 in a tertiary facility is inefficient as the cost of the service provision is at a higher scale of costs, in particular the specialists' (paid for) time. SBAH does not see any L1 patients because of reasons already advanced, that is the District hospital within walking distance. Therefore, if the hospital referral system were to be effective there would be tremendous efficiency gains within the public health care delivery platform in general. Whilst tertiary and central hospital beds are not supposed to serve only the Gauteng population, the number of those from outside Gauteng served within the tertiary and central hospital beds in the province ought to be determined to correctly determine the gap between demand and supply of tertiary services. The results confirm to some extent the pressure as listed in Table 4.4 were SBAH has the least of pressure and CHBAH has the highest. The L1 workload varies considerably (-6% for SBAH, 2% for CMAH, 51% for DGMAH and 52% for CHBAH). Mixing L1 conditions with other tertiary conditions breeds serious variation in case-mix and makes hospital specific characteristics / random effect more pronounced. The random effect is indirectly evident from the NTSP report.

In April 2014, the Health Systems Trust (HST) released a report entitled "*In-depth analysis of the Gauteng Province Hospital Efficiency Indicators: 2008/09 to 2012/13*" by Van Schaik et al (2014). The objective of which was to conduct an in-depth analysis on Hospital efficiency indicators for Gauteng Province using a five year period (2008/09 to 2012/13). The report used linear quantile regression in projecting expected ranges and values for the efficiency indicators and, unlike what has been done in this research, generated very large standard errors due to (i) a shorter two-year period (ii) a classical approach that failed to account for the hospital specific characteristics / random effect. In addition, causality and the magnitudes in rate of growth of the indicators were not modelled. The study noted that the national average ExPDE for central hospitals was exceeded by Gauteng central hospitals, and that due to the small number of central hospitals, ExPDE trends could be unreliable. This confirms earlier findings that the indicators are hospital specific, indicative of different practices and guidelines between the hospitals. The report also concluded that hospital managers had very little authority in determining, managing and controlling resources, yet still had to account in that regard.

Common qualitative overlaps between the HST findings and those contained in this research are:

- A lack of understanding of essential data elements by clerks, clinical staff and management.
- Data not readily adopted for assessing performance and decision making.
- CHBAH had considerably higher number of normal deliveries, causing the C-section rates to appear low.
- Geographical configurations coupled with other challenges resulted in some of the regional and tertiary hospitals providing L1 services and that obscured performance measurement and target setting.

The report suggested reasons for high ExPDE possibly emanating from the fact that facility managers do not have full authority for determining, managing and controlling budgets. Hence, even though funding of facilities is based on ExPDE, in theory, there was little incentive to manage and control the costs. The assumption is that perhaps managers think the greater the facility ExPDE, the greater the likelihood of a higher budget allocation in mitigation. Hopefully, if true, that is a misconception which this research has already hinted on. Unless an accurate cost structure of health care service provision is determined, it is not clear if the current funding levels are adequate or inappropriately or inefficiently used. The first step would be the need to become efficient and address inappropriate utilisation of resources.

The focus should in the context of this research, be to find ways of enhancing efficiencies and benchmarking expenditure against performance of efficiency data. This suggestion is in line with the HST report which states that the majority of hospitals in Gauteng have ExPDE above the national average, suggesting opportunities for efficiency gains may be apparent. This is further testimony of the congruence of research findings determined in this research study.

In its conclusion, the HST report stated that opportunities existed for improving the efficiency of hospitals in Gauteng and that data quality should be prioritised, followed by addressing the cost drivers. Setting of efficiency targets would be better enabled when data quality is not suspect. However, Van Schaik et al (2014) raised some key questions of interest, and the questions point to a need for strengthening efficiencies within the hospital referral system, such as:

- Is staff adequately skilled to perform required procedures?
- What are the referral pathways for the hospital and how well are they working? Are there step-down facilities and NGOs that can assist with the early discharge / transfer out if ALOS is persistently high?
- What type of outreach services are available to the hospitals?

5.4 EFFICIENCY INFORMATION MANAGEMENT TOOL (EIMT)

The focus of the research was not a practical focus of knowledge but rather a contribution in theory; however, a part of the research problem and question was to infer on the development of strategies or interventions required to mitigate against hindrances to efficiency indicator utilisation by way of crafting an implementation strategy that is optimal and best suited to enhance evidence-based management practices. The Performance and Accountability Framework (PAF) requires a range of mechanisms to ensure that more appropriate, efficient and effective public services are delivered. It was indicated that PFA is more suitable for evaluation of health care performance using indicator frameworks, so as to get a more holistic picture of the ability of a hospital to make the best possible use of the available resources in order to maximise its performance. That is, what was done? How well was it done and at what cost was it done?

A call for managers to use information such as costs and volume of activities in order to decide on the best configuration of resources as part of hospital performance was first made within the new millennium by among others, Shaw (2003). To address the problems of translating indicator information from theory into practice, it is imperative that focus be directed towards finding means to enable planning frameworks to assist demand and capacity analyses including process mapping with a view to reducing waste and inefficiencies. This can be done through the development of a tool showing the transformation of efficiency information to implementing changes to be made as a result of the indicators. First, though, one must take into account some of the more common sentiments among the senior managers across all four hospitals, these were:

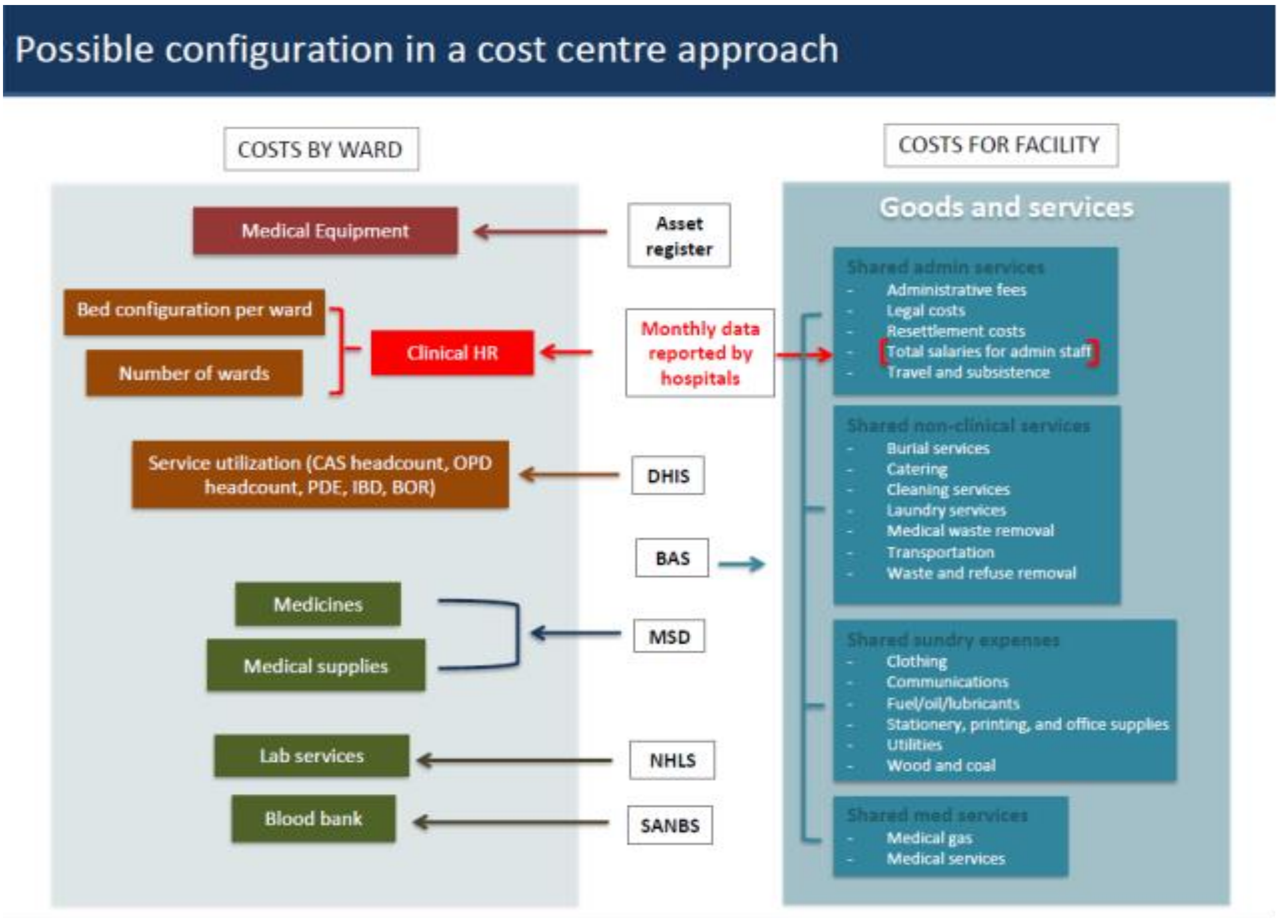
- Provision of all levels of care (L1, L2 and L3) was having an adverse effect in that the hospital might seem effective but not necessarily efficient.
- More needed to be done in turning knowledge into strategic and operational activities.
- Establishment of cost centres throughout would ease the hospital efficiency design.
- A more harmonious, consistent and standardised efficiency framework was necessary to avoid indicator implications being interpreted widely and variedly.
- Special statistics committees be established, whose mandate would be to validate, analyse and interpret data to management structures in order to impact on decision making.
- Develop an efficiency indicators pocket-size booklet for managers.

When selecting indicators, their potential use for quality improvement is considered central. According to the multidimensional and integrated PAF model (Figure 1.11); the main message to convey to the hospitals is that assessing indicator performance cannot be in isolation of other hospital operations. The following are steps proposed in developing the Efficiency Indicator Management Tool (EIMT):

Step 1:

As proposed by the managers, it is imperative to set up cost centers to allow for data to be collected at the lowest level preferably by ward or clinical area / discipline. Collecting hospital information as close as possible to the point of care is important and allows for immediate data verification and validation if necessary. The benefits include interpretability (ALOS per clinical condition is more relevant as a tracker of severity of that condition than ALOS at the hospital level). Given that it is less helpful to examine efficiency indicators at higher levels within a particular hospital (as observed with the masking emanating from hospital effect); there would also be ward / discipline specific effects and so one advantage of collecting information at ward level is that interpretability of efficiency indicators is improved.

Figure 5.4: *Cost centre establishment.*



If ALOS is examined at ward level, values less than the set target could suggest potential poor quality of services (deficiencies within the quality of care, patient probably not well enough) whilst those above could suggest excesses of quality of care (patient should have been discharged but is retained in care at state expense) within the hospital system. Likewise, a BUR of less than the set target could suggest possible inefficiencies, whilst above, could point to poor or weak managerial features.

Step 2:

Set up an excel spreadsheet with formulae for all variables and calculations, that is the tool, Efficiency Indicator Management Tool (EIMT).

Figure 5.5: *EIMT Excel formula sheet.*

Beds	1069		Total possible IPD	97279		Day Patients		
Useable	1069		IPD at Target BUR 78%	75877.62		OPD		
84% Useable Beds	897.96					Emerg. Head Count		
IPD at current BUR	81714.36							
PDE	Inpatient days + 0.5 Day Patients + 0.33 OPD Head count + 0.33 Emergency Head count		PDE	Inpatient days + 0.5 Day Patients + 0.33 OPD Head count + 0.33 Emergency Head count		PDE	Inpatient days + 0.5 Day Patients + 0.33 OPD Head count + 0.33 Emergency Head count	
81714.36	Inpatient Days		81714.36	Inpatient Days		81714.36	Inpatient Days	
0	Day Patients		20696	Day Patients		20696	Day Patients	
0	OPD Head Count		0	OPD Head Count		177129	OPD Head Count	
0	Emergency Head Count		0	Emergency Head Count		7118	Emergency Head Count	
81714.36	PDE		92062.36	PDE		153454.30	PDE	
	Total Available Budget		R 0.00	Total Available Budget			Total Expenditure	
81714.36	PDE 4 above set up		92062.36	PDE 4 above set up		153454.30	PDE 4 above set up	
0.00	Exhaust Expenditure / PDE		0.00	Exhaust Expenditure / PDE		0.00	Exhaust Expenditure / PDE	
R 310 514 568.00	Total Budget Required		R 349 836 968.00	Total Budget Required		R 583 126 340.00	Total Expenditure	
81714.36	PDE		92062.36	PDE		153454.30	PDE	
3800	Expenditure / PDE Target		3800.00	Expenditure / PDE		3800.00	Expenditure / PDE	
R 310 514 568	Additional Expenditure		R 349 836 968	Additional Expenditure		R 583 126 340	Additional Expenditure	
R 310 514 568.00	Budget for scenario 1		R 349 836 968.00	Budget for scenario 2		R 583 126 340.00	Budget for scenario 3	
Inpatients	R 310 514 568.00	100%	Inpatients	R 310 514 568.00	89%	Inpatients	R 310 514 568.00	53%
			Day Patients	R 39 322 400.00	11%	Day Patients	R 39 322 400.00	7%
					0%	OPD Head Count	R 224 363 400.00	38%
					0%	Emergency	R 9 016 133.33	2%

Step 3:

Fill in different scenarios (patient numbers by patient type, BUR, ALOS and ExPDE) and realise the cost, volume and category of patients adjust for a fixed set of indicators. For instance, (real quarterly data) in the above 1069 bed hospital operated at a BUR of 84% per quarter against a target of 78% and ExPDE target of **R**3800, the following become apparent:

- Scenario 1 shows that at the 84% occupancy, 81714.36 inpatient days were generated in that quarter and that alone (assuming ALOS = 1) amounts to **R**310 514 568.
- In Scenario 2, 20696 Day patients seen for the same quarter are added, taking the total budget to **R**349 836 968, split as 89% inpatients and 11% Day patients.
- In Scenario 3, the 177129 OPD and 7118 Emergency cases attended to in the quarter are factored in, taking the total budget in the quarter to **R**583 126 340 and the corresponding split is highlighted in orange.

Remember required hospital expenditure for the specified indicator values = ExPDE x PDE.

Step 4: Decision Making

The three scenarios presented above, will allow management to establish key crucial strategic decisions and interventions. As indicated earlier on, the Division of Revenue Act (DORA) framework places emphasis, on among other things, data recording, interpretation and management aligned to the hospital business plans. For the first time, managers can now get a clear view of the costs by patient type per quarter. For example, for CMAH, populating the actual figures realised as per above, the following are shown for quarters 1-4 for the 2014/15 financial year:

Figure 5.6: *2014/15 EIMT output (for CMAH).*

Quarter 1

Inpatients	**R** 310 514 568.00	53%
Day Patients	**R** 39 322 400.00	7%
OPD Head Count	**R** 224 363 400.00	38%
Emergency	**R** 9 016 133.33	2%

Quarter 2

Inpatients	**R** 325 667 600.00	54%
Day Patients	**R** 21 015 900.00	3%
OPD Head Count	**R** 245 656 066.67	41%
Emergency	**R** 8 784 333.33	1%

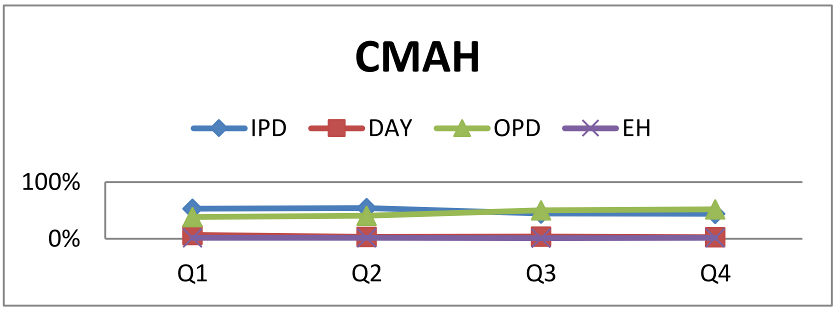
Quarter 3

Inpatients	**R** 273 687 400.00	44%
Day Patients	**R** 22 701 200.00	4%
OPD Head Count	**R** 310 335 866.67	50%
Emergency	**R** 8 610 800.00	1%

Quarter 4

Inpatients	**R** 271 270 600.00	44%
Day Patients	**R** 17 746 000.00	3%
OPD Head Count	**R** 319 685 133.33	52%
Emergency	**R** 8 895 800.00	1%

Profile of % cost by patient type (CMAH 2014/15)



A pattern begins to emerge in that CMAH inpatient days have gradually decreased (possibly due to faster discharges, that could be checked by examining the BUR and ALOS).

A gradual increase in OPD possibly triggers the decrease in Inpatient Days (IPD). In which case, more resources and efforts should be made to ensure that OPD is well capacitated as a strategy to mitigate against high Inpatient numbers. That confirms findings in literature by Schwartz and Mendelson (1994), that a reduction in ALOS is associated with a decrease in the number of IPD. Managers can for the first time, have credible evidence on how much is spent by patient type and the associated budgetary implications, which should prove valuable in building a picture of service utilisation and assessing the extent to which resource allocation (budget) and utilisation (expenditure, BUR, ALOS) are responding to the principles of equity, access, quality, efficiency and sustainability within a hospital.

The excel based tool is easy to set up and operate, and would replace the current form of historical budgeting which is devoid of any basis in informing the budget allocation. It is at present, unknown if the current hospital budgets are adequate relative to the true cost of service provision or if the resources are adequate or even are adequate but inefficiently utilised. The tool, will shed light and tell a previously untold story as all the parameters are captured within the DHIS, but more importantly, management is able to assess the impact on the budget, the type and number of patients they are admitting and, where applicable, refer to scientific evidence in requesting for say more funding during budget negotiations or forecasting future distribution by expenditure by patient type against other norms and benchmarks on institutions offering similar services.

For example, if the ceiling for Day patients is 10% at a particular central hospital, then in the above instance, the onus is on managers to start acting and putting in place appropriate measures which may include increased down referrals. At the very least, efficiency indicators' dashboards will create a picture for the boardroom, allowing for more informed discussions. Evaluation of expenditure and services at the tertiary level has been an area of growing concern, as has been the need for evidence-based decision-making, quantifiable improvement and information useful for benchmarking that should translate to needs or utilisation-based budgeting. The tool will contribute towards closing that gap.

Through careful analysis of efficiency indicators (as done with EIMT), valuable information building a picture of service utilisation (how much is spent by patient type) and assessing the extent to which resource allocation (budget) and utilisation (expenditure, BUR, ALOS) within a hospital becomes achievable. This will help administrators and hospital managers to use objective measures and methods for efficient management of their resources with greater levels of efficiency and accountability. Results below from the EIMT tool show that for the 2014/15 financial year, CMAH is correctly funded, CHBAH is underfunded by 17% whilst SBAH is overfunded by 18% (these figures are premised on ExPDE target of **R**3800 and the budgets derived as a function of patient numbers by patient type), as shown in Figure 5.7 below.

Figure 5.7: *2014/15 EIMT output (for all 4 hospitals).*

Hospital	BUR	IPD	Days Patients	OPD	CH/EH	ExPDE at facility	Budget as per actual ExPDE	Budget As Per Facility	Budget from Central Office (IYM-Audited)	Budget as per Tool	Variance (Facility Budget - Tool estimate)	% Deviation from Tool
SBAH	78	56819	3521	107187	5299	4586	440 518 182	435 453 500	450 825 250	365 017 246	70 436 254	19%
SBAH	82	59866	1648	117702	5977	4515	460 062 291	435 453 500	450 825 250	387 206 358	48 247 142	12%
SBAH	81	57265	1860	107792	5182	4217	404 139 259	435 453 500	450 825 250	364 175 761	71 277 739	20%
SBAH	76	55513	1957	110496	5548	3998	380 427 051	435 453 500	450 825 250	361 586 492	73 867 008	20%
TOTAL								**1 741 814 000**	**1 803 301 000**	**1 477 985 857**	263 828 143	18%
DGMAH	80	112442	3561	94530	11568	3207	479 606 658	476 836 017	465 264 750	568 289 772	-91 453 755	-16%
DGMAH	83	116160	1762	95400	11735	3188	486 850 797	487 154 842	465 264 750	580 311 490	-93 156 648	-16%
DGMAH	77	107814	1840	87308	10907	3237	457 828 256	457 860 723	465 264 750	537 456 711	-79 595 988	-15%
DGMAH	78	109331	1746	92413	11197	3148	455 526 125	453 877 460	465 264 750	549 872 704	-95 995 244	-17%
TOTAL								**1 875 729 042**	**1 861 059 000**	**2 235 930 677**	-360 201 635	-16%
CHBAH	79	176018	20174	142120	15845	3936	939 551 474	738 876 750	768 269 000	907 087 296	-168 210 546	-19%
CHBAH	80	183713	8448	147699	13949	3225	779 718 473	738 876 750	768 269 000	918 738 046	-179 861 296	-20%
CHBAH	70	180875	10380	145204	11890	3634	866 309 381	738 876 750	768 269 000	905 882 126	-167 005 376	-18%
CHBAH	77	174064	10248	139692	15837	3147	726 888 427	738 876 750	768 269 000	877 717 198	-138 840 448	-16%
TOTAL								**2 955 507 000**	**3 073 076 000**	**3 609 424 666**	-653 917 666	-18%
CMAH	84	81419	20696	177129	7118	4399	387 123 804	596 988 500	615 173 000	582 003 972	14 984 528	3%
CMAH	88	85702	11061	193939	6935	3316	307 547 018	596 988 500	615 173 000	601 036 056	-4 047 556	-1%
CMAH	79	72023	11948	245002	6798	3359	293 592 253	596 988 500	615 173 000	615 249 158	-18 260 658	-3%
CMAH	78	71387	9340	252383	7023	4052	374 728 595	596 988 500	615 173 000	617 508 575	-20 520 075	-3%
TOTAL								**2 387 954 000**	**2 460 692 000**	**2 415 797 761**	-27 843 761	-1%
					TOTAL BUDGET FOR CENTRAL HOSPITALS			**R 8 961 004 042**	**9 198 128 000**	**R 9 739 138 961**	**-R 778 134 919**	**-8%**

Given that the lion's share of health services expenditure is invested in central hospitals in Gauteng, evaluation of the efficiency in expenditure at that level has also been of growing concern. Figure 5.7 above shows the EIMT output for 2014/15 for all four hospitals in Gauteng. The design of EIMT analytics or dashboard reports must follow the interests and authority of the users and the structure of accountability and authority within the institution. EIMT is flexible and comprehensive framework, which should be relevant in different contexts even though hospital performance is indeed a complex and multidimensional phenomenon. The tool essentially contains two sets of evidence-based indicators (financial and utilisation) and suggests ways for its strategic use in hospital performance assessment. The tool can enable CHBAH for example, to present evidence that CHBAH's 2014/15 budget was inadequate for the services they provide by patient numbers and type and request for an adjustment. Furthermore, hospitals can correlate their expenditure to the number and type of patients on a quarterly basis or proactively forecast in advance (and have an idea of the estimated costs based on the populated information).

TARGET SETTING AND FORECASTING USING EIMT

Target setting is a very delicate balancing act in that if the target is never attained as seen earlier on with ALOS (DGMAH) or C-section (SBAH), then there is a danger of treating the target as a tracking indicator is devoid of any control measures applicable. This creates a culture of merely reporting rather than using the information. Dlamini et al (2008) argue that in fact, poor understanding of indicators is rampant within the public health care delivery system as there is little regard for using the information for decision-making. Rather information is collected out of compliance. The more reliable estimates derived in Table 4.12 can be harnessed for planning purposes by way of forecasting levels of utilisation for each indicator through linear interpolation. That is, using the mean GEE levels as a starting point and incrementally taking the growth rates realised in each indicator to a given or required time point. Time points greater than 29 are futuristic in as far as the model is concerned (linear extrapolation). The results are displayed in Table 5.3 below.

Table 5.3: *Comparison of the efficiency indicator targets*.*

Revised and forecasted targets for efficiency indicators using the LMM estimates.

QTR	Time	ExPDE_Revised	ALOS_Revised	BUR_Revised	C-section_Revised
Q1_2008/9	1	2136.415641	5.56367	71.726601	41.762931
...	..	..	..	..	..
...	..	..	..	..	..
Q4_2014/15	28	3324.870078	7.470248	80.148387	46.290642 %
Q1_2015/16	29	R 3368.886909	7.540862	80.460305 %	46.458335 %
Q2_2015/16	30	R 3412.90374	7.611476	80.772223 %	46.626028 %
Q3_2015/16	31	R 3456.920571	7.68209	81.084141 %	46.793721 %
Q4_2015/16	32	R 3500.937402	7.752704	81.396059 %	46.961414 %

Comparison of set vs. forecasted targets.

Year	ExPDE	ALOS	BUR	C-section rate
2014/15 Targets set by NDoH	R 3800	6.2	78 %	46.0 %
2014/15 EIMT Forecast	R 3259	7.4	79.7 %	46.0 %
2015/16 EIMT Forecast	R 3435	7.6	80.9 %	46.7 %

Comparison with HST recommended targets.

2014/15 Recommended Target Range	ExPDE_HST	ALOS_HST	BUR_HST	C-section_HST
Acceptable Range (90%)	2468-4641	3.3 - 8.5	74 % - 79 %	36 % - 85 % *
Acceptable Range (95%)	2468-4641	3.3 - 8.5	74 % - 79 %	36 % - 85 % *

Note: values are extrapolated with linear regression according to the trend in the last two years (same procedure as per Caesarean rates) * - Nationally determined for all types of hospitals including central.

*It must be understood that the targets above assume a closed system and only premised in relation to the interaction of that system for instance, in the case of BUR, that no additional beds are brought into circulation as doing so would ultimately lower BUR.

The EIMT targets shown in Table 5.3 are empirically determined using LMM and contrasted against those for the 2014/15 financial year prescribed by NDoH as well as against those realised by Van Schaik et al (2014) in the HST study. The following observations can be made:

- The research (EIMT) targets are within the 95% confidence interval range of those proposed by Van Schaik et al, (2014) with the exception of a 0.7% variance in BUR.
- The Van Schaik et al, (2014) confidence intervals are much wider and therefore have less predictive power. The HST report covered a 2-year period and used simple linear regression, compared to the 7-year longitudinal LMM approach used in this research.
- Estimates from this research are more pointed with shorter confidence intervals / lower standard errors. This is because by way of accounting for the variability due to the hospital specific characteristics / random effect, predictions are enhanced as error variability is correctly apportioned, thereby increasing forecasting precision (linear extrapolation).

Admission beds in public hospitals are increasingly becoming a scarce and costly resource as population numbers increase owing to immigration from other provinces and countries within the region as also confirmed by the 2011 census results. Managers can begin to make realisable forecasts, for instance given that BUR is a function of the number of beds available relative to the underlying population serviced, if the number of beds were to remain a constant then, as BUR grows at the rate of 1.24% annually (0.31% per quarter x 4). The implication is that, within four years, the benchmark of 85% would have been attained (a figure determined through stochastic simulation to be the threshold beyond which bed shortage risk becomes unstable as presented in the literature); beyond which it would then become extremely difficult to get a hospital bed if no bedding additions are made.

Examining current BUR trends and in discussions with hospital managers, it was clear that the current problems are a result of (i) lower level patients being admitted in high care facilities indiscriminately that is L1 patients in tertiary hospitals (ii) a lack of coordinated response and efficiency (iii) a lack of coordinated response and efficiency within the hospital referral system. For example timeous discharges and coordination between hospitals areas in the same hospital as seen with the UK system within 4 hours, as well as wards in the same hospital. The findings in this research study contribute to some extent towards remedying the lack of general knowledge and provides evidence to support the concept of evidence-based management as noted by Yozgat and Sahin, (2013). This contributes towards addressing the fact that health care requires measurements with valid, reliable and relevant performance indicators as raised by Klazinga et al, (2011). As South Africa prepares for NHI, this study has contributed towards equipping senior managers at central hospitals in Gauteng in capacitating them to use indicator information as part of evidence based decision-making. The EIMT tool already caters for this development and this will improve inferences and enable more targeted interventions.

In that regard, the study contributes towards reconfiguring management frameworks to instill a culture and need to integrate and build informed evidence-based decision making. Generally, a sustained benefit to efficiency indicator information requires not only an end-to-end understanding and incorporation of the theory and algorithm of the data, but also a change in management culture, ownership of the data and it's processing, stronger and more proactivity in data driven decision making. All essential components must be addressed timeously especially in a resource-constrained environment. At all times, there exists a need to enhance the value of efficiency data so that it is understood as a strategic function rather than administrative routine by senior managers at hospitals. As that is achieved, the problem that application of scientific management principles and emphasis on effectiveness and efficiency in the management of health services is lacking in most African countries raised by Adindu (2013) begins to be addressed.

Klazinga et al (2011) noted that in order to identify misuse of indicators their meanings as well as their embedding in governance and managerial structures, and processes must be known. Managers should therefore do more than just display collected data in annual reports or at management reviews. One of the recurring suggestions from the questionnaires' responses was a need to utilise efficiency indicators in decision-making, the (EIMT) tool addresses this and is therefore realised as an implementational strategy for efficiency indicators.

The tool will prove valuable in building a picture of service utilisation and to assess the extent to which resource allocation (budget) and utilisation (expenditure, BUR, ALOS) have responded to some of the public health care challenges as a planning and diagnostic tool. It can therefore, inform planning and priority setting for the financial year ahead, enhancing evidence-based decision making in response a need identified as a disconnect between efficiency indicator development and ultimate usage, possibly attributed to the fact that the true extent managers synthesize technical information remains undetermined (Shahhoseini, Tofighi, Jaafaripooyan and Safiaryan, 2011). It however remains crucial that to make headway in the utilisation of hospital efficiency data, accurate and valid synthesis must be regarded as an integral part of the hospital strategic function rather than administrative routine.

Indicators are flags requiring cautious interpretation in light of local circumstances. Indicators do not measure performance, rather its people who do and they should therefore give directions. Ultimately, the (EIMT) tool should support hospitals to move from mere data collection of measurements to interpretation and taking of actions as a result. Furthermore, EIMT should also contribute to the improvement of information systems and data quality and reinforce the credibility of performance measurement systems and confidence of hospitals' data they assess and the necessary interventions, thereby promoting accountability in management frameworks.

5.5 VALIDITY AND LIMITATIONS

Ultimately the reliability of efficiency indicators is premised upon the quality of data. Data used in this research was retrospectively collected from DHIS; however, in a few instances, there are obvious quality issues such as very low ExPDE levels. Generally it is difficult to ascertain efficiency if expenditure data is questionable or emanating from inappropriate utilisation. Reservations regarding quality, accuracy and timeliness of DHIS data have long been raised as a matter that compromises its usefulness (Dlamini et al, 2008). Nevertheless, DHIS is still regarded as the single verifiable data management system in South Africa and NDoH is responsible for its operational maintenance. Poor data quality not only affects reliability of inferences, but also inhibits comparisons for equity analysis and the establishment or adjustment of appropriate norms necessary for efficient resource allocation. To correct for this in the EIMT, the target, as opposed to the realised facility ExPDE, is used.

The research proceeded on the basis that the few questionable ExPDE values did not render the dataset not to be integral. The influence of poor data quality in the few instances, would be made up for and compensated by the fact that over a 7-year period (of 28 quarters), mathematically both the Granger-causality and the Linear Mixed Method would self-correct as the approaches both capitalise on longitudinally determined attributes of the data over multiple time-points, creating an averaging effect. In discussions with data managers, they indicated that whilst efforts are made to clean and verify the accuracy of the data as part of quality control before being signed off by designated managers; no editing is permitted beyond the 45 – 60 days after which the database is locked as a matter of policy.

Another limitation is that data that monitors adverse events should be included as that would provide additional indicators serving as a measure of the effectiveness of quality of care (Van Schaik et al, 2014). Nevertheless, the focus of this research deliberately excluded clinical outcomes as the intent was to determine efficacy on expenditure, planning and management frameworks using efficiency data.

As stated earlier on, Granger-causality may not necessarily imply true causality and may produce misleading results when the true relationship involves more than two variables. Whilst it's given that expenditure is a product of many other considerations, to mitigate against that fact the study regressed each efficiency variable (against expenditure) one at a time to minimise spurious relationships as a result of random chance rather than the result of an underlying causal mechanism. This is common if the model is not well-specified or the information design matrix is considered inadequate. It must however, be pointed that at each stage, model diagnostics were done and no serious violations of underlying assumptions were detected.

5.6: EIMT SESSIONS TO STAKEHOLDERS AND INTERNATIONAL PRESENTATIONS

This study has important theoretical and practical relevance for the improvement of health management capacity in South Africa. Section 38 (1) (b) of the Public Finance Management Act (PFMA) of 1999 outlines among the duties of the accounting officer to include the following:

- To provide a framework for the budget reprioritisation approach and implementation of cost reduction measures.
- To regulate spending in respect of specified expenditure items with the view of realising savings and direct such savings to critical and core spending programmes.
- To ensure uniformity in terms of the application of the policy across all institutions and programmes.

The EIMT can enable the above to be realised, hence its importance as a management tool which has attracted various stakeholders. Annexure C shows correspondences regarding the feedback sessions, collaborations and invitations to seminars held with various stakeholders and international agencies regarding the tool's workings. The research findings were first presented to the Gauteng Department of Health on the 16th October 2015 during the Knowledge Management Forum as indicated. This was followed by an invitation to deliver a plenary address on the 12th – 13th November 2015 at the University of the Free State in collaboration with the Free State Department Of Health on the occasion of the 4th Annual Free State Provincial Health Research Day (see attached invitation letter and certificate). A week later, the same findings were presented at Statistics South Africa's 2nd ISIbalo Symposium on evidence-based decision-making (also attached). In June 2016, an invitation was received from World Health Organisation (WHO) to participate in the technical committee meeting for measuring and monitoring action on the social determinants of health, this was on the strength of the research findings. The researcher has since been asked to chair a session in November 2016, on strengthening good governance for health through action across public sectors and social protection policies.

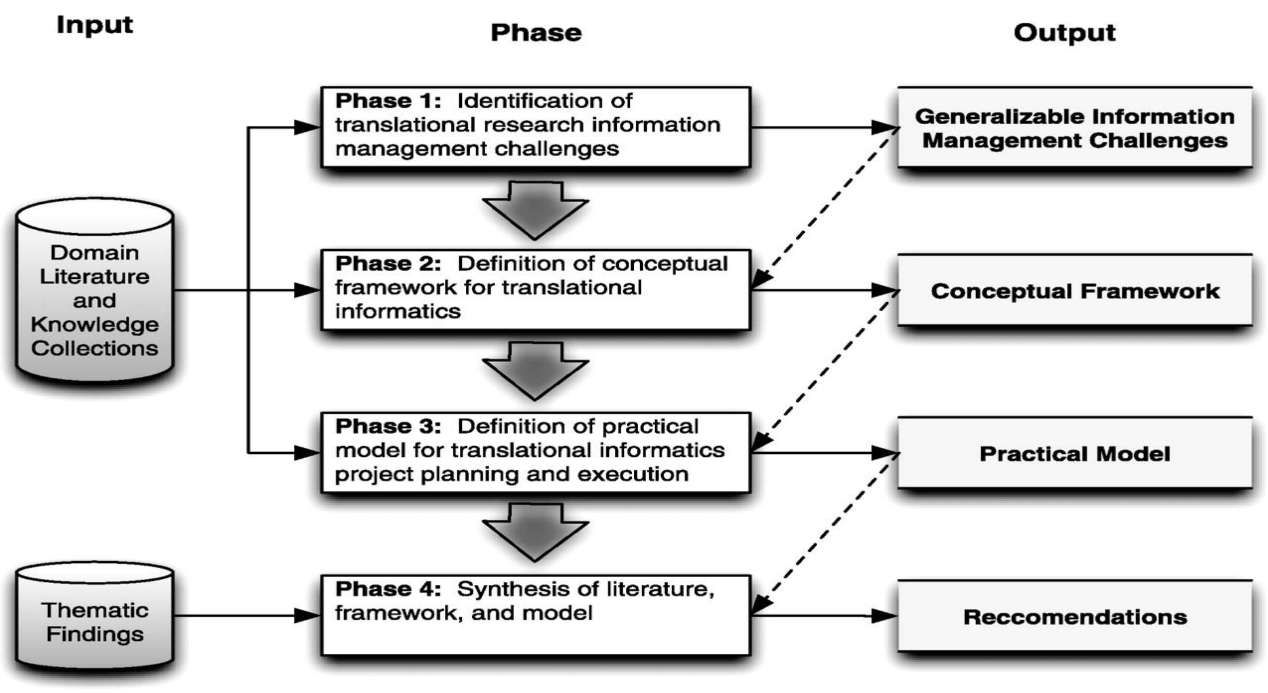
Statistics South Africa (Stats SA) is considering developing EIMT tool as an application for cell phones, tablets or laptops for use by both hospital managers and the agency, as it does collect health data for some of its Statistical Releases. The feedback received during the above sessions has strengthened the research. In Gauteng, the EIMT and growth estimates were well received, in particular the advantage of comparing hospitals using variance between the budget and the actuals projected by the tool per quarter was seen as a positive step to correct for excess expenditure in between consecutive quarters. In the Free State, there was general consensus that the tool would help guide costs by patient type in the wake of NHI as it would enable crucial data to be easily determined such as the number of individuals making use of the hospital services (that is, under-utilisation by patients and low bed utilisation) particularly outpatient visits as they are often under-reported. However, the tool like all else, is premised on good quality data.

5.7: SUMMARY OF RESEARCH FLOW PLAN AND CHAPTER 5 CONCLUSION

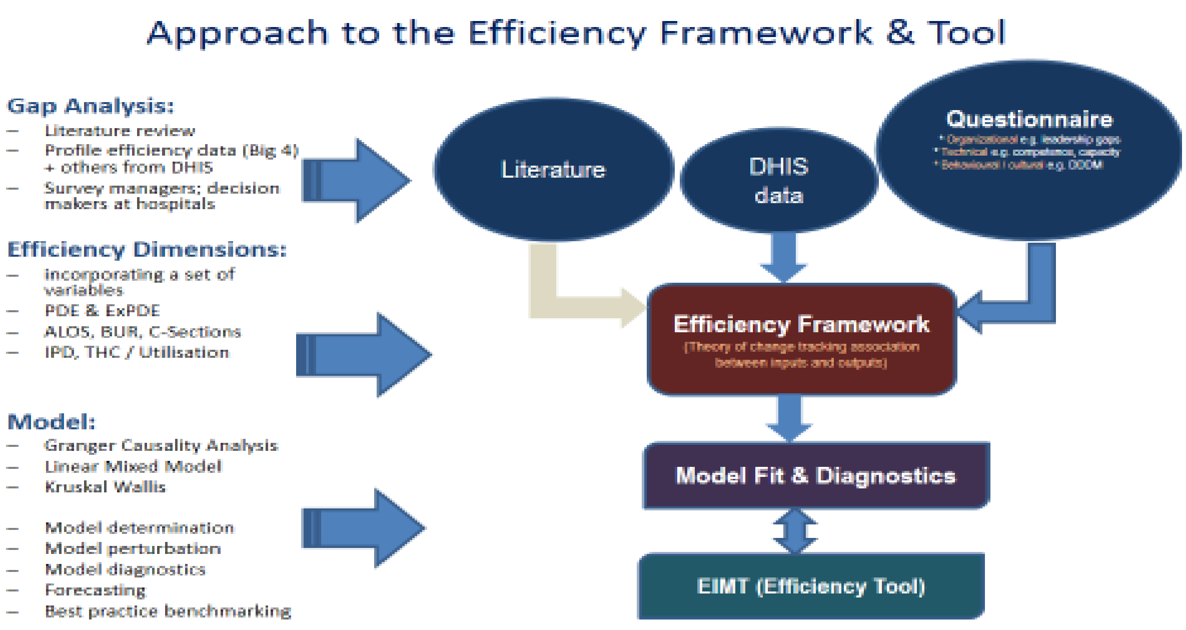
Figure below is a near graphical depiction of the research flow plan envisaged and followed.

Figure 5.8: *Summary of Research and Efficiency Framework flow plans.*

Envisaged research flow plan:



Efficiency framework process flow:



The research sought to realise a resource framework that would undertake an in-depth investigation of the causal nature between observed resource inputs and the health outputs that could be expected as a result. The work drew attention to the fact that hospitals are affected differently when it comes to efficiency indicators. Inferences from theory of causality and linear mixed modelling was articulated, and whilst some relationships to ExPDE and efficiency indicator dimensions were evident; some could not be determined from the present data. A common thread throughout the results presented is the significance of the hospital specific characteristics / random effect, that is indicative of different factors, practices and guidelines affecting the hospitals. That also distorts both the cost structure and funding model for service provision by packages of services that can mask associations such as seen with the C-sections at CHBAH.

Contextually and individually evaluated indicators that are monitored on a routine basis can serve as the foundation for the strategic planning of hospital activities. Conclusions reached, suggest a need to cover a broader set of indicators than the current four prescribed ones, given that not a single hospital had all four efficiency and auxiliary indicators being significant throughout. In that regard, it should be recognised that not all indicators can be applied equally to all four hospitals in the current form, without considering each hospital’s specific and unique characteristics, as seen with the C-sections rate at CHBAH. Generally, indicators, irrespective of their nature are best assessed within the context of the individual hospital unless exogenous factors are even. A case in point is that at CHBAH, 52% of the workload is L1 whereas there is no such at SBAH. The imposition of the same efficiency targets becomes meaningless and is akin to creating efficiency without appropriateness (Veillard et al, 2003); since half of the hospital (CHBAH) operates as a district hospital. In such situations, policy must articulate as to whether the hospital referral system should strictly be enforced even if it may mean turning away patients seeking to enter at the higher level of care or L1 services must be regularised as the system becomes a ‘mixed system’.

Public hospital managers receive voluminous quantities of data from a wide variety of sources, but are unable to distil the essential data they require to make good decisions. The research should help improve the practice of health care management in many different ways. By improving the quality of managerial decisions for instance, if managers proactively examine the efficiency measures, that can lead to prompt identification of early warnings in operational weakness and be able to implement the necessary corrective actions. For instance, CMAH keeps IPD down by increasing OPD, a result picked up by EIMT. That has a direct bearing on costs as the former are more expensive than the latter to treat. By increasing IPS (discharge rate), the tool suggests a greater inclination towards keeping the costs further down. Finally the EIMT tool adds value by building a picture of service utilisation (how much is spent by patient type) and assessing the extent to which resource allocation (budget) and utilisation (expenditure, BUR, ALOS) are responding to the principles of performance, efficiency and sustainability within the hospital.

CHAPTER 6: CONCLUSION, IMPACT AND RECOMMENDATIONS

6.1 CONCLUSION

This research confirmed some issues raised in literature such as in studies by Jha et al (2009), as well as Vitikainen et al (2010) just to mention a few; which determined that the quality of hospital performance varied widely across different indicators and that individual hospitals varies in their performance according to indicators and conditions. This study modelled both the objective (quantitative) as well as the subjective (qualitative) inferences of hospital expenditure and related efficiency dimensions. Efficiency indicators in theory enable patterns and trends in hospital performance contexts to be examined and to become better understood, including the causal nature of the drivers to performance outcomes. The results suggest that indeed, indicators do provide for guidelines to standardise managerial strategies at public central hospitals in Gauteng.

This research, which focused on central hospitals in Gauteng, quantified the magnitude of the hospital specific characteristics - random effect as well as the quarterly rates of changes in efficiency indicators' magnitudes as part of its original contribution. The importance of that being that hospital managers and health care policy makers ought to recognise that health care performance indicators whether financial or operational, are best assessed within the context of the individual hospital. Contextually and individually evaluated indicators can serve as the basis for managing resource expenditure in central hospitals. Efficiency indicator modelling as presented in this research project can be used by hospital managers for the evaluation, forecasting and improvement of hospital operations in particular, controlling for expenditure. The hospitals on their part, should be more responsive to efficiency indicator information.

This research supported the view that indicator frameworks do assist in assessing the extent to which resource allocation (budget) and utilisation (expenditure, BUR, ALOS) align to evidence-based decision-making and can lead to public hospitals receiving a needs-based budget premised on their utilisation trends and demands. There has been a gap in the evaluation of efficiency in expenditure generally, and as a result, historical budgeting has often been the norm at public hospitals. This has been exacerbated by the absence of normative costing of service packages for the level of services and coverage (how much do the service packages cost and how much should they cost). The research provided an alternative method to activity based costing by way of creating a baseline or point of comparison to analyse hospitals' expenditure, identify opportunities for resource reallocation and determine additional funding needs for both current and the future by way of the EIMT tool. This should lead to the delivery of health care services in a cost effective, economical and efficient manner as well as ensuring cost effective optimal resource allocation.

Even though the research combined all costs (fixed and variable including operational costs - all of which are components of ExPDE) to realise the budget, the EIMT tool can be adapted to include measuring the impact of resource allocation on health outcomes as opposed to health expenditure without much of a difficulty. This would make it easier for researchers, health care policymakers and hospital managers to be more acquainted to linkages between inputs and non-financial outputs and outcomes.

According to Hibbert et al (2013), the choice of indicators depends to a considerable extent on purpose and availability of data; there is no reason as to why South Africa should retain a few indicators in comparison to other countries as shown. Attribution of indicators systems must be underpinned by the particular ways in which efficiency targets are designed and enforced. The high values of the hospital / random effects in some instances, such as in C-sections rates make both the indicator and the accompanying target redundant. There is too much variability in SS_{IC} emanating largely from DGMAH (Box-plot mean analyses by hospital and Kruskal-Wallis test) such that even the Hessian matrix cannot be computed. This makes the indicator statistic superfluous, or ‘no longer useful or needed’; a situation that defeats the whole notion of measuring the indicators in the first place. The same scientific evidence is likely to be applicable to very high variance components for the hospital / random effects, in particular C-section rates. An easier alternative to such a problem would be to introduce more relevant constructs or dimensions that capture and apportion for the variability, hence the call for an increased number of efficiency indicators from the current four.

There are four efficiency indicators promulgated for empirically grounded management practices in the South African public health care system. Based on the research findings, and whilst there is no simple way of determining how many indicators are considered enough for such a purpose; it is apparent that the four are inadequate. The levels and extent of attribution and variation in the modelling across the hospitals would require more indicators than currently provided for, in order to satisfactorily ascertain and model the indicators to realise a more stable and standardised set of indicators whose effects are common across all hospitals. When a contrast is made with other countries, it is clear that most countries incorporate indicator sets that include measures of patient experiences, none of the current four efficiency indicators do that. The problem becomes the extent and nature of ‘health care appropriateness’. In literature, it was for instance indicated that Australia’s PAF includes indicators dimensions of effectiveness, appropriateness and efficiency or that C-section rates are an important indicator of appropriateness of care. Unless the context is defined, then tracking the appropriateness of expenditure can be akin to ‘efficiency without appropriateness’ (Veillard et al, 2003) if at the end of the day, the outcome can only be regarded as appropriate in financial prudence terms excluding the patient’s experiences. Attribution is especially pertinent to indicator measurement as there are many determinants of health care performances and outcomes.

In essence, this research identified the need for senior hospital managers to have adequate knowledge regarding the DHMIS policy to enhance processing and adaption to evidence based decision-making. The DHMIS policy focuses on seven high level priority areas namely, Health information coordination and Leadership; Indicators; Data management, Data security, Data analysis and Information products, Data dissemination and finally Health information system resources. Most if not all of the above aspects, are achieved through the use of the EIMT tool. The development of the EIMT tool fulfills the call made, that administrators running hospitals are in dire need of objective measures and methods for efficient management of their material resources in the light of limited financial resources (Usman et al, 2015).

The output of the research was a predictive model, EIMT, realised as an implementation strategy to enable management craft planning frameworks to enhance evidence based management within public hospitals. The EIMT tool will enable hospital managers to use efficiency measures and methods for resource management with greater levels of efficiency and accountability, which will assist by strategically providing for a review of utilisation patterns and disparities in health care usage between central hospitals as flagships of the public health care system. Hospital efficiency data is rich yet still underused and so a tool such as EIMT, can guide public hospitals on how they should manage costs in relation to services provided based on evidence. This will ensure that efficiency indicator utilisation translates to administrative efficiency gains in synergy with other hospital operations and creates ownership of the data such that when data-informed decisions are made, there is also the necessary buy-in to ensure that decisions are implemented and interventions sustained (Nutley, 2012).

Predictive validity, being crucial was tested for the determination of the degree of correspondence between the measures involved. The smaller standard errors enhanced predictive capability. The assumptions of ‘test theory’ and the endemic presence of error which can be introduced in the measurement process, impacting on the reliability and validity of instruments is appropriately divided between fixed and random (hospital) effects. Nevertheless, there remains room for more work to be done in identifying factors within and outside of the hospital that influence the utilisation of hospital efficiency data, depending on local hospital contexts, specific needs and attributes such as of different capacity and depth of hospital management styles. This study outlined a new approach for management in general and health care management in particular referred to as evidence based management of resource expenditure in public central hospitals. The study recognised that there is no single ‘road map’ to efficiency indicator management approach, but that either each hospital must adapt PAF to its specificities in the context of varying dynamics or else, more effort should be directed to ensure standardisation of the many factors giving rise to hospital specific characteristics / random effects. As such, the study does assist in improving on the practice of healthcare management in many different ways, but most of all by improving the quality of managerial decisions.

In this section, the main research findings are presented in summary, aligned to the research problems and questions. The main research problem emanated from the need to ascertain the role indicators could play in bringing about health care efficiency in public hospitals, in light of rapidly increasing health care expenditures. The research problem was stated:

(i) Is there a cause and effect relationship between hospital efficiency indicators (as a dimension of hospital performance) and hospital expenditure in and across the public central hospitals in Gauteng?

- It appeared initially that the nature of the cause-effect system generating longitudinal efficiency trends was random and mild. However, central hospital efficiency data must be modelled by hospital to account or control for the hospital / random effects. This proved to be preferable as the indicators are affected differently across the central hospitals. That is there are cause - effect relationships, but these are only contextual by hospital with DGMAH being the more consistent one in that regard. For instance, ExPDE and BUR were uncorrelated disregarding the hospital specific characteristics / random effect but significant when the hospital specific characteristics / random effect is controlled for (that is taken into account). The causal relationship between ExPDE and BUR is uni-directional at SBAH and bi-directional at DGMAH. There is no attribution at CHBAH and at CMAH. At CHBAH, the ExPDE and CSR correlation is significant before and after controlling for the hospital specific characteristics / random effect because almost all the modelled variability resides with CHBAH. The above outlined the consequences of the hospital specific characteristics / random effect. It is clear that if the random effect is not accounted for (where it exists and is significant), then the extent efficiency indicators purport to be measuring what they are intended to measure is far from being straight forward as the measurements then encompasses large standard errors as shown in Table 4.12 and become less precise and less valid.

The sub-problems sought to determine:

(ii) The effect of efficiency indicators and their linkages to hospital operations.

- This study determined a plausible way of accounting for hospital variability to enhance forecasting. Results showed differences by hospital; for instance, a significant effect on an indicator in the expenditure pattern at one hospital is not necessarily reproduced at another hospital. Also, there is always the possibility that the cause-effect may be instantaneous or non-linear or confounding between the indicators, especially where variability across hospitals is pronounced; implying different practices and guidelines between the hospitals. The cost pressure was highest at CHBAH and lowest at SBAH for instance. The drag of Level 1 patients and more specifically, the high number of natural births at CHBAH confounding the C-sections creates a situation that is not common with any other hospital. It is due to such different dynamics specific to certain hospital/s and not to all that results in the linkages of efficiency indicators to hospital operations being very robust. A proxy for case-mix analyses was realised and that demonstrated a significant effect and variation between the hospitals. A need arises to standardise central hospital operations; as confirmed by differences in SS_{UA} across the hospitals for instance. This implies policy makers must determine whether central hospitals should be streamlined (that is offer tertiary services strictly) or mixed (offer tertiary and non tertiary services) as the latter makes service provision inefficient as that occurs at a higher scale of costs.

(iii) The extent efficiency indicators purport to be measuring what they are intended to measure.

- A balance needs to be found between what an indicator can be postulated to do and the data available to ascertain attribution in this regard. The problem of attribution is especially pertinent to indicator measurement because there are commonly many determinants of a health care outcomes, some of which are spurious, for instance, ALOS and BUR are susceptible to the random fluctuations in patient numbers, case-mix, age and gender as outlined in the literature. However, based on Table 5.3, the fact the modelled data produced estimates with smaller standard errors that could be triangulated against other targets (NDoH and HST) does indeed indicate a high degree of construct validity. As also observed in the literature problems intrinsic to indicators in general, include scientific validity and reliability and even the most commonly collected indicators have been exposed in the literature as problematic in this regard.

(iv) Factors or gaps that influence managerial operational activities in response to efficiency-indicator information.

- Professional background played a key role in the utilisation of indicator information with those with a medical / clinical background or currently within patient care 1.14 times more likely, to comprehend efficiency data compared to those from a business / management background. The above findings suggest a variation in capacity and depth premised on professional background, which was an affirmation of what is presented in the literature. The absence (or weak existence) of a standardised framework was apparent as managers asked for statistical booklets to guide them synthesize efficiency indicator information. Also, a rudimentary understanding of the DHMIS policy (which sets out the framework for the measurement and reporting of the hospital indicators as part of the Health Information Systems) is a factor in so far as the utilisation of efficiency information is concerned.

(v) *Strategies and interventions required to synthesize efficiency-indicator information from a resource management accountability point of view.*

- Managers are well aware of the obligations of data driven decision-making, but a lack in experiences in both using and taking ownership of the data has meant that there has been little regard for using indicator information for decision-making. Given that hospital managers often receive voluminous data, for which they are unable to distil important evidence from it, the EIMT tool is therefore realised as a major output of this research.

(vi) *Develop a model that utilises efficiency indicators to enhance on forecasting hospital expenditure as part of evidence-based decision making within public hospitals*

- The EIMT tool was realised as a management tool in which the application and synthesis of hospital efficiency indicator information in public hospitals could guide how hospitals should manage costs in relation to services provided including budget scenarios. The tool should inform financial planning and priority setting (by patient type and patient numbers) thereby enhancing evidence-based decision making in public hospitals. It must be stressed that the tool is not meant to be exhaustive or used in isolation, but rather in conjunction with or as part of a suite of other managerial tools.

Pursuant to the above, the research question in respect to the big four efficiency measures used in national central hospitals in Gauteng was:

(i) *Apart from describing the change, can hospital efficiency indicators explain changes in expenditure and guide managerial strategies at public central hospitals in Gauteng?*

- The research question sought to not only describe the change, but also rather explain how changes in indicator constructs and expenditure are causal to one another as well as how they impact on resource operations. To explain changes in expenditure or to guide managerial strategies; the magnitude of the hospital variations is such that this cannot be applied equally to all hospitals without recourse to the context and dynamics of each individual hospital. Therefore accounting for changes in expenditure through indicator measurement is best assessed within the context of each of the individual hospitals as evidenced by the significant hospital specific characteristics / random effect. That variation across the hospitals was a key finding in that it implies the domain of efficiency indicators need to be expanded on so that the variability across hospitals is adequately accounted for by a larger matrix of indicators; otherwise there are limitations to existing individual indicator metrics hospital by hospital.

The sub-questions sought to determine:

(ii) *The impact (variation, magnitude and lag) of the efficiency indicators across the hospitals and subsequent association to resource expenditure?*

- ExPDE has a rate of change of **R**44.016831 per quarter (from a mean level of **R**2092.398810 before the start of quarter 1, 2008/09). ALOS has a rate of change of 0.07 days per quarter (from a mean level of 5.49 days before the start of quarter 1, 2008/09). BUR has a rate of change of 0.31% per quarter (from a mean level of 71.4% before the start of quarter 1, 2008/09). C-sections have a rate of change of 0.17% per quarter (from a mean level of 41.6% before the start of quarter 1, 2008/09). The magnitude of the variations in the hospital / random were determined 93.6% in C-section rate, 48.2% in ALOS, 35.3% in BUR and 23.4% in ExPDE and all are above the acceptable 10% threshold set in theory.

(iii) What institutional challenges do managers as decision-makers face as they interact with efficiency-related hospital activities?

- Managers rated mostly the appropriateness of the four efficiency indicators. The rationale of tracking of expenditure against efficiency data attracted the least approvals, followed by the rationale on implications for deviations. A serious challenge faced by managers is that they are uncertain of what to do when the set 'efficiency targets' are not attained. For all indicators, the percentage of managers utilising efficiency data in planning and decision is less than those comprehending it, that is, there is some reluctance or holding back in applying all that managers know. ExPDE is the least understood and least applied in planning and management. ALOS and BUR are rated the most understood and applied as well as the most used efficiency indicators in planning and management. The widest gap between having knowledge of the indicator and its being applied in planning and management decision making is with BUR, followed by C-Section rates. In addition, understanding and application of efficiency data information is not the same across all the four central hospitals. Synergy, communication and organisational challenges (a part of leadership gaps) are more dominant. Workload or being over-burdened is viewed as having the least impact on the utilisation of efficiency information in management. In addition, 89.7% of the managers indicated a need be more proficient in the use and synthesis of efficiency information and to have adequate training and knowledge regarding the DHMIS policy.

(iv) What implementation strategy for efficiency indicators is optimal and best suited to enhance evidence-based management within public hospitals?

- The use of hospital efficiency indicators should allow for the creation and implementation of an efficient system of control and measurement to introduce improvements within the public hospital system. Managers suggested publishing key information on criteria underpinning indicators alongside a “statistics booklet or manual procedure” to enable them learn as well as track robust indicator movement and development processes. Through careful analysis of efficiency indicators (as done with EIMT tool), valuable information building a picture of service utilisation is realised. The tool calculates how much is spent by patient type and assesses the extent to which resource allocation (budget) and utilisation (ExPDE, BUR, ALOS) within a hospital becomes obtainable to help administrators and hospital managers use objective measures and methods for efficient management of resources with greater levels of efficiency and accountability. This, as the implementation strategy for efficiency indicators best suited to enhance evidence-based management within public hospitals, would also be useful for diagnostic and possibly quality assuring serious departures from prescribed service package (such as too many day patients), burden of disease or severity (an increase in BUR and ALOS). For instance, whilst BUR and ALOS are greatly influenced by the hospital referral pattern, those that are well supported tend to manage the indicators with ease.

  The EIMT tool is premised along a model that builds on the work done by Ioan et al (2012), on the relevance of key performance indicators in a hospital performance management context, where the dimension of performance is hospital expenditure. This research contributed towards closing the gap by providing for an evidence-based decision-making tool, which should translate to utilisation-based budgeting, including strategically providing for a review of the public health care system and reduction of disparities in health care usage between central hospitals. Additionally, the rates of growth per indicator realised should prove vital in informing managers of anticipated increments and better prepare them in their planning processes. The tool demonstrates the role of indicator information to include accountability, facilitate resource allocation and utilisation, monitor progress of performance in line with budget, report on outcomes, design appropriate interventions and assess the sum total of the impact, key elements of the PAF. Through the realisation of the tool, the research has shown how the use of hospital efficiency indicators can provide for the creation and implementation of an efficient system of hospital expenditure. As a result, efficiency data can provide insight and guidance on effective management interventions within the public health care delivery platform.

6.2 IMPACT OF STUDY

Indicator measurement is central to the concept of performance and quality improvement and so should therefore be designed to measure the achievement of predetermined objectives. Indicators define the evidence to be collected to measure progress and enable actual results achieved over time to be compared with planned results. This study equips managers to better measure change in indicators so as to monitor their progress, report on successes and improve less effective areas. As earlier on presented, a gap identified in literature was that hospitals are largely unfamiliar with efficiency methodologies. Calls for technical assistance to be provided to hospitals were as a result, made to that effect (Boussabaine et al, 2012). Indeed, public hospitals are in dire need of new perspectives on the role efficiency indicators can play in guiding hospital expenditure in a cost-effective way to enable more effective management decisions in so far as service utilisation (how much is spent by patient type) is concerned. The results are generalisable to public hospitals offering tertiary services package provided their funding levels and structure mimick those in Gauteng. However, differences in policies across provinces imply adjustments between provinces may be necessary.

The research results and in particular the EIMT tool are significant and will have positive implications by informing allocation (budget) and tracking the appropriateness of expenditure. Estimates can be derived, utilising percentage cost by patient type and numbers together with efficiency growth parameters, which provides for empirical evidence in determining appropriate budgets that are hospital specific and in line with utilisation trends. As decisions have to be made on a regular basis regarding the allocation of scarce resources across competing interventions, it is vital that administrative decisions in hospital operations are also premised on cost effective analytics as provided for by hospital efficiency indicators to improve on allocative efficiency through appropriate utilisation of services within the health care delivery system. The world over, health care has become a big and complex platform, delivering a wide range of services and the current trend of simulating models in health care as a vehicle for testing potential improvements has never been greater (Virtue, Thierry and John, 2013).

This study has made a contribution in that, in the absence of a cost structure informed by activity based-costing or normative costing of health care service provision, reasonable adjustment factors emanating from the EIMT tool can be adopted. The research contributes valuable input towards the White paper on the transformation of health care services in South Africa in that it sought to strengthen the transformation of health care services; it is essential that managing expenditure at the central hospital level is done as efficiently and as easily as is possible. Christian (2012), concluded that more than a mere increase in inputs, the public health sector requires an improvement in the level of efficiency.

6.3 RECOMMENDATIONS AND AREAS OF FURTHER RESEARCH

Efficiency indicators are management indicators that are meant to guide and ensure resources are used in the most effective, economical and efficient manner. Firstly, evidence presented showed that the C-sections rates indicator in its current form, is confounded by a high number of normal deliveries in the denominator causing a mismatch between what the indicator rate is intended to measure in the population (obstetric complications) and what is happening in the labour wards. Apart from that high number of normal deliveries occurring at a higher scale of costs; as a facility based indicator, it naturally over-estimates the true population effect. It is recommended that the C-section rate (CSR) should be read in reverse with a target as close to 100% as possible (to cater for some tolerance) to promote the near elimination of normal, uncomplicated deliveries in central hospitals.

Secondly, as is the case in other developing countries, clinicians should be encouraged to estimate the projected date of discharge for all patients admitted and then monitor deviations from the projected departure date to model the average length of stay (ALOS). The ALOS is an important indicator of the efficiency of hospital resource utilisation. The data analysed has a very high causal association between ALOS and ExPDE and so monitoring ALOS would enable managers to control hospital expenditure. It is important that in the process of doing so, ethics are not violated. Thirdly, there are obvious and practical limitations in determining hospital efficiency but there exists a need for the development of a broader set of indicators for benchmarking performance within public hospitals, including a determination of how the targets should be set and in a process that involves all stakeholders. Whilst the study has made some contribution in that regard, the following areas are further highlighted as areas for future research emanating from study findings and the literature presented:

- Future work should aim to investigate the impact on efficiency emanating from a multitude of factors such as institutional quality, population density and so on. This should include understanding where and why patients access tertiary services relative to the area of locality (Statistics South Africa, 2013). This will address a major element missing, which is the linkage of the data from a particular hospital to the geography of the population being served. However, it must be emphasised that, at the central hospital level, the services are not governed by geographical demarcations but, in the absence of an effective hospital referral system, the build-up of pressure and demand on resources generates a knock-on-effect obscuring service provision and the management thereof if not checked.

- Efficiency is one dimension of performance, more research on cause - effect should be carried out on other dimensions and sub-dimensions of the PAF as well, such as those shown in Figure 1.11.

- Whilst opportunities for measuring efficiency should include the optimal use of all available resources including utilisation levels, staffing ratios, financial management and so on; the limitation in this research study was that all such are lumped together in the ExPDE variable. Individual dynamics such as attrition rates for example must be separately and individually modelled and so on as should all such elements. That warrants further research.
- ExPDE is a proxy for average costs premised per patient. Knowing the average cost only though useful, is however not sufficient to reach decisive conclusions regarding the sources of hospital efficiency (including the appropriateness of the expenditure). This is so because the PDE ideal when standards of service are uniform across hospitals, severity of cases treated, case-mix, qualification of staff, work schedules, functional building capacity, medical equipment and technology and so on. A failure to ensure as seen, results in hospital characteristics distorting the cost structure. Future research should explore the use of alternatives to averaged values.

Efficiency in central hospitals offering tertiary care is, in theory, also a function of supply versus demand at the tertiary level of care. In Gauteng the distribution of approved hospital beds is skewed towards higher levels of care, creating an inverted triangle where demand for tertiary services outweighs that of preventative primary and secondary care. The National Tertiary Services Plan (2013) recommendations require the distribution of acute beds to be 12% in tertiary and central hospitals, 29% in regional hospitals and 59% in district hospitals. The EIMT can help generate the cost structure for such a restructuring and provide a view of anticipated costs.

Finally, it has been a while since calls for the efficiency of expenditure to be investigated to understand the cost drivers involved have been made (Pillay, 2006). As South Africa prepares for the roll out of the NHI in the face of limited resources, decision-making regarding the allocation of scarce resources across competing interventions within the public health care delivery platforms must be well thought out. A lack of ability to synthesize efficiency data in public hospitals compromises evidence based decision-making. The research study has, through gaps identified in literature, contributed in theory and by way of a framework, contributed towards understanding hospital efficiency as well as inputs vital for the development and improvement of many facets of the public health care information network. Without doubt, efficiency indicators are of great importance, not only in assessing quality of care and policy-making, but also in determining how best the use of existing resources can be structured, especially in accounting for expenditure in a cost-effective and guided manner as well as in assisting with priority setting. That should enable the description, quantification of within and between-hospital variability. As hospital efficiency designs are determined, efficiency indicator utilisation can no longer be ignored if there are to be improvements on the performances of the public hospital health care delivery system.

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ANNEXURE A: QUESTIONNAIRE

IMPACT OF HOSPITAL EFFICIENCY-INDICATOR UTILISATION ASSESMENT TOOL

INTRODUCTION

The primary objective of this research study is to assess the routine utilization by senior managers of hospital efficiency indicator data and the impact this has in the planning and management of health services' resources at central hospitals and in particular, the impact on expenditure and management of resources i.e. what promotes or confounds (barriers) their usage in the planning and administration of hospital operations. Express your opinion freely and with honesty as all responses will be treated confidentially and will remain anonymous. Your co-operation and assistance in completing this study research being conducted by Mr Adiel Chikobvu (cellphone 072 234 7713; Adiel.Chikobvu@gauteng.gov.za) is greatly appreciated.

Hospital Name: ....

* EITHER TICK (**√**) or CROSS (**X**) THE MOST APPROPRIATE RESPONSE IN EACH CASE

THE 4 HOSPITAL EFFICIENCY INDICATORS ARE: * AVERAGE LENGTH OF STAY (ALOS): * CAESAREAN SECTION RATE: * BED UTILISATION RATE (BUR) OR BED OCCUPANCY RATE (BOR): * EXPENDITURE PER PATIENT DAY EQUIVALENT OR COST PER PATIENT DAY EQUIVALENT:		
1	Your professional background or training largely is in	Clinical or Medical ☐ Management or Business ☐ Other ☐
2	Your rank or its equivalent is	Deputy Director ☐ Director ☐ Chief Director ☐ DDG ☐ Other ☐
3	Your highest educational qualification attained	Matric or below ☐ Certificate ☐ Diploma ☐ Degree + ☐ Other ☐
4	Total period (in years) worked in healthcare environment in general	3 or Less ☐ 4-10 ☐ 11-20 ☐ 21-30 ☐ 31+ ☐
5	Your Gender	Female ☐ Male ☐
6	Your main role, falls under	Clinical/Patient care ☐ Administration/Support ☐ Other ☐
7	As an individual, the extent and ability you synthesize technical information	Very poor ☐ Poor ☐ Average ☐ Good ☐ Very good ☐
8	As an individual, the extent and ability you understand efficiency indicators	Very poor ☐ Poor ☐ Average ☐ Good ☐ Very good ☐
9	The extent your work requires use of or interaction to efficiency indicators in planning or management	No-never ☐ Yes-few times ☐ Yes-most times ☐ Yes-always ☐
10	In your view, do the efficiency indicators meet that requirement or provide any/some benefit?	No-never ☐ Yes – few times ☐ Yes-most times ☐ Yes-always ☐
11	The extent and ability you want to be able to use efficiency indicators if and when necessary or if required	No-never ☐ Yes-few times ☐ Yes-most times ☐ Yes-always ☐
12	Your knowledge or implication of District Health Management Information System Policy	Very Poor ☐ Poor ☐ Average ☐ Good ☐ Very good ☐

IMPACT OF HOSPITAL EFFICIENCY-INDICATOR UTILISATION ASSESMENT TOOL

To what extent are the following statements true for your hospital and/or management

CHOOSE THE MOST APPROPRIATE FROM 1=STRONGLY DISAGREE 2=DISAGREE 3=NEUTRAL OR AVERAGE 4=AGREE 5=STRONGLY AGREE		
13	The rationale and usage of the four current efficiency indicators is appropriate in this hospital	☐
14	The efficiency indicators are operationally well-defined to enable planning and resource management	☐
15	Efficiency indicators are well-benchmarked to enable planning and resource management	☐
16	Use of efficiency indicators for purposes of planning and resource management is cost effective	☐
17	Expenditure tracking and resource planning is benchmarked against efficiency data in this hospital	☐
18	The implication of deviation / missed "efficiency targets" is understood and acted upon	☐
19	Efficiency data is a part of the hospital resource / strategy formulation and implementation process	☐
20	Current efficiency measures are aligned to the overall hospital strategy and subsequent performance	☐
21	Management periodically reviews reports of and analyses of the hospital efficiency data	☐
22	Allocation and utilization of resources has controls systems to monitor their management thereof	☐

CHOOSE TWICE IN EACH QUESTION 1=STRONGLY DISAGREE 2=DISAGREE 3=NEUTRAL OR AVERAGE 4=AGREE 5=STRONGLY AGREE				
23	Caesarean Section Rates are well understood	☐	and / or used in planning and decision making	☐
25	Bed Occupancy / Utilisation Rate is well understood	☐	and / or used in planning and decision making	☐
27	Average Length Of Stay is well understood	☐	and / or used in planning and decision making	☐
29	Cost or Expenditure per PDE is well understood	☐	and / or used in planning and decision making	☐
31	In patient days are well understood	☐	and / or used in planning and decision making	☐
33	Total headcount is well understood	☐	and / or used in planning and decision making	☐
35	Hospital expenditure is well understood	☐	and the information used in planning & decision making	☐
37	Management of resources is well understood	☐	and the information used in planning & decision making	☐

CHOOSE THE MOST APPROPRIATE FROM 1=STRONGLY DISAGREE 2=DISAGREE 3=NEUTRAL OR AVERAGE 4=AGREE 5=STRONGLY AGREE		
39	***Organizational challenges*** e.g. leadership gaps influence "efficiency data utilization" in management	☐
40	**Technical *issues*** e.g. competence / capacity gaps influence "efficiency data utilization" in hospital	☐
41	**Behavioural *challenges*** e.g. cultural norms influence "efficiency data utilization" in managing resources	☐
42	***Synergy and communication*** pose a challenge to the utilisation of efficiency indicator - information	☐
43	***Dynamism*** - the efficiency indicators over time have become redundant, an overhaul is necessary	☐
44	***Load*** - Attending fully to efficiency indicators examination is resource intensive in relation to service package	☐

Thank you. If there any suggestions you may have: ....

....

....

ANNEXURE B: RESEARCH LETTERS

Graduate School of Business Leadership, University of South Africa, PO Box 392, Unisa, 0003, South Africa
Cnr Janadel and Alexandra Avenues, Midrand, 1685, Tel: +27 11 652 0000, Fax: +27 11 652 0299
E-mail: sbl@unisa.ac.za Website: www.unisa.ac.za/sbl

SCHOOL OF BUSINESS LEADERSHIP
RESEARCH ETHICS REVIEW COMMITTEE (GSBL CRERC)

24 April 2015

Ref #:2015_SBL/DBL_003_RA
Name of applicant: Mr A Chikobvu
Student #: 78420784

Dear Mr A Chikobvu

Decision: Ethics Approval

Student: Mr Adiel Chikobvu, adiel.chikobvu@gauteng.gov.za , 0722347713 / 011 355 3890

Supervisor: Dr Allan Feldman, feldmja@unisa.ac.za , 011 652 0336

Project Title: The impact of efficiency indicator utilization on expenditure and management of resources within public central hospitals.

Qualification: Doctorate in Business Leadership (DBL)

Thank you for applying for research ethics clearance, SBL Research Ethics Review Committee reviewed your application in compliance with the Unisa Policy on Research Ethics

Outcome of the SBL Research Committee:
Approval is granted for the duration of the Project

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E-mail: sbl@unisa.ac.za Website: www.unisa.ac.za/sbl

The application was reviewed in compliance with the Unisa Policy on Research Ethics by the SBL Research Ethics Review Committee on 10/11/2014.

The proposed research may now commence with the proviso that:

1) The researcher/s will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.
2) Any adverse circumstance arising in the undertaking of the research project that is relevant to the ethicality of the study, as well as changes in the methodology, should be communicated in writing to the SBL Research Ethics Review Committee. An amended application could be requested if there are substantial changes from the existing proposal, especially if those changes affect any of the study-related risks for the research participants.
3) The researcher will ensure that the research project adheres to any applicable national legislation, professional codes of conduct, institutional guidelines and scientific standards relevant to the specific field of study.

Kind regards,

5/5/2015

Prof R Ramphal
Chairperson: SBL Research Ethics Committee
011 – 652 0363/ramphrr@unisa.ac.za

5/05/2015

Dr R Mokate
CEO and Executive Director: Graduate School of Business Leadership
011- 652 0256/mokatrd@unisa.ac.za

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Email: sbl@unisa.ac.za Website: www.sblunisa.ac.za

REQUEST FOR PERMISSION TO CONDUCT RESEARCH AT GAUTENG DEPARTMENT OF HEALTH

"The impact of efficiency indicator utilization on expenditure and management of resources within public central hospitals"

To: Dr Bridget Ikalafeng

Room 1704, BOL Building, 37 Sauer Street

Policy, Planning & Research

011 355 3408 / 082 461 9354; Bridget.Ikalafeng@gauteng.gov.za

Dear Dr B. Ikalafeng

Your permission is herewith requested to allow **Adiel Chikobvu**, a student in the Doctor of Business Leadership at the UNISA Graduate School of Business Leadership (SBL), to conduct academic research in your organisation.

Your company has been selected to participate because the study examines efficiency measures at central hospitals and all research to be conducted in a Gauteng Department of Health (GDoH) instituitions that involves GDoH staff, patients or access to GDoH data requires approval.

The purpose of the study is to investigate the impact of as well as use of efficiency indicators captured within DHIS on expenditure and management of resources. The study will entail analyzing efficiency indicator data longitudinally for the past 3 years as well as surveying hospital managers regarding application and experiences in the use of the data.

GDoH's participation in this study is very important, however GDoH may choose not to participate or withdraw from the study at any time without any negative consequences.

The results of the study will be used for academic purposes only and may be published in an academic journal. We will provide you with a summary of our findings on request. Please contact my supervisor, Dr Allan Feldman (feldmja@unisa.ac.za) if you have any questions or comments regarding the study. Please sign below to indicate your willingness to participate in the study.

Yours sincerely

Adiel Chikobvu **05/03/2015**

I, **Dr Bridget Ikalafeng**, herewith give my permission for the study to be conducted in GDoH facilities.

Signature 06 Dec 2015 **Date**

First in Leadership Education in Africa

GAUTENG PROVINCE
HEALTH
REPUBLIC OF SOUTH AFRICA

Enquiries: *Bongani Redebe*
Tel: *011 355 3373*

REQUEST FOR PERMISSION TO CONDUCT RESEARCH AT GAUTENG DEPARTMENT OF HEALTH

"The impact of efficiency indicator utilization on expenditure and management of resources within public central hospitals"

To: Mr Levy Mosenogi
Chief Director: Policy, Planning, Research, M&E.
18th Floor, BOL Building, 37 Sauer Street
011 355 3373 / 082 496 5509; Levy.Mosenogi@gauteng.gov.za

Dear Sir,

Your permission is herewith requested to allow **Adiel Chikobvu**, a student in the Doctor of Business Leadership at the UNISA Graduate School of Business Leadership (SBL), to conduct academic research in your organisation.

Your company has been selected to participate because the study examines efficiency measures at central hospitals and all research to be conducted in a Gauteng Department of Health (GDoH) institutions that involves GDoH staff, patients or access to GDoH data requires approval.

The purpose of the study is to investigate the impact of as well as use of efficiency indicators captured within DHIS on expenditure and management of resources. The study will entail analyzing efficiency indicator data from DHIS longitudinally for the past 3 years as well as surveying hospital managers regarding application and experiences in the use of the data. GDoH's participation in this study is very important, however GDoH may choose not to participate or withdraw from the study at any time without any negative consequences.

The results of the study will be used for academic purposes only and may be published in an academic journal. We will provide you with a summary of our findings on request. Please contact my supervisor, Dr Allan Feldman (feldmja@unisa.ac.za) if you have any questions or comments regarding the study. Please sign below to indicate your willingness to participate in the study.

Yours sincerely

Adiel Chikobvu **25 /03 / 2015**

I, **Mr Levy Mosenogi,** herewith give my permission for the study to be conducted in GDoH facilities.

Signature 25/03/2015 **Date**

1

Graduate School of Business Leadership, University of South Africa PO Box 392 Unisa 0003 South Africa
Cnr Smuts and First Avenue Midrand 1685 Tel: +27 11 652 0000 Fax: +27 11 652 0299
Email: sbl@unisa.ac.za Website: www.sblunisa.ac.za

Informed consent for participation in an academic research project

"The impact of efficiency indicator utilization on expenditure and management of resources within public central hospitals"

Dear Respondent

You are herewith invited to participate in an academic research study conducted by **Adiel Chikobvu**, a student in the Doctor of Business Leadership at UNISA's Graduate School of Business Leadership (SBL).

The purpose of the study is to investigate the impact of as well as use of efficiency indicators captured within DHIS on expenditure and management of resources. The study will entail analyzing efficiency indicator data longitudinally for the past 3 years as well as surveying hospital managers regarding application and experiences in the use of the data. All your answers will be treated as confidential, and you will not be identified in any of the research reports emanating from this research.

Your participation in this study is very important to us. You may however choose not to participate and you may also withdraw from the study at any time without any negative consequences.

Please answer the questions in the attached questionnaire as completely and honestly as possible. This should not take more than 15-20 minutes of your time.

The results of the study will be used for academic purposes only and may be published in an academic journal. We will provide you with a summary of our findings on request.

Please contact my supervisor, Dr Allan Feldman (feldmja@unisa.ac.za) if you have any questions or comments regarding the study. Please sign below to indicate your willingness to participate in the study.

Yours sincerely

Adiel Chikobvu **05/03/2015**

I, ... herewith give my consent to participate in the study. I have read the letter and understand my rights with regard to participating in the research.

______________________ ______________________

Respondent's signature **Date**

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Graduate School of Business Leadership, University of South Africa, PO Box 392, Unisa, 0003, South Africa
Cnr Janadel and Alexandra Avenues, Midrand, 1685, Tel: +27 11 652 0000, Fax: +27 11 652 0299
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29 September 2014

TO WHOM IT MAY CONCERN

The title of Mr A Chikobvu doctoral thesis is:

"The impact of efficiency indicators for resource and quality management of public central hospitals"

This letter serves to confirm that **Mr Chikobvu** student number **78420784** is a registered student with Unisa Graduate School of Business Leadership studying for his Doctor of Business Leadership degree.

He presented his research proposal and literature review which was accepted at the colloquium on the29 September 2014 at Unisa Graduate School of Business Leadership. He was advised to proceed to the next phase of his research methodology.

For further enquiries please do not hesitate to contact the undersigned.

Thank you for your co-operation.

Yours sincerely

for

UNISA GRADUATE SCHOOL OF BUSINESS LEADERSHIP
29 SEP 2014

Prof: AA Okharedia
Academic Director
UNISA Graduate School of Business Leadership
Cnr Janadel and Alexandra Avenues
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1686
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E-mail: sbl@unisa.ac.za Website: www.unisa.ac.za/sbl

23 February 2015

TO WHOM IT MAY CONCERN

The title of Mr A Chikobvu doctoral thesis is:

"The impact of efficiency indicators on expenditure and management of resources within public central hospitals in Gauteng"

This letter serves to confirm that **Mr Chikobvu** student number **78420784** is a registered student with Unisa Graduate School of Business Leadership studying for his Doctor of Business Leadership degree.

He presented his research methodology which was accepted at the colloquium held on the 17 February 2015 at Unisa Graduate School of Business Leadership. He was advised to proceed to the last phase of his findings.

For further enquiries please do not hesitate to contact the undersigned.

Thank you for your co-operation.

Yours sincerely

Prof: AA Okharedia
Academic Director
UNISA Graduate School of Business Leadership
Cnr Janadel and Alexandra Avenues
MIDRAND
1686
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30 September 2015

TO WHOM IT MAY CONCERN

The title of Mr A Chikobvu doctoral thesis is:

"The impact of efficiency indicator utilization on expenditure and management of resources within public central hospitals"

This letter serves to confirm that **Mr Chikobvu** student number **78420784** is a registered student with Unisa Graduate School of Business Leadership studying for his Doctor of Business Leadership degree.

Mr Chikobvu presented his last phase of research findings which was accepted at the colloquium that was held on the 28 September 2015 at Unisa Graduate School of Business Leadership. He was advised to submit his final thesis for examining

For further enquiries please do not hesitate to contact the undersigned.

Thank you for your co-operation.

Yours sincerely

Seopa

Ms Tumi Seopa
Programme Administrator (DBL)
UNISA Graduate School of Business Leadership
Cnr Janadel and Alexandra Avenues
MIDRAND
1686
Tel: (011) 652 0210

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30 SEP 2015

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ANNEXURE C: SESSIONS TO STAKEHOLDERS AND INTERNATIONAL PRESENTATIONS

GAUTENG PROVINCE
HEALTH
REPUBLIC OF SOUTH AFRICA

KNOWLEDGE MANAGEMENT FORUM

Final Programme

Date: 16/10/2015

Venue: Ann-Latsky Nursing College – Main Auditorium

Time:	Topic:	Speaker:
08h30 - 08h55	Tea & Registration	ALL
09h00 - 09h10	Opening & Welcome	Programme Director
09h10 - 09h50	Research Findings: An Analysis Of The Functional State & Cost Of Maintenance & repair Of capital Medical Equipment At Dr. Yusuf Dadoo Hospital Discussion (Master of Public Health) Degree)	Mr. P. Sofohlo
09h50 - 10h30	An efficiency indicator model for managing resource expenditure in public central hospitals". (PhD)	Mr. Adiel Chikobvu
10h30 - 11h00	Refreshments -	
11h00 - 11h55	Directive on Compulsory Capacity Development - Mandatory Training Days for SMS members Minimum entry requirements for SMS members Discussion	DPSA
11h55 - 12h00	Wrap up and closure	Programme Director

health

Department of
Health
FREE STATE PROVINC

7 October 2015
Mr Adiel Chikobvu
Director: Statistics & Healthcare Utilisation
Health Economics and Finance:
Gauteng DoH
Email: Adiel.Chikobvu@gauteng.gov.za

4th Annual Free State Provincial Health Research Day: Showcase of health research and evidence towards universal health coverage and optimal care, 12-13 November 2015

On behalf of the Free State Provincial Health Research Committee, we would like to invite you to attend this exciting Research Day and to deliver a plenary presentation on **"An efficiency indicator model for managing the increasing resource expenditure in public central hospitals"** as indicated on the attached Abstract. The plenary will be presented on the 12th of November 2015; venue: Education Auditorium, University of the Free State (UFS), Bloemfontein Campus. We would like you to share the UNAIDS perspective of the 90 90 90 concept.

The Research Day – presented collaboratively by the Free State Department of Health (FSDoH) and the University of the Free State (UFS). The presentation of the 4th Annual Health Research Day is a tangible and practical expression of the continued commitment of the FSDoH to ensure a sustainable interdisciplinary engagement in and more systematic uptake of research. This will result in increased practical utilisation of research to better inform policy and practice as well as to address the health systems challenges in the Province. The main theme of this year's Research Day is ***How to improve equity and access to quality health care services for all in the Province in an effort to achieve UNAIDS 90/90/90?*** Attached please find the call for abstracts.

Depending on the nature of the abstracts received, the **primary tracks** will include:

- Clinical care; Health care ; Health systems and health information
- Health equity, governance and finance;
- Health services, training and human resources for health
- Health advocacy and communication; HIV and AIDS and Tuberculosis
- National Health Insurance, Primary Health Care Re-engineering.

Your presence and delivery of a Plenary at the Research Day will be greatly appreciated. Should you be available, we will communicate the programme and specific arrangements to you as soon as possible. The Free State department of Health will cover your transport and accommodation.

Please confirm your availability with Me Khuse at KhuseMJ@fshealth.gov.za Tel 051 408 1646 or Fax 051 408 1556 on or before 16th of October 2015.

Yours sincerely

Dr D Motau
Chairperson: Free State Provincial Health Research Committee
HOD: Free State Department of Health

Head : Health
PO Box 227, Bloemfotein, 9300
4th Floor, Executive Suite, Bophelo House, cnr Maitland and, Harvey Road, Bloemfotein
Tel: (051) 408 1107/1108 Fax: (051) 408 1950, e-mail: motaud@fshealth.gov.za /HCOPA@fshealth.gov.za

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FREE STATE DEPARTMENT OF HEALTH IN COLLABORATION WITH UNIVERSITY OF THE FREE STATE

CERTIFICATE FOR DELIVERING A PLENARY ADDRESS FOR THE 4TH ANNUAL FREE STATE PROVINCIAL HEALTH RESEARCH DAY

12-13 November 2015

NAME OF PRESENTER

Mr A Chikobvu

Title of paper

AN EFFICIENCY INDICATOR MODEL FOR MANAGING RESOURCE EXPENDITURE IN PUBLIC CENTRAL HOSPITALS

MEC OF THE FREE STATE DEPARTMENT OF HEALTH

Statistics South Africa

The South Africa I know, the home I understand

PROGRAMME

2nd ISIbalo Symposium on evidence based decision making
Date: 18 November 2015
Venue: The Lakes Hotel, Benoni
Programme Director: Mr. Thabo Manchidi

Wednesday, 18 November 2015

TIME	ITEM		
08h00 – 08h30	**Registration and Tea**		
08h30 – 08h35	**Opening Remarks : Programme Director**		
08h35 – 08h45	Welcome and Purpose of the Workshop: Dr. Mahlape Mohale: Provincial Executive Manager		
08h45– 09h00	Keynote address:		
09h00 - 09h20	George Sibanda/Cheryl Taylor - Gauteng Province at a glance		
09h20 – 09h40	Stats Products : Gaongalelwe Phakedi (Stakeholder Relations)		
09h40 – 10h00	Shaakira Karolia (City of Tshwane) - The impact of water scarcity on Tshwane residents		
10h00 – 10h10	Questions & Discussion		
11h45 – 12h30	**BREAKAWAY SESSIONS**		
	Session1:CENSUS/SURVEYS **Venue** : PLENARY **Chair:** Dr. Mahlape Mohale **Scribe** : Ruwayda Guman/Thokozani Vilakazi	**Session 2: GORVENANCE** **Venue** : ROOM1 **Chair**: Thabo Manchidi **Scribe** :Bongani Majeke/ Ben Bosch	**Session 3: SOCIO - ECONOMICS** **Venue** : ROOM 2 **Chair**: Maurice Mommen **Scribe** : Mpho Dibakoane /Judas Ngobeni
	(a) **Jeremy Gumbo (WITS)-** Undercounting Controversies in South African Censuses	(a) **Dr.Koech Cheruyiot (GCRO)** : Patterns and Determinants of dissatisfaction with Govt. performance in the Gauteng City Region: A comparison across three govt. spheres	(a) **Kagiso Monnapula –** Using stats to understand the influence and financial culture of township economies
	(b) **Dr.Njeri Wabiri (HSRC)** "Census for better national health survey design to track equity in maternal health in South Africa"	(b) **Mphahle Nkadimeng (Office of the Premier)** : The theory and practice of research utilisation to inform policy development in the public sector	(b) **Carel Basson(Stats SA):** The economic impact of a changing urban mining region: The case of the West Rand District Municipality in Gauteng province
TIME	**ITEM**		
	(c) **Dr. Samuel Manda(SA Medical Research Unit**)- A Comparison of Geographic Distribution and Correlates of Childhood and Adult Mortality in South Africa using Civil Registration System and Census Datasets, 2011	(c) **ADIEL CHIKOBVU (GT Department of Health**) - An efficiency indicator model for managing resource expenditure in public central hospitals.	(c) **Xaven Pillay (Stats SA)** Business clustering along the N1-M1-N3 corridor in Northern Johannesburg, 2001-2012
	QUESTIONS AND DISCUSSIONS		

The South Africa I know, the home I understand

GAUTENG PROVINCE
HEALTH
REPUBLIC OF SOUTH AFRICA

Enquiries: *Mr. A. Chikobvu*
Tel: *011 355 3890*

TO: **DR. T.E. SELEBANO**
HOD: HEALTH

DATE: **12th May 2016**

SUBJECT: **Request for Approval: Travel to Ottawa, Canada.**

1. PURPOSE

To request the Head of Department to authorize a trip to Ottawa, Canada at the invitation of The World health Organization (WHO) from 20th to 22nd June 2016.

2. BACKGROUND

The Rio Political Declaration mandated the World Health Organization (WHO) to ensure that the Social Determinants of Health (SDH) and subsequent actions are robustly measured and monitored to enable better progress tracking on the SDH agenda over time. To fulfil this mandated function, the EQUAL indicator system on the SDH is being developed with a related but distinct indicator system. About 40 participants from from 21 countries / regions have been invited to a technical meeting, which will be held in Ottawa, Canada from the 20th - 22nd June 2016. The meeting will advance technical approaches and capacities for measuring and monitoring action on the SDH and craft a joint proposal for a sound indicator system for monitoring action on the SDH primarily in quantitative terms. Against the above background, the Working Group invited me to do a presentation highlighting the (PhD) work I did in developing and refining indicators for M&E methodologies and how policies and priorities should reaffirm the value placed on addressing social determinants of health, including the development of country profiles using appropriate indicators.

3. FINANCIAL IMPLICATIONS

There are no financial implications whatsoever for GDoH, all costs for the travel are to be borne by the World Health Organization (WHO).

4. RECOMMENDATIONS

It is recommended that HoD approve the trip as outlined above i.e. travel to the Technical Meeting on Measuring and Monitoring Action on the Social Determinants of Health, Ottawa, Canada from 20th to 22nd June 2016.

DATE: 12/05/2016.

MR A. CHIKOBVU
DIRECTOR: HEALTH ECONOMICS AND FINANCE (H.E & F)

RECOMMENDED / ~~NOT RECOMMENDED~~

DATE: 13/05/2016

MR G. MAHLANGU
CHIEF FINANCIAL OFFICER: GAUTENG DEPARTMENT OF HEALTH.

APPROVED / ~~NOT APPROVED~~

Selebano

DATE: 18 May 2016

DR T.E. SELEBANO
HEAD OF DEPARTMENT: GAUTENG DEPARTMENT OF HEALTH.

World Health Organization

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E-mail : brandesbarbierc@who.int

In reply please refer to:

Your reference:

Dr Adiel Chikobvu
Statistics and Healthcare Utilisation
Health Economics and Finance
Gauteng Department Of Health
37 Sauer Street
Johannesburg
Afrique du Sud

0 9 MAY 2016

Dear Dr Chikobvu,

Technical Meeting on Measuring and Monitoring Action on the Social Determinants of Health
<u>Ottawa, Canada, 20-22 June 2016</u>

The World Health Organization (WHO), with the Public Health Agency of Canada (PHAC) and the Canadian Institutes of Health Research - Institute of Population and Public Health (*CIHR-IPPH*), are honored to invite you to attend the upcoming *Technical Meeting on Measuring and Monitoring Action on the Social Determinants of Health (SDH)*, to take place on 20-22 June 2016 in Ottawa, Canada *(pls see attachment 1, Provisional Agenda)*.

This high-level, technical meeting will review the proposal being put forward by the *WHO / PHAC / CIHR-IPPH Working Group on Monitoring Action on the Social Determinants of Health (SDH)* and make recommendations to WHO on global SDH monitoring and on supporting national capacity development for SDH measurement and monitoring. The draft proposal will be shared prior to the meeting for comment.

The mandate for routine monitoring of actions on the SDH at national and global levels originates from the *Rio Political Declaration on the Social Determinants of Health* and World Health Assembly Resolution 65.8 on *Outcome of the World Conference on Social Determinants of Health*. The World Health Organization's 2016/17 Programme Budget includes a global output on monitoring trends and progress on action on the social determinants of health (SDH), which is linked to United Nations-wide approach of the Sustainable Development Goals.

Your participation in the Technical Meeting will be greatly welcomed. The meeting will provide an opportunity for you to meet counterparts from other countries, with shared interests in the monitoring of actions to address SDH. Participating countries will also be invited to take forward the development of country profiles, using the indicators discussed in the Technical Meeting.

We would request that you please confirm your participation at the latest by 13 May 2016 with the Secretariat at email <u>brandesbarbierc@who.int</u>, Christina Brandes-Barbier.

Please note that WHO will be responsible for the cost of your return travel at the cheapest available economy class ticket regardless of length of travel. You will be provided with a per diem to cover your accommodations and meals in Ottawa.

If you would like further information of the content of the meeting please do not hesitate to contact the responsible officer, Ms Nicole Valentine (valentinen@who.int). For technical assistance regarding administrative matters, do not hesitate to contact Ms Christina Brandes-Barbier (tel: +41 22 791 5837; email:<u>brandesbarbierc@who.int</u>).

We very much hope to see you in Canada and look forward to hearing from you soon.

Your sincerely,

pp

Maria Neira
Director
Public Health, Environmental and Social Determinants of Health

IMPLEMENTING RIO: MONITORING ACTION ON THE SOCIAL DETERMINANTS OF HEALTH

|BACKGROUND PAPER|

Technical Meeting for Measuring and Monitoring Action on the Social Determinants of Health

|OTTAWA | CANADA | 20–22 June 2016|

World Health Organization

Acknowledgements

Implementing Rio: Monitoring Action on the Social Determinants of Health was developed by the World Health Organization (WHO) in collaboration with the Public Health Agency of Canada (PHAC), the Canadian Institutes of Health Research - Institute of Population and Public Health (CIHR-IPPH) and the Working Group for Monitoring Action on the Social Determinants of Health that the organizations constituted.

The Working Group for Monitoring Action on the Social Determinants of Health were: Professor Aluisio Barros, Professor Abdesslam Boutayeb, Dr Christine Brown, Dr Hazel Dean, Dr Erica Di Ruggiero, Dr Rita M. Ferrelli, Dr Patricia Frenz, Professor John Glover, Mana Herel, Dr James Humuza, Dr Doris Kirigia, Professor Patricia O'Campo, Dr Frank Pega, Professor Srinath Reddy, Agata Stankiewicz, Tone P. Torgesen, Nicole B. Valentine and Dr Eugenio R. Villar Montesinos.

The Working Group Chair, Professor Patricia O'Campo, coordinated the Working Group input and compiled the first draft of the full report at the University of Toronto.

WHO (Dr Frank Pega and Nicole B. Valentine) provided overall guidance on the report, and edited and finalized the final report.

We would like to acknowledge and thank the secretariats of WHO (Christina Brandes Barbier, Dr Frank Pega, Nicole B. Valentine, Dr Eugenio R. Villar Montesinos), PHAC (Marie DesMeules, Maha Hammond, Mana Herel, Dr. Filippo Speranza, and Agata Stankiewicz), the CIHR-IPPH (Dr Erica Di Ruggerio), and the University of Toronto (Philip Baden, Michelle Dimitris, Professor Patricia O'Campo, Ariel Pulver, and Kandace Ryckman) for supporting the Working Group's administrative and operational activities.

For the preliminary feedback on an earlier draft of this background paper and the monitoring system it proposes, we would like to thank colleagues from Canada (coordinated by Mana Herel, PHAC) and South Africa (coordinated by Adiel Chikobvu, Statistics & Healthcare Utilisation, Health Economics and Finance, Gauteng Department of Health). Dr Arijit Nandi (McGill University, Canada) suggested selected sources for indicators. Valuable feedback from WHO regional offices on an earlier draft of this background paper was received from: Dr Hala About Tajeb (EMR), Dr Anjana Bushan, Dr Suvajee Good (SEAR) and Dr Hala Sakr Ali (EMR).

World Health Organization

National Health and Family Planning Commission of China

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In reply please refer to:

Your reference:

Dr Adiel Chikobvu
Director, Statistics and Healthcare Utilization
Health Economics and Finance
Gauteng Department of Health
Johannesburg
Afrique du Sud

25 August 2016

Dear Dr Chikobvu,

Ninth Global Conference on Health Promotion:
"Health Promotion in the Sustainable Development Goals"
Shanghai, China, 21 to 24 November 2016

We have the honour to invite you to the Ninth Global Conference on Health Promotion (9GCHP) which is being co-organized by the World Health Organization (WHO) and the National Health and Family Planning Commission of the People's Republic of China and will be held at the Shanghai International Convention Center in Shanghai, China, from 21 to 24 November 2016. It is the latest in the series of global health promotion conferences of experts and policy makers organized by WHO and a host country. The title is "Health Promotion in the Sustainable Development Goals".

We would be most grateful if you could moderate Parallel session 11 – "Social protection policies: How can progress on SDGs 1, 5 and 10 be accelerated by strengthening good governance for health through action across government sectors?" on Tuesday morning, 22 November 2016. Dr Davison Munodawafa (munodawafad@who.int), WHO Technical Focal Point, will be contacting your office to brief you on the session.

This Global Conference on Health Promotion will bring together about 750 participants consisting of ministers from several sectors and high-level government officials including from the Government of China, mayors, high-level experts and policy makers, intergovernmental organizations and international nongovernmental organizations as well as academic and research institutes. The working language will be English with simultaneous interpretation into Arabic, Chinese French, Russian and Spanish in all plenary sessions. The parallel sessions will be held in English. Participation is by invitation only.

The Conference will focus on examining the contribution of health promotion not only to health and health equity over the past 30 years since the birth of the Ottawa Charter in 1986, but also its contribution to realizing the Sustainable Development Goals (SDG) over the next 15 years. It will also investigate how governments can reflect health promotion in national SDG policies and plans, as well as how non-State actors, research and academic institutions, the UN agencies and other international partners can make their expertise available to governments at all stages of policy and plan development and implementation.

cc: Department of International Cooperation, National Health and Family Planning Commission of China, Beijing

9th Global Conference on Health Promotion
SHANGHAI 2016

ANNEXURE D: EFFICIENCY INDICATOR MONITORING TOOL (EIMT) = Excel based.

Beds	1652
Useable	1236
80% Useable Beds	988.8
Max Day Patients/30days	29664

Inpatient days (30)	37080
Target BUR 80%	29664

Day Patients	5000
OPD	15000
Emerg. Head Count	2000

Scenario 1

PDE	**Inpatient days + 0.5 Day Patients + 0.33 OPD Head count + 0.33 Emergency Head count**
29664	Inpatient Days
0	Day Patients
0	OPD Head Count
0	Emergency Head Count
29664.00	PDE
R 133 000 000.00	Total Available Budget
29664.00	PDE 4 above set up
4483.55	Exhaust Expenditure / PDE
R 112 723 200.00	Total Budget Required
29664.00	PDE
3800	Expenditure / PDE Target
R -20 276 800	**Additional Expenditure**
R 112 723 200.00	**Target Expenditure**

This R112 723 200 is what will be used based for the month on the curret ExPDE Target of R3800, since inorder for all of it to be used, the ExPDE should have as shown above, been R4483. At this stage, using sheet 1, ALOS = completely unconstrained. R20 276 800 remains available since not all allocated is used.

Scenario 2

PDE	**Inpatient days + 0.5 Day Patients + 0.33 OPD Head count + 0.33 Emergency Head count**
29664	Inpatient Days
5000	Day Patients
0	OPD Head Count
0	Emergency Head Count
32164.00	PDE
R 133 000 000.00	Total Available Budget
32164.00	PDE 4 above set up
4135.06	Exhaust Expenditure / PDE
R 122 223 200.00	Total Budget Required
32164.00	PDE
3800.00	Expenditure / PDE
R -10 776 800	**Additional Expenditure**
R 122 223 200.00	**Target Expenditure**

R10 876 800 is what remains of the R133 000 000 monthly allocation after adding 5000 Day Patients to the 29664 Inpatient Days (80% Bed Occupancy). Using sheet 1 or 1(4), ALSO for the above = 6.4 days vs target of 6.2 Days.

Scenario 3

PDE	**Inpatient days + 0.5 Day Patients + 0.33 OPD Head count + 0.33 Emergency Head count**
29664	Inpatient Days
5000	Day Patients
15000	OPD Head Count
2000	Emergency Head Count
37824.00	PDE
R 133 000 000.00	Total Available Budget
37824.00	PDE 4 above set up
3516.29	Exhaust Expenditure / PDE
R 143 731 200.00	Total Expenditure
37824.00	PDE
3800.00	Expenditure / PDE
R 10 731 200	**Additional Expenditure**
R 143 731 200.00	**Target Expenditure**

In this third scenario, assume Total separations = 1010 then ALOS is 5.4 days vs a target of 6.2 Days {sheet 1(4)}. The addition of 15000 OPD and 2000 Emergency will require an additional R10 731 200 per month.

29664 Inpatients	R 112 723 200.00	100%	29664 Inpatients	R 112 723 200.00	92%	29664 Inpatients	R 112 723 200.00
			5000 Day	R 9 500 000.00	8%	5000 Day	R 9 500 000.00
					0%	15 000 OPD	R 19 000 000.00
					0%	2000 Emergency	R 2 533 333.33

Beds	1652
Useable	1236
Inpatient days (30)	37080
Target BUR 80%	29664
Days in a month /quarter	30 / 90

BUR	**Inpatients + 0.5 Day Patients**
	Usuable Beds X Days in the month

29664	Inpatient Days
5000	Day Patients
1236	Usuable Beds
30	Days in the months
86.74%	Actual BUR

80% BUR Target

ALOS

29664
5000
1010
5.35

6.2

Inpatient Seperations
500
10
500
1010

Inpatient Days + 0.5 Day Patients
Total Seperation + Day Patients

Inpatient Days	
Day Patients	
Total Seperations	
Actual Days ALOS	

ALOS Target

Inpatients discharges+ inpatient deaths + Inpatients Transfers
Inpatient discharges
Inpatient deaths
Inpatient transfer outs
Inpatient Seperations (Total)

BUR	**Inpatients + 0.5 Day Patients**
	Usuable Beds X Days in the month

	Inpatient Days
	Day Patients
	Usuable Beds
	Days in the months
	BUR

78% BUR Target

ALOS	**Inpatient Days + 0.5 Day Patients**
	Total Seperation + Day Patients

29664	Inpatient Days
6000	Day Patients
1000	Total Seperations
4.67	Days ALOS

6.2 ALOS Target

C/S Rate	**Number of Caesarean sections performed**
	Total number deliveries in facility

3565	Number of Caesarean sections performed
10435	Total number deliveries in facility
34.16%	C/S Rate

46% **C/S Target**

PDE	**Inpatient days + 0.5 Day Patients + 0.33 OPD Head count + 0.33 Emergency Head count**

219082	Inpatient Days
15451	Day Patients
182018	OPD Head Count
50998	Emergency Head Count
304309.51	PDE

PDE Target

Expenditure /PDE	**Total Expenditure / PDE**

	Total Expenditure

	PDE
#DIV/0!	Expenditure / PDE

Expenditure / PDE Target

Inpatient Seperations	**Inpatients discharges+ inpatient deaths + Inpatients Transfers**

42523	Inpatient discharges
2524	Inpatient deaths
654	Inpatient transfer outs
45701	Inpatient Seperations

OPD Headcount	**OPD Head count (Not Refferred New + Refferred New + Follow up**

39031	OPD Head count - Not reffered New
79974	OPD Head count - Reffered New
63013	OPD Head count - Follow up
182018	OPD Headcount

ANNEXURE E: RESPONSE DATA, SELECTED RESULTS, PROGRAMS AND OUTPUTS

Results from the objective dataset:

QTR	Hospital	Time Point	ExPDE	ALOS	BUR	PDE	CSR	IPD	IPS	OPD	CH	Hospitals
Q1_2008	1	1	1471	5	81	113782	57	56412	11431	164825	4734	1=SBAH
Q2_2008	1	2	2553	5.2	82	120132	60	57305	11192	180572	5690	2=DGMAH
Q3_2008	1	3	2226	4.9	78	112538	61	54263	11304	166622	5848	3=CHBAH
Q4_2008	1	4	2274	5.4	50	80821	56	35066	6534	131902	4108	4=CMAH
Q1_2009	1	5	2438	5.2	81	111941	55	56236	11021	158604	6173	
Q2_2009	1	6	2517	5.1	83	112753	57	57706	11378	157453	5203	
Q3_2009	1	7	2477	5.3	76	117933	57	55720	10753	179078	5307	
Q4_2009	1	8	2784	5.3	76	105187	55	56154	10723	138790	6042	
Q1_2010	1	9	4086	5.6	77	84882	59	56882	10302	76062	5513	
Q2_2010	1	10	2876	5.5	79	106777	58	58583	10745	136078	5979	
Q3_2010	1	11	3117	5.1	75	111156	58	55372	11111	159680	5184	
Q4_2010	1	12	2662	5.3	72	110362	56	53819	10207	164100	3269	
Q1_2011	1	13	3341	6.3	74	106364	54	55234	8933	147837	3297	
Q2_2011	1	14	2687	6.3	78	118023	57	58429	9395	172859	3536	
Q3_2011	1	15	3754	6.2	75	104011	59	53979	8883	144331	3396	
Q4_2011	1	16	3573	6.4	73	99920	49	52329	8276	136376	3795	
Q1_2012	1	17	3786	5.3	77	113769	63	55609	10678	168470	3418	
Q2_2012	1	18	3728	5.3	79	92858	62	56683	10928	102233	3544	
Q3_2012	1	19	4501	5	75	90001	61	53614	10840	102534	3998	
Q4_2012	1	20	3892	5.5	78	90665	61	53407	9824	104838	4626	
Q1_2013	1	21	2249	6.6	81	92963	57	55046	8509	106956	4558	
Q2_2013	1	22	4866	6.4	80	94369	54	55939	8868	107943	4884	
Q3_2013	1	23	4117	6.2	77	91832	57	53767	8806	107386	4241	
Q4_2013	1	24	4200	6.7	76	91927	61	54361	8184	105335	4949	
Q1_2014	1	25	4586	8	78	95138	56	56819	7175	107187	5299	
Q2_2014	1	26	4515	8.2	82	102022	54	59866	7445	117702	5977	
Q3_2014	1	27	4217	7.9	81	95901	58	57265	7340	107792	5182	
Q4_2014	1	28	3998	8.5	76	95150	57	55513	6620	110496	5548	
Q1_2008	2	1	1018	6.9	66	119876	31	93367	13517	70215	7945	
Q2_2008	2	2	2141	7.4	69	123862	33	96708	13195	72006	8123	
Q3_2008	2	3	1750	6.6	61	114215	30	85819	13085	75333	8553	
Q4_2008	2	4	1895	7.3	42	79021	33	58610	8059	55257	5269	
Q1_2009	2	5	1890	7.5	60	107666	33	84253	11288	62117	7055	
Q2_2009	2	6	1814	7.5	70	124912	34	97993	13052	71577	8067	
Q3_2009	2	7	2328	7.3	69	124088	37	97056	13266	70981	8981	
Q4_2009	2	8	2077	7.7	68	122840	37	95123	12416	73568	8433	
Q1_2010	2	9	2169	7.9	71	127021	36	99849	12676	71820	8447	
Q2_2010	2	10	2274	7.1	58	106097	34	81620	11536	64865	7542	
Q3_2010	2	11	2735	6.8	63	115411	36	89063	13237	68981	8835	
Q4_2010	2	12	2261	7.2	67	122883	38	93938	13076	76775	8681	
Q1_2011	2	13	2522	8.3	69	123528	38	97702	11808	68563	7654	
Q2_2011	2	14	2424	8.4	71	125690	40	99435	11912	71078	6525	
Q3_2011	2	15	2913	7.8	66	119944	40	93472	11990	70645	7713	
Q4_2011	2	16	2301	8.3	67	123001	39	94608	11458	77867	6301	
Q1_2012	2	17	2372	7.6	75	134975	35	105476	14029	79511	6869	
Q2_2012	2	18	2481	6.6	74	139113	36	103391	15753	93008	10891	
Q3_2012	2	19	2604	7.7	73	133406	34	102172	13262	83323	8822	
Q4_2012	2	20	2559	7.5	66	127223	36	93191	12468	92804	7456	
Q1_2013	2	21	1316	9	78	144831	37	108608	12204	97305	8055	
Q2_2013	2	22	3298	8	78	147380	38	109599	13780	98257	12291	
Q3_2013	2	23	2858	7.8	73	137291	39	102682	13278	89658	11336	
Q4_2013	2	24	2824	8.2	74	139910	38	104230	12775	94411	10200	
Q1_2014	2	25	3207	8.6	80	148689	38	112442	13210	94530	11568	
Q2_2014	2	26	3188	8.8	83	152792	43	116160	13346	95400	11735	
Q3_2014	2	27	3237	7.9	77	141425	40	107814	13769	87308	10907	
Q4_2014	2	28	3148	8.3	78	144839	39	109331	13353	92413	11197	
Q1_2008	3	1	1601	4.7	79	225289	33	185003	40254	78990	26339	
Q2_2008	3	2	1931	4.7	78	235040	32	182394	39969	116287	26874	
Q3_2008	3	3	1719	4.8	80	238267	32	186584	40139	112123	27845	
Q4_2008	3	4	1714	4.4	52	157542	33	120528	28492	80097	18733	
Q1_2009	3	5	1957	5	79	241034	35	184366	37843	127424	27601	
Q2_2009	3	6	2127	5	81	251647	32	189111	38866	143735	29201	
Q3_2009	3	7	2275	5	82	245661	33	190397	39448	122174	28814	
Q4_2009	3	8	2924	4.9	79	242934	36	184401	38367	132891	27772	

Q1_2010	3	9	2406	4.8	82	249018	34	191820	41279	130103	25423	
Q2_2010	3	10	2442	4.8	74	223948	33	171462	36415	116626	26710	
Q3_2010	3	11	2824	4.8	73	225394	37	171899	36839	122003	26270	
Q4_2010	3	12	2341	5	77	228904	35	178990	36659	110678	25971	
Q1_2011	3	13	3201	6.5	69	201172	36	160534	25329	99605	8647	
Q2_2011	3	14	3028	6.5	73	220122	36	170427	27122	124958	8507	
Q3_2011	3	15	3285	6.2	67	208441	36	156649	26164	130183	11623	
Q4_2011	3	16	2291	6.7	77	232175	39	176511	26826	140634	13701	
Q1_2012	3	17	3716	5.3	72	212472	35	165402	31064	126800	12766	
Q2_2012	3	18	3148	5.7	79	233212	37	177457	32060	140214	14982	
Q3_2012	3	19	3087	5.5	79	232140	37	175833	32968	138301	16549	
Q4_2012	3	20	2663	5.5	78	229824	35	173530	32414	139720	15611	
Q1_2013	3	21	1782	7.4	81	232403	39	175927	24361	139053	15618	
Q2_2013	3	22	2849	7.7	83	238021	36	181190	24253	138924	16336	
Q3_2013	3	23	482	7.4	81	232758	36	176947	24379	140580	17131	
Q4_2013	3	24	1957	7.8	81	235187	36	176288	23100	145360	16618	
Q1_2014	3	25	3936	7.8	79	232897	30	176018	23037	142120	15845	
Q2_2014	3	26	3225	8.1	80	242786	29	183713	23427	147699	13949	
Q3_2014	3	27	3634	7.2	70	238364	38	180875	23199	145204	11890	
Q4_2014	3	28	3147	7.8	77	231088	37	174064	22968	139692	15837	
Q1_2008	4	1	2150	6.4	78	117792	43	76083	12038	109475	14455	
Q2_2008	4	2	2954	6.4	80	124926	43	80337	12680	116232	16137	
Q3_2008	4	3	2352	6.4	78	122542	40	78164	12250	115405	16573	
Q4_2008	4	4	2883	6.3	54	82510	42	52081	8291	80114	10382	
Q1_2009	4	5	2671	6.4	82	124157	40	82907	12988	107430	15140	
Q2_2009	4	6	2681	6.8	83	131935	42	85910	12726	120383	16525	
Q3_2009	4	7	3005	6.6	80	126054	45	82634	12640	112900	16204	
Q4_2009	4	8	3309	6.6	79	130698	47	82364	12600	126857	16912	
Q1_2010	4	9	2971	6.8	85	134542	46	88464	12989	120653	16655	
Q2_2010	4	10	2999	6.5	77	123584	44	79768	12355	114880	15493	
Q3_2010	4	11	3347	6.6	81	128452	48	84168	12843	116306	15588	
Q4_2010	4	12	2126	6.7	78	191841	50	83113	12464	309224	15904	
Q1_2011	4	13	2424	7.3	86	195255	48	90024	12724	301976	6349	
Q2_2011	4	14	2286	7	86	201386	49	90822	13289	318058	5725	
Q3_2011	4	15	2852	7	81	188552	51	85977	12605	292646	6836	
Q4_2011	4	16	2736	7.1	82	193875	51	87031	12569	306047	6101	
Q1_2012	4	17	2682	4	83	198345	51	86288	22958	313044	7438	
Q2_2012	4	18	2525	4	85	203461	53	88615	23706	320947	7740	
Q3_2012	4	19	2934	4.1	83	193090	51	85813	22229	301053	6130	
Q4_2012	4	20	2528	3.8	81	188553	50	84371	23529	290731	7029	
Q1_2013	4	21	867	7.1	81	195759	50	85140	12633	308377	8030	
Q2_2013	4	22	819	7.2	87	214426	47	91354	13354	345757	7792	
Q3_2013	4	23	946	6.8	85	192402	49	83439	12990	302904	7376	
Q4_2013	4	24	872	7.1	83	187755	50	80527	12199	297068	7662	
Q1_2014	4	25	4399	7.1	84	148365	47	81419	12184	177129	7118	
Q2_2014	4	26	3316	7.3	88	158634	47	85702	12580	193939	6935	
Q3_2014	4	27	3359	6.9	79	160626	51	72023	11075	245002	6798	
Q4_2014	4	28	4052	6.9	78	162552	48	71387	10958	252383	7023	

Results from the subjective dataset:

Record	Hospital	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q23
002	1	1	1	4	3	1	1	3	3	3	3	3	3	5	5	5	4	4	5	5	4	4	5	4
003	1		5	1	4	2	2	3	4	4	4	3	3	3	3	3	3	3	3	3	3	3	3	5
004	1	2	5	3	1	1	2	4	4	4			3	4	4	4	4	4	4	5	4	4	4	3
005	1	3	5	3	2	1	2	4	4	2		2	3	4	4	4	3	3	4	3	3	4	3	
006	1	1	1	4	3	2	1	4	4	4	4	2	3	4	4	4	4	4	4	5	4	4	4	3
007	1	1	5	3	5	2	1	4	4	3	3	3	3	3	3	1	1	1	1	1	1	1	1	3
008	1	1	5	3	5	1	1	4	4	2	1	2	2	4	3	3	3	2	3	4	4	3	4	
009	1	1	5	4	3	1	1	3	1	2	1	2	3	4	2	2	3	2	4	4	2	4	4	3
010	1	2	5	4	3	1	2	4	3	3	3	2	1	4	4	4	3	4	3	2	2	4	4	

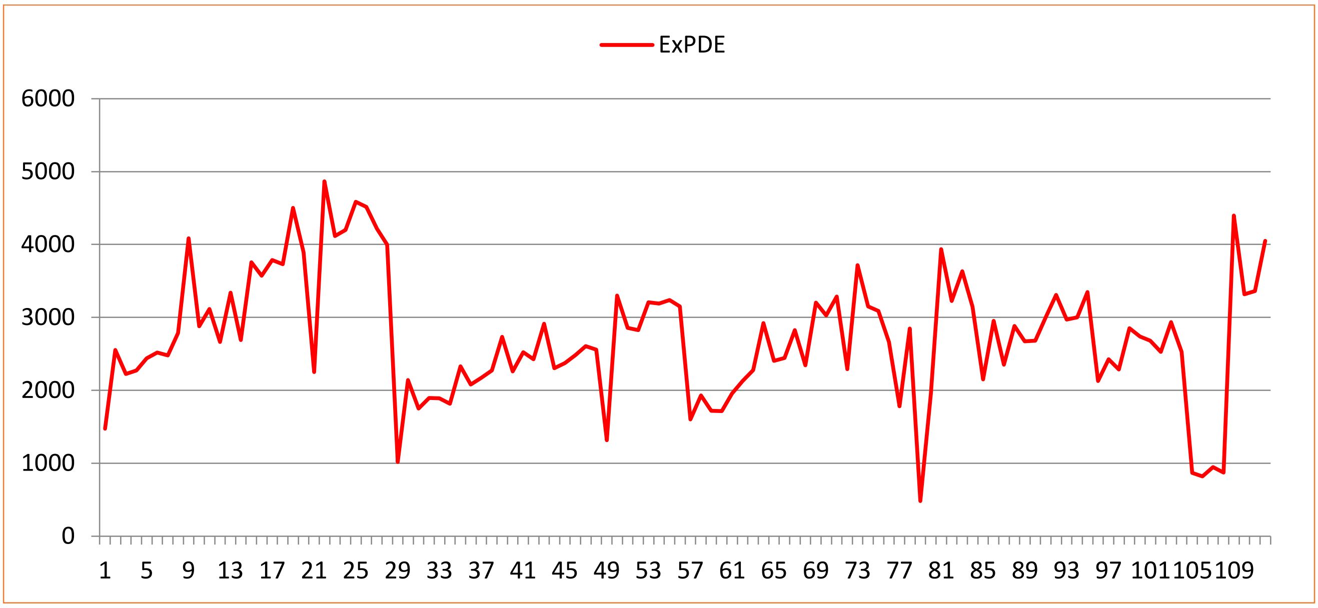
011	1	2	5	3	1	2	2	4	3	4	4	4	3	5	3	4	3	4	4	5	4	3	4	3
012	1	2	1	3	3	2	2	3	4	2		3	4	1	1	1	1	1	1	1	3	3	3	1
013	1	1	1	4	3	1	1	4	4	4	3	3	4	4	4	3	3	4	4	4	4	5	4	3
014	1	2	5	4	3	1	1	3	4	4	3	4	4	4	4	4	4	3	3	4	3	3	2	4
015	1	1	5	4	4	2	1	5	5	4	3	3	3	4	4	4	4	4	3	4	4	3	3	3
016	1	2	1	4	5	1	2		4	4	3	3	4	5	4	4	5	5	4	4	5	5	5	5
017	1	1	1	4	2	1	1	3	3	2	2	3	3	4	3	3	3	3	4	4	4	4	3	4
018	1	2	1	3	1	2	2	5	4	3	3	4	3	4	4	3	3	5	4	4	4	4	4	4
019	1	1		3	4	1	1	4	4	3	3	3	4	4	4	4	4	3	3	5	4	5	5	4
020	1	1	5	4	4	1	2	4	3	2	2	3	1	4	4	4	4	2	2	2	2	2	4	4
021	1	2	2	5	3	2	2	4	4	3	2	4	3	4	3	2	2	2	3	2	2	3	3	2
022	1	2	5	3	4	1	2	3	4	3	2	3	2	4	3	3	3	3	3	4	4	4	4	3
023	1	1	5	4	5	1	2	4	4	3	3	4	4	4	3	4	4	3	3	3	3	3	4	3
024	1	1	4	4	3	3	2	2	5	5	3	4	4	5	5	5	5	5	4	5	5	5	5	5
025	1	1	5		4	1	1	3	3	2	2	3	2	3	3									
026	1																							
027	1	2	5	4	4	1	2	4	4	3	3	3	4	5	4	3	3	3	3	3	3	3	3	
028	1	1	2	4	5	2	2	4	5	4	3	4	4	3	4	3	4	3	4	5	4	5	4	5
029	1	2	5	3	4	1	2	4	4	4		4	3	5	4	3	3	3	4	3	3	4	4	4
030	1	2	5	1	4	1	2	5	4	3	4	4	4	5	5	5	5	5	4	5	5	5	5	4
031	1	1	5	3	4	1	1	3	4	4	3	3	4	4	3	4	3	3	4	3	4	3	4	3
032	1	1	5	3	4	1	1	3	4	4	2	3	3	2	3	3	3	3	2	2	2	3	3	3
033	1	1	5	3	5	1	1	4	4	3	4	3	2	5	4	4	4	2	2	4	4	4	4	4
034	1	2	5	4	1	1	2	4	4	3	4	4	3	4	4	5	4	5	4	5	5	5	5	5
035	1	2	1	4	3	2	2	4	4	3	3	3	3	3	3	2	3	2	2	3	3	4	4	3
036	1	1	1	4	5	1	1	4	5	3	4	4	4	5	5	4	4	5	4	4	5	4	4	5
037	1	1		2	4	1	1																	
038	1	1	5	4	5	1	1	4	4	4	3	3	4	4	4	3	3	4	2	4	3	4	4	4
039	1	1	1	4	5	1	1	5	5	4	4	4	2	4	4	4	4	3	2	2	3	4	2	2
040	1	1	5	3	4	1	1		5	4	3	3	4		4	3	5	4	4	4	4	4	5	5
041	1	1	5	4	5	1	2	3	4	3	2	4	1	4	4	1	3	3	4	4	3	3	4	4
042	1	3	5	1	4	1	2	3	5	4	3	4	2	2	2	2	4	1	1	1	1	1	1	2
043	1	3	5	3	2	2	2	4	5	2	4	4	4	4	4	4	5	4	5	5	4	4	4	4
001	1	1	1	4	2	2	1	3	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
001	2	1	1		5	1	1	5	5	4	4	3	1	3	4	3	3	3	4	3	5	4	4	1
002	2	1	1	4	3	2	2	5	5	3	3	4	3	3	3	4	4	4	3	5	3	5	2	3
003	2	1	1	4	4	1	1	4	4	3	3	4	5	5	3	3	4	3	2	4	5	4	3	5
004	2	1	1	4	3	1	1	5	5	4	4	4	3	5	4	5	4	3	3	3	3	2	2	3
005	2	1	5	5	4	2	1	5	5	4	4	4	5	4	4	4	4	4	4	4	4	4	4	4
006	2	2	5	4	1	1	2		3	2	2	3	3	3	3	3	3	3	3	4	4	3	4	4
007	2	1	5	3	3	1	1	5	5	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
008	2	2	1	4	2	2	2	3	3	3	3	3	3	4	4	4	4	4	4	4	4	4	4	4
009	2	2	5	3	2	1	2	4	4	4	4	4	4	4	4	4	4	4	5	4	4	4	4	4
010	2	2	2	3	4	2	2	4	4	4	4	4	5	5	5	5	4	4	4	4	4	5	4	5
011	2	1	1	4	3	1	1	5	5	4	4	4	4											5
012	2	2	1	3	2	1	2	3	3	2	3	4	2	3	3	3	3	3	3	3	3	3	3	3
013	2	1	1	4	2	2	1	4	4	4	4	4	5	5	4	5	5	4	4	5	4	4	5	5
014	2	2	1	3	5	2	3	5	4	3	3	3	4	5	4	4	3	3	4	4	4	3	3	5
015	2	2	5	3	2	2	2	4	4	4	4	4	4	4	4	4	5	5	5	5	5	5	5	5
016	2	2	1	2	3	2	2	3	4	3	3	4	3	4	3	4	2	2	3	3	3	3	3	

017	2	1	5	4	3	2	1	5	4	4	4	4	5	4	4	4	4	4	4	4	4	4	4	4
001	3	1	1	4	2	1	2	4	4	4	3	4	4	3	2	2	3	2	2	2	2	3	2	4
002	3	2	1	4	2	1	2	4	4	4	3	4	5	4	4	4	4	4	4	4	4	4	4	
003	3	2	1	1	4	2	2	2	3	2	1	3	2	3	1	3	1	2	3	3	3	2	2	4
004	3	2	5	3	4	1	2	3	3	3	1	1	2	3	2	2	2	2	2	3	3	3	3	3
005	3	1	1	4	4	2	2	4	5	4	4	4	4	4	4	4	2	4	4	4	4	4	4	4
006	3	2	1	2	4	2	2	4	3	3	3	3	3	4	4	4	4	4	4	4	4	4	4	4
007	3	2	5	1	4	2	2	4	4	3	3	4	3	3	1	1	1	3	1	2	2	2	2	3
008	3	2	5	3	1	1	2	3	4	4	3	3	2	3	3	3	3	3	3	3	3	3	3	3
009	3	1	5	4	2	2	2	5	4	3	2	3	5	5	4	4	4	4	4	4	4	4	4	3
010	3	1	3	4	3	2	3	5	5	4	2	4	5	3	2	2	3	1	1	3	2	1	1	4
011	3	2	1	4	4	1	2	4	4	3	2	3	3	2	2	2	3	3	4	3	3	3	3	4
012	3	3	5		4	1	2	3	3	3	1	1	2	3	3	3	3	3	3	3	3	3	3	3
013	3	1	2	5	4	1	2	4	4	4	3	4	3	4	4	4	3	3	3	4	3	3	2	4
014	3	1	2	4	4	2	2	4	5	3	3	3	4	4	4	4	3	3	2	2	2	2	2	4
015	3	1	1	4	4	1	1	4	4	4	4	4	4	5	4	4	5	4	4	5	4	4	3	5
016	3	1	1	4	5	1	2	4	3	2	2	3	2	2	2	2	4	4	2	3	2	3	3	4
017	3	1	1	4	4	1	1	4	4	4	3	3	3	5	4	4	4		5	5	5	5	5	5
018	3	2	2	4	5	1	1	5	4	4	1	4	3	4	4	2	1	5	5	4	4	4	5	5
019	3	1	1	4	4	1	1	4	3	4	3	4	3	5	4	4	3	3	3	4	4	5	4	5
020	3	1	5	4	5	1	1		4	4	2	3	3	5	4	3	4	5	4	4	3	4	5	3
021	3	1	1	4	4	1	1	4	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	
022	3	2	5	1	4	1	2	3	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
023	3	1	5	4	3	1	2	5	4	4	3	4	4	4	4	4	4	4	4	4	4	4	4	4
024	3																							
025	3	2	5	5	3	1	2	4	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
026	3	2	1	3	3	2	2	4	4	3	2	3	3	4	3	3	4	3	4	4	4	4	3	3
027	3	3	5	1	4	1	2	3	4	3	3	3	4	2	4	3	3	4	4	4	3	4	3	2
028	3	2	2	3	3	2	2	3	4	3	2	2	2	2	2	2	3	2	3	4	3	2	3	4
029	3	3	1	3	5	1	2	4	3	2	2	3	3	3	3	3	3	3	3	3	3	3	3	
030	3	1	1	4	3	1	2	4	4	4	3	4	4	2	4	4	4	2	2	2	2	2	2	3
001	4	3	5	4	3	1	2	4	4	3	3	3	3	4	4	4	4	3	2	4	4	3	3	4
002	4	3	5	4	3	1	2	4	4		2	2	3	2	3	2	2	2	2	4	4	4	3	3
003	4	2	5	3	5	2	2	4	4	4	4	4	3	5	4	4	5	4	4	5	5	4	5	4
004	4	3	5	3	1	1	2	3	4	2														
005	4	1	1	4	4	2	1	5	5	5	3	3	5	5	5	4	5	5	5	5	4	4	5	5
006	4	1	1	4	5	1	1	4	5	3	3	3	4	5	5	4	4	5	4	4	4	4	4	4
007	4	1	1	4	4	1	1	4	5	3	3	3	4	5	5	4	5	4	4	4	4	4	4	
008	4	3	1		2	2	2	5	5	4	4	3	4	4	4	5	5	5	4	5	5	5	5	
009	4	1	5	3	5	1	1	5	4	4	3	3	2	3	3	3	3	3	4	3	3	3	2	3
010	4	1	5	4	3	1	1	3	4	3	3	4	3	4	4	4	5	4	4	5	5	5	5	3
011	4	2	5	4	3	1	1	4	5	4	4	3	3	5	5	4	4	4	3	4	4	4	5	5
012	4	3	5	1	5	1	2	3	3	2	2	3	2	3	3	3	3	3	4	3	3	3	3	3
013	4	2	5	3	3	2	2	4	4	3	4	4	4	5	5	4	4	5	5	4	5	5	4	5
014	4	3	5	3	4	1	2	3	4	3	2	2	5	5	5	4	4	4	3	3	4	3	3	3
015	4	1	5	4	2	1	2	5	5	4	2	4	5	5	3	2	4	2	2	2	2	4	3	5
016	4	3	5	3	2	2	2	3	3	3	2	4	2	3	3	4	5	3	3	3	3	3	2	3
017	4	2	1	3	1	1	2	3	4	3	3	4	2	5	3	3	3	2	4	5	4	4	3	5
018	4	2	5	4	1	2	2	4	4	3	3	3	4	4	4	4	4	4	4	4	5	4	4	4
019	4	2	1	3	5	2	2	3	3	2	3	3	3	4	4	4	4	4	4	5	4	4	4	4
020	4	2	5	3	2	1	2	5	5	4	3	4	2	3	3	3	3	3	3	3	3	3	3	4
021	4	1	1	4	3	2	2		4	2	3	2	3	4	3	3	3	3	3	3	3	3	3	4
022	4	2	1	5	1	1	2	5	3	3	2	4	2	2	2	2	5	1	3	4	3	3	2	3

Record	Q24	Q25	Q26	Q27	Q28	Q29	Q30	Q31	Q32	Q33	Q34	Q35	Q36	Q37	Q38	Q39	Q40	Q41	Q42	Q43	Q44	SS_13_22	SS_23_38	SS_39_44
002	4	4	4	4	4	4	4	5	5	5	5	4	4	4	4	4	4	4	4	4	4	46	68	24
003	5	4	4	4	4	5	5	4	4	4	5	5	5	5	5	5	5	5	5	5	4	30	73	29
004	3	3	3	4	4	4	4	4	4	4	5	4	3	3	3	4	3	5	5	3	3	41	58	23
005																	3					35	0	3
006	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	5	5	5	4	2	3	41	62	24
007	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	3	1	5	5	14	48	18
008				4	4			4	3	2	2	3	3	3	3	4	4	5	4	3	4	33	31	24
009	3	4	4	4	4	4	3	4	4	4	3	4	3	4	3	3	3	2	2	2	4	31	58	16
010	3		3		4		3		3		3		4		4	5	5	2	5	5	5	34	27	27
011	3	4	4	3	3	3	3	3	3	3	3	4	4	4	4	4	4	2	5	5	5	39	54	25
012	3	1	3	1	3	1	3	1	3	1	3	4	4	4	4	3	3	5	2	4	3	16	40	20
013	3	5	4	5	4	4	4	5	5	5	5	5	5	4	4	3	3	5	4	4	4	39	70	23
014	3	5	4	4	3	4	3	3	3	4	3	4	4	4	3	4	4	3	4	3	4	34	58	22
015	3	4	4	3	4	3	3	4	4	4	4	3	4	4	4	4	3	3	4	2	3	37	58	19
016	5	5	5	5	5	5	5	5	5	4	4	5	5	5	5	4	4	3	3	2	3	46	78	19
017	4	4	4	4	4	4	4	4	4	3	3	4	4	4	4	3	3	3	3	3	3	35	62	18
018	4	4	4	5	4	4	5	5	5	4	5	5	5	5	4							39	72	0
019	4	4	4	3	3	3	3	3	3	4	4	3	3	4	4	4	3	4	4	3	3	41	56	21
020	2	4	4	4	4	4	4	4	4	4	4	4	5	4	5	2	5	2	4	2	5	30	64	20
021	2	4	2	4	2	3	2	4	2	3	3	2	2	3	3	5	5	4	4	4	4	26	43	26
022	4	3	4	4	4	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	35	61	24
023	3	4	4	5	5	4	4	5	4	5	4	5	5	5	5	4	5	4	5	3	3	34	70	24
024	3	5	4	5	4	5	5	4	4	5	5	5	5	5	5	1	1	4	4	4	4	49	74	18
025																						6	0	0
026																						0	0	0
027										5	5	5	5	5	5	3	5	5	3	3	3	33	30	22
028	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	3	4	4	4	4	2	39	80	21
029	4	5	5	5	5	5	5	5	5	3	3	4	4	4	4	3	4	3	3	3	2	36	70	18
030	4	5	5	5	5	5	5	5	5	3	3	4	4	4	4	3	4	3	3	3	2	49	70	18
031	3	3	3	3	3	4	4	4	4	4	4	4	4	4	4	3	3	4	3	4	4	35	58	21
032	3	3	3	3	3	3	3	3	3	4	3	2	3	2	3	4	4	3	4	4	4	26	47	23
033	3	4	4	4		4	4	4	4	4	4	4	4	4	4	3	4	4	3	3	4	37	59	21
034	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	3	3	1	2	5	46	80	15
035	3	3	3	3	3	3	3	3	3	3	3	4	3	4	3	4	4	3	2	1		29	50	14
036	4	5	4	5	4	5	4	5	4	5	4	5	4	4	4	4	3	4	4	2	4	44	71	21
037																						0	0	0
038	4	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	2	35	78	27
039	2	2	2	2	2	2	2	4	4	2	2	2	2	2	3	4	4	3	3	3	3	32	37	20
040	5	5	5	4	4			3	3	5	5	5	5	5	5	5	5	5				37	64	15
041	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	33	64	24
042	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	5	5	5	5	3	4	16	33	27
043	4	4	4	4	4	4	4	4	3	5	4	4	4	4	3	4	5	3	5	3	4	43	63	24
001	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	30	48	19
001	3	2	4	3	5	2	2	3	3	4	4	2	3	1	4	3	5	2	3	3	4	36	46	20
002	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	5	5	5	5	5	3	36	62	28
003	2	3	3	4	2	2	2	2	2	5	5	2	2	4	2	4	4	4	4	4	4	36	47	24
004	3	4	4	4	4	4	4	4	4	3	3	3	3	3	3	5	5	4	5	4	4	34	56	27
005	3	4	3	4	4	4	4	4	4	4	4	4	4	4	4	2	1	1	1	2	2	40	62	9
006	3	4	3	4	3	4	3	4	3	4	3	4	4	4	4	5	5	4	4	3	3	33	58	24
007	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	2	1	1	1	1	2	40	64	8
008	4	5	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	40	65	24
009	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	3	41	64	19
010	5	5	5	5	5	4	4	4	4	5	5	4	5	5	5	2	2	1	1	1	2	44	75	9
011	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	3	1	1	1	1	2	0	80	9
012	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	30	48	18
013	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	2	1	1	1	1	5	45	80	11

014	4	5	4	5	4	3	3	5	4	5	4	3	3	4	3	5	5	5	4	2	4	37	64	25
015	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	2	2	1	1	1	2	47	80	9
016	3		3	3	3	4	4	3	4	4	3	3	2	2	4	4	4	4	1	3	2	30	45	18
017	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	2	1	1	1	1	2	40	64	8
001	2	4	4	4	4	4	2	3	2	4	4	4	3	4	3	3	4	4	3	4	2	23	55	20
002																2	3	3	3	3	3	40	0	17
003	3	4	3	4	3	2	2	4	3	4	3	4	3	2	2	4	4	3	5	5	4	23	50	25
004	3	3	3	3	3	3	3	3	3	3	3	4	4	4	4	3	3	3	3	2	3	25	52	17
005	4	4	4	4	4	4	3	4	4	4	4	4	4	4	4	5	4	4	4	5	4	38	63	26
006	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	2	2	2	4	40	64	18
007	3	5	3	5		3	3	3	3	3	3	3	3	3	3	5	5	5	5	3	3	18	49	26
008	3	3	3	3	3	1	3	1	3	3	3	2	3	2	3	3	3	3	3	3	3	30	42	18
009	2	4	2	4	2	4	2	4	2	4	2	4	2	4	2	4	4	5	4	4	4	41	47	25
010	1	4	1	4	1	4	1	2	1	2	1	3	1	1	1	4	4	2	4	5	3	19	32	22
011	4	4	3	4	3	4	3	4	3	3	3	3	3	3	3	3	2	3	3	3	3	28	54	17
012		3		3		3		3		4	4	4	4	3	4	3	3	3	3	3	3	30	38	18
013	4	4	3	4	3	3	2	4	3	4	3	4	3	4	3	5	5	2	4	5	1	33	55	22
014	3	4	2	4	2	4	2	4	2	4	2	4	2	4	2	2	2	2	4	4	2	28	49	16
015	5	5	4	5	5	4	4	5	5	5	4	5	4	5	4	5	5	5	4	5	4	42	74	28
016	2	2	2	2	2	2	2	4	2	4	2	3	3	2	2	2	2	2	4	4	2	27	40	16
017	5	5	5	5	5	4	5	5	5	5	5	5	5	4	5	4	3	4	5	4	5	42	78	25
018	1	5	1	5	1	5	1	5	1	5	1	5	1	5	1	4	4	5	5	5	5	38	48	28
019	5	4	4	4	4	3	3	3	3	3	3	3	3	3	3	4	4	4	4	3	2	39	56	21
020	4	5	5	5	4	4	4	5	4	5	4	5	3	5	3	3	4	3	2	2	3	41	68	17
021																3	3	3	3	3	3	30	0	18
022	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	30	48	18
023	4	3	3	3	3	4	4	3	3	4	4	4	4	3	3	4	4	4	4	4	4	40	56	24
024																						0	0	0
025	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	2	2	2	2	2	30	48	13
026	3	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	4	3	4	36	62	21
027	2	2	2	2	2	2	2	2	2	2	2	4	4	3	3	2	3	3	3	3	3	34	38	17
028	2	4	2	4	2	4	2	4	2	4	2	4	2	4	2	3	3	3	5	4	4	26	48	22
029	3		3		3		3		3		3		3		3	3	3	3	3	3	3	30	24	18
030	2	3	2	3	2	3	2	3	2	3	2	3	2	3	2	4	4	4	4	2	4	26	40	22
001	4	4	4	4	4	3	3	4	4	4	4	3	3	4	4	4	4	4	4	4	4	35	60	24
002	3	4	3	4	4	3	3	3	3	4	4	4	3	4	3	3	3	3	4	4	4	28	55	21
003	4	4	4	4	4	4	4	4	4	4	4	3	3	5	5	5	5	2	5	4	4	45	64	25
004																						0	0	0
005	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	4	4	5	4	2	2	47	80	21
006	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	2	3	43	64	21
007	4		4		4		4		4		4		4		4	4	4	4	4	2	4	43	32	22
008	4	4		4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	47	56	24
009	3	4	4	4	4	4	4	4	4	4	4	3	3	3	3	4	4	4	4	3	3	30	58	22
010	3	5	5	4	4	4	4	4	4	4	4	3	5	4	4	5	5	4	4	4	4	45	64	26
011	5	5	5	5	5	4	4	5	5	5	5	4	4	4	4	5	4	5	4	3	3	42	74	24
012	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3	3	4	31	48	20
013	4	5	4	5	5	5	4	5	4	5	4	5	4	4	4	2	3	2	2	3	3	46	72	15
014	3	3	3	4	5	3	3	3	3	4	4	4	4	3	3	3	1	2	2	3	3	38	55	14
015	2	5	3	5	3	5	3	3	3	5	3	5	5	5	4	2	3	4	4	4	4	29	64	21
016	3	3	3	3	3	2	2	3	3	3	3	2	2	2	2	4	4	4	3	3	3	32	42	21
017	5	5	5	4	4	5	4	5	4	5	5	5	4	4	4	4	3	5	4	3	3	36	73	22
018	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	2	2	2	4	41	64	18
019	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	2	2	4	4	2	4	41	64	18
020	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	3	2	3	5	5	30	64	21
021	3	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	31	50	18
022	3	4	2	4	4	3	3	4	3	4	3	3	3	3	3	4	4	4	5	3	3	27	52	23

Profie of response variable ExPDE:



Selected Attributes from some questions:

ITEM = **Rationale**	RATIONALE OF EFFCIENCY INDICATORS		
	% Disagree	% Average	% Agree
Q13 = appropriateness	9.4	23.6	67
Q14 = well defined	11.2	30.8	58
Q15 = well benchmarked	17	30.2	52.8
Q16 = cost effectiveness	9.4	38.7	51.9
Q17 = expenditure tracking	19	37.1	43.9
Q18 = deviations understood	18.9	30.2	50.9
Q19 = part of strategy formulation	12.3	27.4	60.3
Q20 = alignment to hospital strategy	13.2	33	53.8
Q21 = periodically reviewed	9.4	34	56.6
Q22 = control systems in place	15.1	32.1	52.8

ITEM = **Understanding & Application**	COMPREHENSION OF INDICATOR			USE OF IN PLANNING & MANAGERIAL DECISION MAKING			GAP
	% Disagree	% Average	% Agree	% Disagree	% Average	% Agree	% Difference Agree-to-Agree
Q23/4 = C-Sections	6.2	34.0	59.8	12.9	41.6	45.5	- 14.3
Q25/6 = BUR	6.1	19.4	74.5	12	29	59	- 15.5
Q27/8 = ALOS	5	21	74	12	25	63	- 11
Q29/30 = ExPDE	10.2	25.5	64.3	17	30	53	-11.3
Q31/2 = IPD	6	26	68	11.8	32.4	55.8	-12.2
Q33/4 = THC	6	20.8	73.2	10.6	30.8	58.6	-14.6
Q35/6 = Hosp. Expenditure	7.9	23.8	68.3	11.5	29.8	58.7	-9.6
Q37/8 = Man. of resources	9.9	20.8	69.3	10.6	30.8	58.6	-10.7

ITEM = **Institutional Challenges**	**INSTITUTIONAL CHALLENGES THAT INFLUENCE EFFICEINCY DATA UTILISATION**		
	% Disagree	% Average	% Agree
Q39 = Organisational challenges	15.2	28.6	56.2
Q40 = Technical issues	14.2	30.2	55.6
Q41 = Behavioural issues	21.9	29.5	48.6
Q42 = Synergy and communication	18.3	24	57.7
Q43 = Dynamism	25	37.5	37.5
Q44 = Load	17.5	35	47.5

Selected Linear Mixed Modelling (LMM) outputs:

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2092.398810	239.234795	5.342	8.746	.000	1489.074571	2695.723048
Quarter	44.016831	8.278789	107	5.317	.000	27.605098	60.428564

a. Dependent Variable: ExPDE.

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	5.493056	.435261	3.757	12.620	.000	4.253094	6.733017
Quarter	.070614	.009799	107	7.206	.000	.051189	.090040

a. Dependent Variable: ALOS.

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	71.414683	2.600600	4.301	27.461	.000	64.389046	78.440319
Quarter	.311918	.072909	107	4.278	.000	.167385	.456452

a. Dependent Variable: BOR.

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	41.595238	5.272722	3.047	7.889	.004	24.960518	58.229958
Quarter	.167693	.031993	107	5.242	.000	.104270	.231116

a. Dependent Variable: CSR.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		.701727	.095938	7.314	.000	.536778	.917365
Hospital [subject = Hospital]	Variance	.651991	.552822	1.179	.238	.123740	3.435370

a. Dependent Variable: ALOS.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		38.847294	5.311093	7.314	.000	29.715764	50.784906
Hospital [subject = Hospital]	Variance	21.194548	18.439062	1.149	.250	3.852003	116.616948

a. Dependent Variable: BOR.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		7.480235	1.022677	7.314	.000	5.721915	9.778880
Hospital [subject = Hospital]	Variance	110.078406	90.096777	1.222	.222	22.131569	547.509997

a. Dependent Variable: CSR.

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	33.403032	2.856667	1.815	11.693	.010	19.826594	46.979470
Manager_id	.002299	.041768	2.312	.055	.961	-.156071	.160668

a. Dependent Variable: SS_R.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		112.355360	15.299246	7.344	.000	86.037359	146.723784
Hospital [subject = Hospital]	Variance	3.397843	7.745482	.439	.661	.038982	296.170697

a. Dependent Variable: SS_R.

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	54.034966	7.633450	3.645	7.079	.003	32.002082	76.067849
Manager_id	.003933	.106831	4.786	.037	.972	-.274412	.282279

a. Dependent Variable: SS_UA.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Residual		366.281144	49.882093	7.343	.000	280.474549	478.338861
Hospital [subject = Hospital]	Variance	45.012918	54.038829	.833	.405	4.280103	473.391154

a. Dependent Variable: SS_UA.

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	18.780888	1.267526	110	14.817	.000	16.268948	21.292828
personid	.006249	.019472	110	.321	.749	-.032340	.044837

a. Dependent Variable: SS_IC.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Residual		44.385639	5.984958	7.416	.000	34.077403	57.812063
Hospital [subject = Hospital]	Variance	.000000[b]	.000000	.	.	.	.

a. Dependent Variable: SS_IC.
b. This covariance parameter is redundant. The test statistic and confidence interval cannot be computed.

Selected Grange Causality Analysis (GCA) outputs:

```
Source |      SS      df      MS          Number of obs =     25
-------------+------------------------------          F( 4,    20) =    3.02
     Model |  6045341.91    4  1511335.48         Prob > F      =  0.0423
  Residual |  10008973.9   20  500448.693         R-squared     =  0.3766
-------------+------------------------------          Adj R-squared =  0.2519
     Total |  16054315.8   24  668929.823         Root MSE      =  707.42

------------------------------------------------------------------------------
     expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      alos |
       --. |  -85.44026    290.568    -0.29   0.772    -691.5545     520.674
       L1. |   477.7551   412.9709     1.16   0.261    -383.6872    1339.197
       L2. |  -60.03616   415.7191    -0.14   0.887     -927.211    807.1387
       L3. |   304.9829   351.3809     0.87   0.396    -427.9847    1037.951
           |
     _cons |  -230.6436   1157.032    -0.20   0.844    -2644.171    2182.883
------------------------------------------------------------------------------

 ( 1)  L.alos = 0
 ( 2)  L2.alos = 0
 ( 3)  L3.alos = 0

     F(  3,    20) =    1.33
          Prob > F =    0.2927

    Source |      SS      df      MS          Number of obs =     25
-------------+------------------------------          F( 4,    20) =    5.26
     Model |  13.6314752    4  3.4078688          Prob > F      =  0.0046
  Residual |  12.9581234   20  .647906169         R-squared     =  0.5127
-------------+------------------------------          Adj R-squared =  0.4152
     Total |  26.5895986   24  1.10789994         Root MSE      =  .80493
```

```
      alos |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
     expde |
       --. |   .0000742   .0002667     0.28   0.784    -.0004822    .0006306
       L1. |   .0002151   .0002512     0.86   0.402    -.0003089     .000739
       L2. |   .0003719   .0002466     1.51   0.147    -.0001425    .0008863
       L3. |   .0003994   .0002535     1.58   0.131    -.0001295    .0009282
           |
     _cons |   2.572959   .8362963     3.08   0.006     .8284756    4.317442
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    3.56
            Prob > F =    0.0326

Vector autoregression

Sample:  6344q1 - 6350q1                     No. of obs      =        25
Log likelihood = -210.2335                   AIC             =  17.93868
FPE            =  218306.5                   HQIC            =    18.128
Det(Sigma_ml)  =  69073.55                   SBIC            =  18.62125

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
alos                 7     .54606   0.7981   98.85067   0.0000
expde                7     684.699  0.4744   22.56203   0.0010
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
alos         |
        alos |
         L1. |   .9031113   .2040912     4.43   0.000     .5030999    1.303123
         L2. |   -.239747   .2756849    -0.87   0.384    -.7800795    .3005855
         L3. |   .1784529   .2498005     0.71   0.475     -.311147    .6680528
             |
       expde |
         L1. |   .0000434   .0001561     0.28   0.781    -.0002625    .0003493
         L2. |   .0001052   .0001545     0.68   0.496    -.0001975    .0004079
         L3. |   .0001547    .000144     1.07   0.283    -.0001276    .0004369
             |
       _cons |   .1023889     .77996     0.13   0.896    -1.426305    1.631083
-------------+----------------------------------------------------------------
expde        |
        alos |
         L1. |   171.7883   255.9076     0.67   0.502    -329.7814     673.358
         L2. |   74.24842   345.6782     0.21   0.830    -603.2684    751.7653
         L3. |    24.3214    313.222     0.08   0.938    -589.5825    638.2253
             |
       expde |
         L1. |   .0584103   .1957131     0.30   0.765    -.3251804    .4420009
         L2. |   .1787552   .1936632     0.92   0.356    -.2008176    .5583281
         L3. |   .2703952   .1805474     1.50   0.134    -.0834711    .6242616
             |
       _cons |   219.6547   977.9832     0.22   0.822    -1697.157    2136.466
------------------------------------------------------------------------------


Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |              alos              expde |  2.609     3    0.456     |
 |              alos                ALL |  2.609     3    0.456     |
 |--------------------------------------+---------------------------|
 |             expde               alos |  1.9823    3    0.576     |
 |             expde                ALL |  1.9823    3    0.576     |
 +------------------------------------------------------------------+
              storage   display    value
variable name   type    format     label      variable label
----------------------------------------------------------------------------------------------------------------------------------
```

```
alos          float   %8.0g              ALOS

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    7.42
      Model |  3670535.31     4  917633.827           Prob > F      =  0.0008
   Residual |  2473698.69    20  123684.935           R-squared     =  0.5974
-------------+------------------------------           Adj R-squared =  0.5169
      Total |     6144234    24   256009.75           Root MSE      =  351.69

------------------------------------------------------------------------------
      expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       alos |
        --. |  -59.03541   132.0531    -0.45   0.660    -334.4933    216.4225
        L1. |   408.2675   135.0877     3.02   0.007     126.4795    690.0554
        L2. |   77.42964   135.4926     0.57   0.574     -205.203    360.0623
        L3. |    365.996   129.8014     2.82   0.011     95.23504    636.7569
            |
      _cons |  -3583.501   1362.819    -2.63   0.016    -6426.292   -740.7103
------------------------------------------------------------------------------

 ( 1)  L.alos = 0
 ( 2)  L2.alos = 0
 ( 3)  L3.alos = 0

       F(  3,    20) =    9.39
            Prob > F =    0.0004

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    2.59
      Model |  2.91411202     4  .728528006           Prob > F      =  0.0676
   Residual |  5.6154889    20  .280774445            R-squared     =  0.3416
-------------+------------------------------           Adj R-squared =  0.2100
      Total |  8.52960093    24  .355400039           Root MSE      =  .52988

------------------------------------------------------------------------------
       alos |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      expde |
        --. |  -.0002937   .0002736    -1.07   0.296    -.0008645    .0002771
        L1. |   .0002872   .0002557     1.12   0.275    -.0002461    .0008206
        L2. |    .000533   .0002599     2.05   0.054    -9.03e-06    .0010751
        L3. |   .0002462    .000256     0.96   0.348    -.0002878    .0007801
            |
      _cons |   5.981218   .6950121     8.61   0.000     4.531448    7.430988
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    3.15
            Prob > F =    0.0475

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -191.9459                      AIC             =  16.47567
FPE            =  50546.39                      HQIC            =  16.66499
Det(Sigma_ml)  =  15993.19                      SBIC            =  17.15824

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
alos                 7     .49034   0.4926   24.27214   0.0005
expde                7    363.241   0.6135   39.67651   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
alos         |
        alos |
         L1. |   .2629104   .1844551     1.43   0.154    -.0986149    .6244357
```

```
      L2. |  -.1816676   .1906944    -0.95   0.341    -.5554218    .1920867
      L3. |  -.4153477    .188705    -2.20   0.028    -.7852028   -.0454927
          |
    expde |
      L1. |   .0006037   .0002471     2.44   0.015     .0001194    .0010879
      L2. |   .0005768   .0002375     2.43   0.015     .0001114    .0010422
      L3. |  -.0000366   .0002158    -0.17   0.865    -.0004597    .0003864
          |
    _cons |   7.561248   1.576615     4.80   0.000     4.471138    10.65136
-------------+----------------------------------------------------------------
expde        |
     alos |
      L1. |   312.1939    136.643     2.28   0.022     44.37843    580.0093
      L2. |   68.59699   141.2651     0.49   0.627    -208.2776    345.4716
      L3. |   357.9142   139.7914     2.56   0.010     83.92812    631.9003
          |
    expde |
      L1. |  -.0345378   .1830217    -0.19   0.850    -.3932538    .3241781
      L2. |   .0114018   .1759029     0.06   0.948    -.3333615    .3561651
      L3. |   .1757204   .1598984     1.10   0.272    -.1376748    .4891156
          |
    _cons |  -3521.753   1167.946    -3.02   0.003    -5810.885   -1232.621
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |              alos              expde |  15.973     3    0.001    |
 |              alos                ALL |  15.973     3    0.001    |
 |--------------------------------------+---------------------------|
 |             expde               alos |  14.472     3    0.002    |
 |             expde                ALL |  14.472     3    0.002    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
--------------------------------------------------------------------------------------------------------------------------------

-----------
alos            float   %8.0g                 ALOS

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    2.22
       Model |  4246485.28     4  1061621.32           Prob > F      =  0.1031
    Residual |  9553460.48    20  477673.024           R-squared     =  0.3077
-------------+------------------------------           Adj R-squared =  0.1693
       Total |  13799945.8    24   574997.74           Root MSE      =  691.14

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        alos |
         --. |  -223.3721   225.9553    -0.99   0.335    -694.7066    247.9623
         L1. |   289.9659   281.1025     1.03   0.315    -296.4036    876.3353
         L2. |  -434.7162   295.2315    -1.47   0.156    -1050.558    181.1259
         L3. |   614.5372   249.7686     2.46   0.023     93.52901    1135.545
             |
       _cons |   1309.487   784.3359     1.67   0.111    -326.6091    2945.583
------------------------------------------------------------------------------

 ( 1)  L.alos = 0
 ( 2)  L2.alos = 0
 ( 3)  L3.alos = 0

       F(  3,    20) =    2.78
            Prob > F =    0.0675

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.21
       Model |   1.491802     4    .3729505            Prob > F      =  0.9273
    Residual |  34.7745985    20  1.73872992           R-squared     =  0.0411
-------------+------------------------------           Adj R-squared = -0.1506
```

```
     Total |  36.2664004    24  1.51110002           Root MSE      =  1.3186

------------------------------------------------------------------------------
      alos |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     expde |
       --. |    .000162   .0003748     0.43   0.670    -.0006198    .0009438
       L1. |   .0001391     .00038     0.37   0.718    -.0006536    .0009317
       L2. |  -.0000247   .0003873    -0.06   0.950    -.0008326    .0007831
       L3. |   .0001834   .0003743     0.49   0.629    -.0005974    .0009642
           |
     _cons |   4.929922   1.410908     3.49   0.002     1.986819    7.873025
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

     F(  3,    20) =    0.16
          Prob > F =    0.9250

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -217.1671                      AIC             =  18.49337
FPE            =    380157                      HQIC            =  18.68268
Det(Sigma_ml)  =  120284.1                      SBIC            =  19.17594

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
alos                 7     .706058   0.7526   76.03943   0.0000
expde                7     701.964   0.3573   13.89691   0.0308
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
alos         |
        alos |
         L1. |   .7259169   .2014489     3.60   0.000     .3310843     1.12075
         L2. |   .1333159   .2663048     0.50   0.617    -.3886319    .6552638
         L3. |   .0518236   .2233216     0.23   0.816    -.3858788     .489526
             |
       expde |
         L1. |  -.0000339   .0001768    -0.19   0.848    -.0003803    .0003126
         L2. |  -.0000894   .0001802    -0.50   0.620    -.0004426    .0002638
         L3. |   .0001676   .0001702     0.98   0.325    -.0001659    .0005011
             |
       _cons |   .5795269    .802047     0.72   0.470    -.9924563     2.15151
-------------+----------------------------------------------------------------
expde        |
        alos |
         L1. |   194.0662   200.2808     0.97   0.333    -198.4769    586.6093
         L2. |  -587.1427   264.7606    -2.22   0.027    -1106.064   -68.22148
         L3. |   617.6523   222.0267     2.78   0.005     182.4881    1052.817
             |
       expde |
         L1. |   .2865538   .1757278     1.63   0.103    -.0578664     .630974
         L2. |  -.0040847   .1791506    -0.02   0.982    -.3552135    .3470441
         L3. |   .0489975   .1691677     0.29   0.772    -.2825651    .3805601
             |
       _cons |   543.2902   797.3962     0.68   0.496    -1019.578    2106.158
------------------------------------------------------------------------------

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |              alos              expde |  1.0659     3    0.785    |
  |              alos                ALL |  1.0659     3    0.785    |
  |--------------------------------------+---------------------------|
  |             expde               alos |  9.8897     3    0.020    |
  |             expde                ALL |  9.8897     3    0.020    |
```

```
 +-----------------------------------------------------------------+

           storage   display    value
variable name   type    format     label      variable label
-----------------------------------------------------------------------------------------------------------------------------

-----------
alos           float   %8.0g              ALOS

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    3.59
       Model |  8560053.42     4  2140013.35           Prob > F      =  0.0232
    Residual |  11935046.7    20  596752.337           R-squared     =  0.4177
-------------+------------------------------           Adj R-squared =  0.3012
       Total |  20495100.2    24  853962.507           Root MSE      =   772.5

------------------------------------------------------------------------------
        expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         alos |
          --. |  -116.0282   187.2646    -0.62   0.543    -506.6553    274.5989
          L1. |   81.17606    226.275     0.36   0.724    -390.8253    553.1775
          L2. |  -20.14027   226.5589    -0.09   0.930    -492.7338    452.4533
          L3. |   533.4348   190.6945     2.80   0.011      135.653    931.2167
              |
        _cons |  -397.1124   1292.548    -0.31   0.762    -3093.321    2299.096
------------------------------------------------------------------------------

 ( 1)  L.alos = 0
 ( 2)  L2.alos = 0
 ( 3)  L3.alos = 0

       F(  3,    20) =    4.72
            Prob > F =    0.0119

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.20
       Model |  1.12023353     4  .280058384           Prob > F      =  0.9377
    Residual |  28.5997674    20  1.42998837           R-squared     =  0.0377
-------------+------------------------------           Adj R-squared = -0.1548
       Total |  29.7200009    24  1.23833337           Root MSE      =  1.1958

------------------------------------------------------------------------------
         alos |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        expde |
          --. |  -.0000257   .0003061    -0.08   0.934    -.0006643    .0006128
          L1. |  -.0000915   .0003502    -0.26   0.797     -.000822     .000639
          L2. |  -.0000927   .0003446    -0.27   0.791    -.0008114    .0006261
          L3. |  -.0001362   .0003191    -0.43   0.674    -.0008019    .0005295
              |
        _cons |   7.276081   1.084759     6.71   0.000     5.013313    9.538849
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.23
            Prob > F =    0.8777

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -227.4602                      AIC             =  19.31682
FPE            =  866129.9                      HQIC            =  19.50613
Det(Sigma_ml)  =  274048.9                      SBIC            =  19.99939

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
alos                 7     .968815   0.4315   18.97792   0.0042
expde                7     758.887   0.4942   24.42683   0.0004
----------------------------------------------------------------
```

```
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
alos         |
        alos |
         L1. |   .6961255   .2030154     3.43   0.001     .2982225    1.094028
         L2. |  -.0285961   .2495358    -0.11   0.909    -.5176773    .4604851
         L3. |  -.1893826   .2171365    -0.87   0.383    -.6149623    .2361971
             |
       expde |
         L1. |   .0000337    .000235     0.14   0.886    -.0004269    .0004943
         L2. |  -.0000152   .0002455    -0.06   0.951    -.0004964     .000466
         L3. |  -.0000819   .0002256    -0.36   0.717    -.0005241    .0003603
             |
       _cons |    3.49476   1.459639     2.39   0.017     .6339194      6.3556
-------------+----------------------------------------------------------------
expde        |
        alos |
         L1. |   77.21666   159.0251     0.49   0.627    -234.4668    388.9001
         L2. |  -40.34256   195.4652    -0.21   0.836    -423.4473    342.7622
         L3. |   452.6481   170.0863     2.66   0.008     119.2851    786.0112
             |
       expde |
         L1. |   .3275752   .1840797     1.78   0.075    -.0332144    .6883648
         L2. |   .0223655   .1923108     0.12   0.907    -.3545568    .3992878
         L3. |   .0192768   .1767201     0.11   0.913    -.3270882    .3656419
             |
       _cons |  -1417.034   1143.358    -1.24   0.215    -3657.974    823.9055
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |              alos              expde |  .18075     3    0.981    |
 |              alos                ALL |  .18075     3    0.981    |
 |--------------------------------------+---------------------------|
 |             expde               alos |  11.802     3    0.008    |
 |             expde                ALL |  11.802     3    0.008    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------

-----------
BUR             byte    %8.0g                 BOR

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    3.05
       Model |  6078259.93     4  1519564.98           Prob > F      =  0.0411
    Residual |  9976055.83    20  498802.791           R-squared     =  0.3786
-------------+------------------------------           Adj R-squared =  0.2543
       Total |  16054315.8    24  668929.823           Root MSE      =  706.26

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         BUR |
         --. |   63.96357   25.55474     2.50   0.021     10.65731    117.2698
         L1. |   61.39328   25.44087     2.41   0.026     8.324556     114.462
         L2. |   55.09948   25.36514     2.17   0.042     2.188734    108.0102
         L3. |   45.72256   25.38955     1.80   0.087    -7.239101    98.68423
             |
       _cons |  -13796.56   5037.265    -2.74   0.013    -24304.11   -3289.011
------------------------------------------------------------------------------

 ( 1)  L.bur = 0
 ( 2)  L2.bur = 0
 ( 3)  L3.bur = 0

       F(  3,    20) =    3.27
```

```
       Prob > F =    0.0425

    Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.05
     Model |   158.86238     4  39.7155951           Prob > F      =  0.4056
  Residual |   754.89762    20   37.744881           R-squared     =  0.1739
-------------+------------------------------           Adj R-squared =  0.0086
     Total |      913.76    24  38.0733333           Root MSE      =  6.1437

------------------------------------------------------------------------------
       bur |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     expde |
       --. |   .0002153   .0020357     0.11   0.917    -.0040312    .0044618
       L1. |   .0008284   .0019172     0.43   0.670    -.0031707    .0048276
       L2. |  -.0001303   .0018821    -0.07   0.945    -.0040562    .0037956
       L3. |   .0023006   .0019351     1.19   0.248    -.0017358    .0063371
           |
     _cons |   65.78115   6.383122    10.31   0.000     52.46619    79.09611
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

     F(  3,    20) =    0.81
       Prob > F =    0.5040

Vector autoregression

Sample:  6344q1 - 6350q1                           No. of obs      =        25
Log likelihood = -265.7232                         AIC             =  22.37785
FPE            =  1.85e+07                         HQIC            =  22.56717
Det(Sigma_ml)  =   5850865                         SBIC            =  23.06042

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
bur                  7     4.91764   0.5236   27.47914   0.0001
expde                7     695.499   0.4577   21.09633   0.0018
----------------------------------------------------------------

------------------------------------------------------------------------------
           |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
bur          |
       bur |
       L1. |  -.4153823   .1648775    -2.52   0.012    -.7385362   -.0922284
       L2. |   -.555063   .1441977    -3.85   0.000    -.8376853   -.2724406
       L3. |  -.3171947    .156851    -2.02   0.043    -.6246171   -.0097723
           |
     expde |
       L1. |   .0018803   .0013152     1.43   0.153    -.0006975     .004458
       L2. |   .0012672   .0012863     0.99   0.325     -.001254    .0037884
       L3. |   .0025017   .0012293     2.04   0.042     .0000923     .004911
           |
     _cons |   156.0518   23.97863     6.51   0.000     109.0546    203.0491
-------------+----------------------------------------------------------------
expde        |
       bur |
       L1. |   21.94643   23.31854     0.94   0.347    -23.75707    67.64992
       L2. |   11.50015   20.39381     0.56   0.573    -28.47098    51.47128
       L3. |   17.03153   22.18336     0.77   0.443    -26.44706    60.51013
           |
     expde |
       L1. |   .0975829   .1860076     0.52   0.600    -.2669852     .462151
       L2. |   .2020339   .1819277     1.11   0.267    -.1545378    .5586056
       L3. |   .3399798   .1738594     1.96   0.051    -.0007785     .680738
           |
     _cons |  -2478.521   3391.285    -0.73   0.465    -9125.318    4168.275
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
```

```
 |        Equation          Excluded |    chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |            bur           expde |  18.867     3    0.000    |
 |            bur             ALL |  18.867     3    0.000    |
 |--------------------------------------+---------------------------|
 |          expde             bur |  1.1508     3    0.765    |
 |          expde             ALL |  1.1508     3    0.765    |
 +------------------------------------------------------------------+
```

```
storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------------------------------------

bur           byte    %8.0g              BUR

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    5.23
      Model |   3140541.6     4  785135.401           Prob > F      =  0.0048
   Residual |   3003692.4    20   150184.62           R-squared     =  0.5111
-------------+------------------------------           Adj R-squared =  0.4134
      Total |     6144234    24   256009.75           Root MSE      =  387.54

------------------------------------------------------------------------------
      expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        bur |
        --. |   5.244394   12.29589     0.43   0.674    -20.40439    30.89318
        L1. |   32.27552   14.19445     2.27   0.034     2.666424    61.88461
        L2. |   5.787223   13.93895     0.42   0.682    -23.28891    34.86336
        L3. |    9.69593   12.78038     0.76   0.457    -16.96347    36.35533
            |
      _cons |  -1158.391   896.8032    -1.29   0.211     -3029.09     712.308
------------------------------------------------------------------------------

 ( 1)  L.bur = 0
 ( 2)  L2.bur = 0
 ( 3)  L3.bur = 0

       F(  3,    20) =    3.83
            Prob > F =    0.0257

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    5.57
      Model |  906.225767     4  226.556442           Prob > F      =  0.0035
   Residual |  813.774233    20  40.6887116           R-squared     =  0.5269
-------------+------------------------------           Adj R-squared =  0.4323
      Total |        1720    24  71.6666667           Root MSE      =  6.3788

------------------------------------------------------------------------------
        bur |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      expde |
        --. |   .0009185   .0032941     0.28   0.783    -.0059528    .0077898
        L1. |   .0014845   .0030781     0.48   0.635    -.0049363    .0079053
        L2. |   .0045458   .0031282     1.45   0.162    -.0019796    .0110712
        L3. |    .008048   .0030814     2.61   0.017     .0016203    .0144758
            |
      _cons |   34.42869   8.366629     4.12   0.001      16.9762    51.88117
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    4.18
            Prob > F =    0.0189

Vector autoregression
```

```
Sample:  6344q1 - 6350q1                    No. of obs     =       25
Log likelihood = -256.6913                  AIC            =  21.6553
FPE            =  8977893                   HQIC           =  21.84462
Det(Sigma_ml)  =  2840662                   SBIC           =  22.33787

Equation         Parms     RMSE     R-sq     chi2     P>chi2
----------------------------------------------------------------
bur               7    6.00605   0.6225   41.22432   0.0000
expde             7    390.762   0.5527   30.88704   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
bur          |
         bur |
         L1. |   .3745386   .1748142     2.14   0.032      .031909    .7171681
         L2. |  -.3304872   .1941976    -1.70   0.089    -.7111074     .050133
         L3. |   .0071259   .1943361     0.04   0.971    -.3737658    .3880177
             |
       expde |
         L1. |   .0029545   .0028941     1.02   0.307    -.0027179    .0086269
         L2. |   .0044856   .0029001     1.55   0.122    -.0011984    .0101697
         L3. |   .0067292   .0024506     2.75   0.006     .0019262    .0115323
             |
       _cons |   32.68791   12.12835     2.70   0.007      8.91677    56.45904
-------------+----------------------------------------------------------------
expde        |
         bur |
         L1. |    27.5577   11.37364     2.42   0.015     5.265772    49.84963
         L2. |   7.643541   12.63475     0.60   0.545    -17.12011     32.4072
         L3. |    2.80118   12.64376     0.22   0.825    -21.98014     27.5825
             |
       expde |
         L1. |  -.0847553   .1882954    -0.45   0.653    -.4538076     .284297
         L2. |    .155659    .188682     0.82   0.409    -.2141509    .5254688
         L3. |   .2242562   .1594384     1.41   0.160    -.0882373    .5367498
             |
       _cons |  -808.8566   789.0867    -1.03   0.305    -2355.438     737.725
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               bur              expde |  13.247     3    0.004    |
 |               bur                ALL |  13.247     3    0.004    |
 |--------------------------------------+---------------------------|
 |             expde                bur |  9.1076     3    0.028    |
 |             expde                ALL |  9.1076     3    0.028    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
----------------------------------------------------------------------------------------------------------------------------

-----------
bur             byte    %8.0g                 BUR

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.11
       Model |  298519.353     4  74629.8381           Prob > F      =  0.9774
    Residual |  13501426.4    20  675071.32            R-squared     =  0.0216
-------------+------------------------------           Adj R-squared = -0.1740
       Total |  13799945.8    24  574997.74            Root MSE      =  821.63

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         bur |
         --. |  -12.56606   25.41288    -0.49   0.626     -65.5764    40.44427
         L1. |  -.2101588   25.15983    -0.01   0.993    -52.69265    52.27233
```

```
         L2. |  -9.842134   25.67513   -0.38   0.706   -63.39952    43.71526
         L3. |   1.183002   25.86087    0.05   0.964   -52.76184    55.12784
             |
       _cons |   4294.896   3651.013    1.18   0.253   -3320.983    11910.78
------------------------------------------------------------------------------

 ( 1)  L.bur = 0
 ( 2)  L2.bur = 0
 ( 3)  L3.bur = 0

       F(  3,    20) =    0.05
            Prob > F =    0.9851

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.36
       Model |  72.2406144     4  18.0601536           Prob > F      =  0.8322
    Residual |  995.759386    20  49.7879693           R-squared     =  0.0676
-------------+------------------------------           Adj R-squared = -0.1188
       Total |        1068    24        44.5           Root MSE      =  7.0561

------------------------------------------------------------------------------
         bur |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -.0010972   .0020055   -0.55   0.590    -.0052807    .0030863
         L1. |   .0008338   .0020333    0.41   0.686    -.0034076    .0050752
         L2. |   -.001833   .0020724   -0.88   0.387     -.006156      .00249
         L3. |   .0013568    .002003    0.68   0.506    -.0028213     .005535
             |
       _cons |   78.24151   7.549964   10.36   0.000     62.49256    93.99046
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.38
            Prob > F =    0.7680

Vector autoregression

Sample:  6344q1 - 6350q1                           No. of obs      =        25
Log likelihood = -280.5306                         AIC             =  23.56245
FPE            =  6.05e+07                         HQIC            =  23.75176
Det(Sigma_ml)  =  1.91e+07                         SBIC            =  24.24502

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
bur                   7     7.42648   0.0705   1.8951    0.9291
expde                 7     823.351   0.1158   3.273202  0.7739
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
bur          |
         bur |
         L1. |   .0785618   .1980876    0.40   0.692    -.3096828    .4668064
         L2. |   .0734962   .1978729    0.37   0.710    -.3143276      .46132
         L3. |  -.0849405   .1998281   -0.43   0.671    -.4765963    .3067153
             |
       expde |
         L1. |   .0005666   .0017887    0.32   0.751    -.0029391    .0040724
         L2. |  -.0019388   .0018618   -1.04   0.298    -.0055879    .0017102
         L3. |   .0013106    .001834    0.71   0.475    -.0022841    .0049052
             |
       _cons |   71.28043   26.29724    2.71   0.007     19.73878    122.8221
-------------+----------------------------------------------------------------
expde        |
         bur |
         L1. |   4.228397   21.96137    0.19   0.847     -38.8151     47.2719
         L2. |   -10.8784   21.93757   -0.50   0.620    -53.87525    32.11844
         L3. |   7.119695   22.15433    0.32   0.748    -36.30199    50.54138
```

```
         |
     expde |
       L1. |   .2532244   .1983047     1.28   0.202    -.1354458    .6418945
       L2. |   .1114171   .2064113     0.54   0.589    -.2931416    .5159757
       L3. |   .0580704   .2033344     0.29   0.775    -.3404577    .4565985
         |
     _cons |   1539.328   2915.495     0.53   0.598    -4174.937    7253.594
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |              bur             expde |  1.3235     3    0.724    |
 |              bur               ALL |  1.3235     3    0.724    |
 |--------------------------------------+---------------------------|
 |            expde               bur |  .36049     3    0.948    |
 |            expde               ALL |  .36049     3    0.948    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------------

-----------
bur             byte    %8.0g                 BUR

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.25
       Model |  985267.344     4  246316.836           Prob > F      =  0.9047
    Residual |  19509832.8    20  975491.641           R-squared     =  0.0481
-------------+------------------------------           Adj R-squared = -0.1423
       Total |  20495100.2    24  853962.507           Root MSE      =  987.67

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         bur |
         --. |  -24.82014    32.1161    -0.77   0.449    -91.81316    42.17288
         L1. |  -11.20542   31.93737    -0.35   0.729    -77.82561    55.41477
         L2. |   14.64369   32.08859     0.46   0.653    -52.29194    81.57932
         L3. |  -2.335714   32.89636    -0.07   0.944    -70.95632    66.28489
         |
       _cons |    4548.95   4603.111     0.99   0.335    -5052.971    14150.87
------------------------------------------------------------------------------

 ( 1)  L.bur = 0
 ( 2)  L2.bur = 0
 ( 3)  L3.bur = 0

       F(  3,    20) =    0.10
            Prob > F =    0.9591

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.80
       Model |  135.881422     4  33.9703556           Prob > F      =  0.5368
    Residual |  844.678578    20  42.2339289           R-squared     =  0.1386
-------------+------------------------------           Adj R-squared = -0.0337
       Total |      980.56    24  40.8566667           Root MSE      =  6.4988

------------------------------------------------------------------------------
         bur |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -.0010858   .0016636    -0.65   0.521     -.004556    .0023845
         L1. |    .000959   .0019032     0.50   0.620    -.0030109     .004929
         L2. |  -.0028997   .0018725    -1.55   0.137    -.0068058    .0010063
         L3. |   .0007815   .0017343     0.45   0.657    -.0028362    .0043993
         |
       _cons |   87.05321   5.895191    14.77   0.000     74.75606    99.35036
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
```

```
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.81
            Prob > F =    0.5028

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs     =       25
Log likelihood = -280.5656                      AIC            =  23.56525
FPE            =  6.06e+07                      HQIC           =  23.75457
Det(Sigma_ml)  =  1.92e+07                      SBIC           =  24.24782

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
bur                  7     6.76692   0.1594   4.741314   0.5774
expde                7     905.197   0.2804   9.740098   0.1360
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
bur          |
         bur |
         L1. |   .1450058   .1950157     0.74   0.457    -.2372181    .5272296
         L2. |  -.0872958   .1878534    -0.46   0.642    -.4554817    .2808901
         L3. |   .1433189   .1931264     0.74   0.458    -.2352019    .5218397
             |
       expde |
         L1. |   .0004464   .0015219     0.29   0.769    -.0025364    .0034292
         L2. |  -.0030699   .0016737    -1.83   0.067    -.0063502    .0002104
         L3. |   .0014359   .0016054     0.89   0.371    -.0017106    .0045824
             |
       _cons |    68.0389   27.08438     2.51   0.012     14.95449    121.1233
-------------+----------------------------------------------------------------
expde        |
         bur |
         L1. |  -9.490271   26.08688    -0.36   0.716    -60.61962    41.63908
         L2. |   20.33312   25.12879     0.81   0.418     -28.9184    69.58465
         L3. |  -11.86742   25.83415    -0.46   0.646    -62.50142    38.76658
             |
       expde |
         L1. |   .5120718   .2035761     2.52   0.012     .1130699    .9110736
         L2. |   .0872699   .2238821     0.39   0.697    -.3515309    .5260706
         L3. |  -.1742549   .2147499    -0.81   0.417     -.595157    .2466471
             |
       _cons |    1605.84   3623.025     0.44   0.658     -5495.16    8706.839
------------------------------------------------------------------------------

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |               bur              expde |  3.6856     3    0.297    |
  |               bur                ALL |  3.6856     3    0.297    |
  |--------------------------------------+---------------------------|
  |             expde                bur |  .86634     3    0.834    |
  |             expde                ALL |  .86634     3    0.834    |
  +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------

-----------
csr             byte    %8.0g                 CSR

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.40
       Model |  1195864.63     4  298966.157           Prob > F      =  0.8046
    Residual |  14858451.1    20  742922.557           R-squared     =  0.0745
-------------+------------------------------           Adj R-squared = -0.1106
       Total |  16054315.8    24  668929.823           Root MSE      =  861.93
```

```
------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         csr |
         --. |   49.91901   59.21154     0.84   0.409     -73.5941    173.4321
         L1. |  -19.91666   57.62392    -0.35   0.733    -140.1181    100.2847
         L2. |   17.80022   56.72818     0.31   0.757    -100.5327    136.1331
         L3. |  -55.41457   58.39996    -0.95   0.354    -177.2348    66.40561
             |
       _cons |   3944.214   7205.161     0.55   0.590    -11085.49    18973.92
------------------------------------------------------------------------------

 ( 1)  L.csr = 0
 ( 2)  L2.csr = 0
 ( 3)  L3.csr = 0

       F(  3,    20) =    0.33
            Prob > F =    0.8005

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.87
       Model |  60.114289     4  15.0285723            Prob > F      =  0.1546
    Residual |  160.445711    20  8.02228555           R-squared     =  0.2726
-------------+------------------------------           Adj R-squared =  0.1271
       Total |     220.56    24        9.19            Root MSE      =  2.8324

------------------------------------------------------------------------------
         csr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   .0006382   .0009385     0.68   0.504    -.0013196    .0025959
         L1. |   .0010397   .0008839     1.18   0.253     -.000804    .0028834
         L2. |   .0012727   .0008677     1.47   0.158    -.0005372    .0030826
         L3. |  -.0019434   .0008921    -2.18   0.042    -.0038043   -.0000825
             |
       _cons |   53.47038   2.942749    18.17   0.000     47.33191    59.60884
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    2.24
            Prob > F =    0.1149

Vector autoregression

Sample:  6344q1 - 6350q1                           No. of obs      =        25
Log likelihood = -250.8721                         AIC             =  21.18977
FPE            =  5636336                          HQIC            =  21.37909
Det(Sigma_ml)  =  1783372                          SBIC            =  21.87234

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
csr                   7     2.96054   0.2847   9.950534   0.1268
expde                 7     639.644   0.5413   29.49827   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
csr          |
         csr |
         L1. |  -.0109577   .1727202    -0.06   0.949    -.3494831    .3275676
         L2. |  -.1426808   .1653853    -0.86   0.388      -.46683    .1814684
         L3. |   .0867473   .1735277     0.50   0.617    -.2533608    .4268555
             |
       expde |
         L1. |   .0009904   .0007896     1.25   0.210    -.0005572     .002538
         L2. |   .0015276   .0007479     2.04   0.041     .0000618    .0029934
         L3. |  -.0016811   .0007634    -2.20   0.028    -.0031774   -.0001848
             |
```

```
      _cons |   57.99748   18.00806    3.22   0.001    22.70233   93.29264
-------------+----------------------------------------------------------------
expde       |
        csr |
        L1. |  -63.11683   37.31738   -1.69   0.091   -136.2575    10.0239
        L2. |  -.8321984   35.73262   -0.02   0.981   -70.86685   69.20246
        L3. |  -78.21514   37.49186   -2.09   0.037   -151.6978  -4.732444
            |
      expde |
        L1. |   .1321953   .1706045    0.77   0.438   -.2021833   .4665739
        L2. |   .2495451    .161582    1.54   0.122   -.0671498   .5662401
        L3. |    .423502   .1649404    2.57   0.010    .1002249   .7467792
            |
      _cons |   9009.005   3890.765    2.32   0.021    1383.245   16634.77
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               csr              expde |  8.5782     3    0.035    |
 |               csr                ALL |  8.5782     3    0.035    |
 |--------------------------------------+---------------------------|
 |             expde                csr |  5.9173     3    0.116    |
 |             expde                ALL |  5.9173     3    0.116    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------------------------------------

-----------
csr             byte    %8.0g                 CSR

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    4.71
       Model |  2980277.24     4  745069.31            Prob > F      =  0.0077
    Residual |  3163956.76    20  158197.838           R-squared     =  0.4851
-------------+------------------------------           Adj R-squared =  0.3821
       Total |     6144234    24  256009.75            Root MSE      =  397.74

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         csr |
         --. |   79.94082   47.22124    1.69   0.106   -18.56097    178.4426
         L1. |   .5962052   51.48763    0.01   0.991   -106.8051    107.9975
         L2. |   56.48075   49.00948    1.15   0.263   -45.75124    158.7127
         L3. |   20.81177   45.12338    0.46   0.650   -73.31396    114.9375
             |
       _cons |  -3291.161   1386.136   -2.37   0.028   -6182.589   -399.7331
------------------------------------------------------------------------------

 ( 1)  L.csr = 0
 ( 2)  L2.csr = 0
 ( 3)  L3.csr = 0

       F(  3,    20) =    1.55
            Prob > F =    0.2334

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    6.07
       Model |  80.4200024     4  20.1050006           Prob > F      =  0.0023
    Residual |  66.2199976    20  3.31099988           R-squared     =  0.5484
-------------+------------------------------           Adj R-squared =  0.4581
       Total |      146.64    24        6.11           Root MSE      =  1.8196

------------------------------------------------------------------------------
         csr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   .0017635   .0009397    1.88   0.075   -.0001966    .0037236
         L1. |   .0020172   .0008781    2.30   0.033    .0001856    .0038488
```

```
       L2. |   .0002162   .0008924    0.24   0.811    -.0016452    .0020777
       L3. |   .0004655    .000879    0.53   0.602    -.0013681    .0022991
           |
     _cons |   26.15037   2.386674   10.96   0.000     21.17185    31.12888
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

     F(  3,    20) =    2.70
          Prob > F =    0.0731

Vector autoregression

Sample:  6344q1 - 6350q1                   No. of obs      =        25
Log likelihood =  -227.32                  AIC             =   19.3056
FPE            =  856467.2                 HQIC            =  19.49491
Det(Sigma_ml)  =  270991.6                 SBIC            =  19.98817

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
csr                  7     1.78413   0.6093   38.98354   0.0000
expde                7     433.991   0.4482   20.30792   0.0024
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
csr          |
         csr |
         L1. |   .4683822   .1802398     2.60   0.009     .1151187    .8216457
         L2. |  -.0032535   .1960879    -0.02   0.987    -.3875788    .3810718
         L3. |  -.2619606   .1901145    -1.38   0.168    -.6345783    .1106571
             |
       expde |
         L1. |   .0016625   .0008517     1.95   0.051    -6.82e-06    .0033317
         L2. |   .0001949   .0008566     0.23   0.820     -.001484    .0018739
         L3. |   .0010358   .0007942     1.30   0.192    -.0005208    .0025925
             |
       _cons |   22.50151    6.06702     3.71   0.000     10.61037    34.39265
-------------+----------------------------------------------------------------
expde        |
         csr |
         L1. |   38.98089   43.84351     0.89   0.374    -46.95082    124.9126
         L2. |   45.34611   47.69859     0.95   0.342    -48.14141    138.8336
         L3. |  -3.142116   46.24556    -0.07   0.946    -93.78175    87.49752
             |
       expde |
         L1. |  -.0357552   .2071737    -0.17   0.863    -.4418081    .3702977
         L2. |   .1476547   .2083733     0.71   0.479    -.2607494    .5560588
         L3. |   .2272555   .1931922     1.18   0.239    -.1513942    .6059053
             |
       _cons |  -1261.653   1475.809    -0.85   0.393    -4154.185    1630.879
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               csr              expde |  5.9558     3    0.114    |
 |               csr                ALL |  5.9558     3    0.114    |
 |--------------------------------------+---------------------------|
 |             expde                csr |  2.6512     3    0.449    |
 |             expde                ALL |  2.6512     3    0.449    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------------------------------------

-----------
csr             byte    %8.0g                 CSR
```

```
    Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.90
     Model |  2095941.18     4  523985.295           Prob > F      =  0.4850
  Residual |  11704004.6    20  585200.229           R-squared     =  0.1519
-------------+------------------------------           Adj R-squared = -0.0177
     Total |  13799945.8    24   574997.74           Root MSE      =  764.98

------------------------------------------------------------------------------
     expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       csr |
       --. |   -77.2622   69.35443    -1.11   0.278    -221.933    67.40861
       L1. |   44.10217   66.71262     0.66   0.516   -95.05792    183.2623
       L2. |  -112.8834   74.42292    -1.52   0.145   -268.1269    42.36007
       L3. |   133.3575   83.66633     1.59   0.127   -41.16741    307.8824
           |
     _cons |   3100.677   3497.864     0.89   0.386   -4195.738    10397.09
------------------------------------------------------------------------------

 ( 1)  L.csr = 0
 ( 2)  L2.csr = 0
 ( 3)  L3.csr = 0

     F(  3,    20) =    1.11
          Prob > F =    0.3684

    Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =   10.03
     Model |  97.4394878     4   24.359872           Prob > F      =  0.0001
  Residual |  48.5605122    20  2.42802561           R-squared     =  0.6674
-------------+------------------------------           Adj R-squared =  0.6009
     Total |         146    24  6.08333333           Root MSE      =  1.5582

------------------------------------------------------------------------------
       csr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     expde |
       --. |   -.000906   .0004429    -2.05   0.054    -.0018299    .0000178
       L1. |  -.0001085    .000449    -0.24   0.811    -.0010452    .0008281
       L2. |   .0019855   .0004577     4.34   0.000     .0010308    .0029401
       L3. |   .0014049   .0004423     3.18   0.005     .0004823    .0023276
           |
     _cons |   29.39537   1.667283    17.63   0.000     25.91748    32.87326
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

     F(  3,    20) =   13.16
          Prob > F =    0.0001

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -237.0485                      AIC             =  20.08388
FPE            =  1865152                       HQIC            =  20.27319
Det(Sigma_ml)  =  590145.6                      SBIC            =  20.76645

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
csr                  7     1.65534   0.6622   49.00285   0.0000
expde                7     777.792   0.2109   6.682365   0.3512
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
csr          |
       csr |
       L1. |  -.2822332   .1656618    -1.70   0.088    -.6069244    .0424581
       L2. |  -.0785105   .1425314    -0.55   0.582    -.3578669     .200846
```

```
        L3. |   .2051791   .1584416    1.29   0.195    -.1053607    .5157189
            |
      expde |
        L1. |  -.0004521   .0004232   -1.07   0.285    -.0012817    .0003774
        L2. |   .0016779   .0004527    3.71   0.000     .0007906    .0025652
        L3. |   .0021033   .0005554    3.79   0.000     .0010147    .0031919
            |
      _cons |   32.37915   6.653249    4.87   0.000     19.33902    45.41928
-------------+----------------------------------------------------------------
expde       |
        csr |
        L1. |   20.47668   77.83952    0.26   0.793    -132.086    173.0393
        L2. |  -109.7349   66.97124   -1.64   0.101    -240.9961    21.52631
        L3. |   118.8983   74.44694    1.60   0.110     -27.015    264.8116
            |
      expde |
        L1. |   .3202407   .1988659    1.61   0.107    -.0695293    .7100106
        L2. |  -.0358655   .2127158   -0.17   0.866    -.4527807    .3810498
        L3. |   .0670337   .2609751    0.26   0.797    -.4444681    .5785354
            |
      _cons |   696.0445   3126.162    0.22   0.824    -5431.12    6823.209
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               csr              expde |  36.667    3    0.000     |
 |               csr                ALL |  36.667    3    0.000     |
 |--------------------------------------+---------------------------|
 |             expde                csr |  3.4184    3    0.331     |
 |             expde                ALL |  3.4184    3    0.331     |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------

-----------
csr             byte    %8.0g                 CSR

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.37
       Model |  4415348.82     4  1103837.2            Prob > F      =  0.2787
    Residual |  16079751.3    20  803987.567           R-squared     =  0.2154
-------------+------------------------------           Adj R-squared =  0.0585
       Total |  20495100.2    24  853962.507           Root MSE      =  896.65

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         csr |
         --. |   26.24763   103.5654     0.25   0.803    -189.786    242.2813
         L1. |   53.12533   107.1688     0.50   0.625   -170.4249    276.6756
         L2. |    39.8331   116.2634     0.34   0.735   -202.6881    282.3543
         L3. |  -184.6278   100.3248    -1.84   0.081   -393.9018    24.64613
             |
       _cons |   5650.745   2759.717     2.05   0.054   -105.9232    11407.41
------------------------------------------------------------------------------

 ( 1)  L.csr = 0
 ( 2)  L2.csr = 0
 ( 3)  L3.csr = 0

       F(  3,    20) =    1.54
            Prob > F =    0.2344

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.28
       Model |  13.5789591     4  3.39473977           Prob > F      =  0.8879
    Residual |  243.061041    20   12.153052           R-squared     =  0.0529
-------------+------------------------------           Adj R-squared = -0.1365
       Total |      256.64    24  10.6933333           Root MSE      =  3.4861
```

```
------------------------------------------------------------------------------
         csr |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -.0008016   .0008924    -0.90   0.380    -.0026631      .00106
         L1. |   .0001824   .0010209     0.18   0.860    -.0019472     .002312
         L2. |   .0002734   .0010045     0.27   0.788    -.0018219    .0023687
         L3. |  -.0005657   .0009303    -0.61   0.550    -.0025063     .001375
             |
       _cons |   50.23262   3.162349    15.88   0.000     43.63608    56.82917
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.13
            Prob > F =    0.9386

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -246.7781                      AIC             =  20.86225
FPE            =  4062144                       HQIC            =  21.05156
Det(Sigma_ml)  =  1285288                       SBIC            =  21.54482

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
csr                  7     1.94999   0.7333   68.74062   0.0000
expde                7     811.151   0.4221   18.26277   0.0056
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
csr          |
         csr |
         L1. |   .5867532   .1689167     3.47   0.001     .2556826    .9178239
         L2. |  -.1303119   .2156731    -0.60   0.546    -.5530234    .2923996
         L3. |   .3603627   .1765278     2.04   0.041     .0143746    .7063509
             |
       expde |
         L1. |   .0003221     .00044     0.73   0.464    -.0005404    .0011845
         L2. |   .0004043   .0004835     0.84   0.403    -.0005433    .0013519
         L3. |  -.0004335    .000452    -0.96   0.337    -.0013194    .0004524
             |
       _cons |   8.394992   5.277869     1.59   0.112    -1.949441    18.73943
-------------+----------------------------------------------------------------
expde        |
         csr |
         L1. |   84.32157    70.2655     1.20   0.230    -53.39629    222.0394
         L2. |   34.53281   89.71511     0.38   0.700    -141.3056    210.3712
         L3. |  -169.1506   73.43156    -2.30   0.021    -313.0738   -25.22736
             |
       expde |
         L1. |   .4516887   .1830452     2.47   0.014     .0929267    .8104507
         L2. |   .0570212   .2011242     0.28   0.777    -.3371749    .4512173
         L3. |  -.2591433   .1880175    -1.38   0.168    -.6276508    .1093642
             |
       _cons |   4292.361   2195.474     1.96   0.051    -10.68778    8595.411
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               csr              expde |  2.3794     3    0.497    |
 |               csr                ALL |  2.3794     3    0.497    |
 |--------------------------------------+---------------------------|
 |             expde                csr |   7.212     3    0.065    |
 |             expde                ALL |   7.212     3    0.065    |
 +------------------------------------------------------------------+
```

```
          storage   display    value
variable name   type    format     label      variable label
----------------------------------------------------------------------------------------------------------------------------------------

-----------
pde            long    %8.0g              PDE

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.56
       Model |  1619411.51     4  404852.877           Prob > F      =  0.6936
    Residual |  14434904.3    20  721745.213           R-squared     =  0.1009
-------------+------------------------------           Adj R-squared = -0.0790
       Total |  16054315.8    24  668929.823           Root MSE      =  849.56

------------------------------------------------------------------------------
        expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          pde |
          --. |  -.0008828   .0009119    -0.97   0.345    -.0027849    .0010194
          L1. |   .0004977   .0009132     0.55   0.592    -.0014072    .0024026
          L2. |  -.0007556   .0009141    -0.83   0.418    -.0026623    .0011512
          L3. |  -.0005197   .0009139    -0.57   0.576     -.002426    .0013867
              |
        _cons |   3721.626    317.083    11.74   0.000     3060.202    4383.049
------------------------------------------------------------------------------

 ( 1)  L.pde = 0
 ( 2)  L2.pde = 0
 ( 3)  L3.pde = 0

       F(  3,    20) =    0.44
            Prob > F =    0.7267

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.41
       Model |  6.6671e+10     4  1.6668e+10           Prob > F      =  0.7959
    Residual |  8.0360e+11    20  4.0180e+10           R-squared     =  0.0766
-------------+------------------------------           Adj R-squared = -0.1081
       Total |  8.7027e+11    24  3.6261e+10           Root MSE      =  2.0e+05

------------------------------------------------------------------------------
          pde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        expde |
          --. |  -14.84542   66.42025    -0.22   0.825    -153.3956    123.7048
          L1. |  -34.62603   62.55162    -0.55   0.586    -165.1064    95.85435
          L2. |  -22.01577   61.40574    -0.36   0.724    -150.1059    106.0744
          L3. |  -4.254603   63.13507    -0.07   0.947    -135.9521    127.4429
              |
        _cons |   396237.8     208262     1.90   0.072    -38189.11    830664.6
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.25
            Prob > F =    0.8579

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -530.8469                      AIC             =  43.58776
FPE            =  3.01e+16                      HQIC            =  43.77707
Det(Sigma_ml)  =  9.52e+15                      SBIC            =  44.27033

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
pde                  7      209899   0.0888   2.434925   0.8757
expde                7     645.623   0.5327   28.49354   0.0001
----------------------------------------------------------------
```

```
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
pde          |
         pde |
         L1. |  -.1152741   .1979903    -0.58   0.560     -.503328    .2727798
         L2. |  -.0438142   .2107446    -0.21   0.835    -.4568661    .3692378
         L3. |   -.037899   .2038531    -0.19   0.853    -.4374437    .3616457
             |
       expde |
         L1. |  -35.66074   59.94317    -0.59   0.552    -153.1472    81.82571
         L2. |  -29.28504   56.64324    -0.52   0.605    -140.3037    81.73366
         L3. |  -15.71239   55.42012    -0.28   0.777    -124.3338    92.90905
             |
       _cons |   436870.3   197157.5     2.22   0.027     50448.69    823291.9
-------------+----------------------------------------------------------------
expde        |
         pde |
         L1. |   .0013091    .000609     2.15   0.032     .0001155    .0025027
         L2. |  -.0002473   .0006482    -0.38   0.703    -.0015178    .0010232
         L3. |  -.0003732    .000627    -0.60   0.552    -.0016022    .0008557
             |
       expde |
         L1. |   .1610939   .1843778     0.87   0.382      -.20028    .5224678
         L2. |   .3289361   .1742277     1.89   0.059    -.0125438    .6704161
         L3. |   .3239252   .1704655     1.90   0.057    -.0101811    .6580314
             |
       _cons |    694.742   606.4323     1.15   0.252    -493.8436    1883.327
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               pde              expde |  2.362     3    0.501     |
 |               pde                ALL |  2.362     3    0.501     |
 |--------------------------------------+---------------------------|
 |             expde                pde |  5.3473    3    0.148     |
 |             expde                ALL |  5.3473    3    0.148     |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------------

-----------
pde             long    %8.0g                 PDE

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    4.84
       Model |  3021317.66     4  755329.415           Prob > F      =  0.0068
    Residual |  3122916.34    20  156145.817           R-squared     =  0.4917
-------------+------------------------------           Adj R-squared =  0.3901
       Total |     6144234    24   256009.75           Root MSE      =  395.15

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pde |
         --. |   .0033081   .0074781     0.44   0.663     -.012291    .0189072
         L1. |   .0144102   .0088268     1.63   0.118    -.0040021    .0328225
         L2. |    .006053   .0087612     0.69   0.498    -.0122226    .0243286
         L3. |   .0017536   .0078762     0.22   0.826    -.0146758    .0181831
             |
       _cons |  -738.6506   813.4017    -0.91   0.375    -2435.377    958.0757
------------------------------------------------------------------------------

 ( 1)  L.pde = 0
 ( 2)  L2.pde = 0
 ( 3)  L3.pde = 0

       F(  3,    20) =    2.83
            Prob > F =    0.0645
```

```
     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =     6.26
      Model |  3.4646e+09     4   866159972           Prob > F      =  0.0020
   Residual |  2.7675e+09    20   138374638           R-squared     =  0.5559
-------------+------------------------------           Adj R-squared =  0.4671
      Total |  6.2321e+09    24   259672194           Root MSE      =   11763

------------------------------------------------------------------------------
         pde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   3.487006   6.074695     0.57   0.572    -9.184586     16.1586
         L1. |   3.604209    5.67641     0.63   0.533    -8.236574    15.44499
         L2. |    8.63065   5.768884     1.50   0.150    -3.403031    20.66433
         L3. |   14.20908   5.682517     2.50   0.021     2.355559     26.0626
             |
       _cons |    57211.6   15429.14     3.71   0.001     25026.97    89396.23
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    4.20
            Prob > F =    0.0185

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -443.7351                      AIC             =   36.6188
FPE            =  2.83e+13                      HQIC            =  36.80812
Det(Sigma_ml)  =  8.95e+12                      SBIC            =  37.30138

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
pde                  7     10610.2   0.6749   51.88783   0.0000
expde                7      392.76   0.5481   30.31985   0.0000
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
pde          |
         pde |
         L1. |   .5338721   .1718493     3.11   0.002     .1970536    .8706906
         L2. |  -.3092735   .2042978    -1.51   0.130    -.7096899    .0911428
         L3. |   .1844786   .1922065     0.96   0.337    -.1922392    .5611965
             |
       expde |
         L1. |   2.368246   5.078604     0.47   0.641    -7.585635    12.32213
         L2. |   5.239344   4.980815     1.05   0.293    -4.522875    15.00156
         L3. |   11.25372   4.274888     2.63   0.008     2.875098    19.63235
             |
       _cons |   32078.99    18820.1     1.70   0.088    -4807.717     68965.7
-------------+----------------------------------------------------------------
expde        |
         pde |
         L1. |   .0124572   .0063614     1.96   0.050    -.0000109    .0249252
         L2. |   .0071191   .0075625     0.94   0.347    -.0077032    .0219414
         L3. |   -.001747    .007115    -0.25   0.806    -.0156921     .012198
             |
       expde |
         L1. |  -.1024454   .1879958    -0.54   0.586    -.4709104    .2660196
         L2. |   .1786178    .184376     0.97   0.333    -.1827525     .539988
         L3. |   .2493662   .1582445     1.58   0.115    -.0607873    .5595196
             |
       _cons |  -518.7665   696.6677    -0.74   0.456     -1884.21     846.677
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
```

```
  |            pde            expde |  9.4482     3    0.024    |
  |            pde              ALL |  9.4482     3    0.024    |
  |--------------------------------------+---------------------------|
  |          expde              pde |  8.7614     3    0.033    |
  |          expde              ALL |  8.7614     3    0.033    |
  +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------------------------------------


-----------
pde            long    %8.0g              PDE

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.03
       Model |  89794.7417     4  22448.6854           Prob > F      =  0.9978
    Residual |    13710151    20  685507.551           R-squared     =  0.0065
-------------+------------------------------           Adj R-squared = -0.1922
       Total |  13799945.8    24   574997.74           Root MSE      =  827.95

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pde |
         --. |   .0002067   .0088783     0.02   0.982    -.0183131    .0187264
         L1. |   .0020659   .0088361     0.23   0.818    -.0163658    .0204976
         L2. |   -.001879   .0088605    -0.21   0.834    -.0203616    .0166037
         L3. |   .0016357   .0089603     0.18   0.857    -.0170552    .0203266
             |
       _cons |   2193.995   4020.379     0.55   0.591    -6192.368    10580.36
------------------------------------------------------------------------------

 ( 1)  L.pde = 0
 ( 2)  L2.pde = 0
 ( 3)  L3.pde = 0

       F(  3,    20) =    0.04
            Prob > F =    0.9876

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.20
       Model |   336876789     4  84219197.4           Prob > F      =  0.9347
    Residual |  8.3668e+09    20   418338535           R-squared     =  0.0387
-------------+------------------------------           Adj R-squared = -0.1536
       Total |  8.7036e+09    24   362651978           Root MSE      =   20453

------------------------------------------------------------------------------
         pde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -.2697017    5.81345    -0.05   0.963    -12.39635    11.85694
         L1. |   4.476827   5.893898     0.76   0.456    -7.817629    16.77128
         L2. |  -3.484283   6.007255    -0.58   0.568     -16.0152     9.04663
         L3. |   -1.11788   5.805996    -0.19   0.849    -13.22898    10.99322
             |
       _cons |   229422.4      21885    10.48   0.000       183771    275073.7
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.27
            Prob > F =    0.8476

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -480.0698                      AIC             =  39.52558
FPE            =  5.18e+14                      HQIC            =   39.7149
Det(Sigma_ml)  =  1.64e+14                      SBIC            =  40.20815
```

```
Equation         Parms     RMSE     R-sq     chi2     P>chi2
----------------------------------------------------------------
pde              7    21540.4   0.0404   1.053235   0.9835
expde            7    825.375   0.1114   3.134679   0.7918
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
pde          |
         pde |
         L1. |   .0304097   .1991243     0.15   0.879    -.3598668    .4206862
         L2. |  -.0141201   .1970149    -0.07   0.943    -.4002621     .372022
         L3. |   .0289179   .1986699     0.15   0.884    -.3604679    .4183038
             |
       expde |
         L1. |   4.475524   5.127188     0.87   0.383    -5.573579    14.52463
         L2. |  -3.691712   5.413312    -0.68   0.495    -14.30161    6.918184
         L3. |  -.9138186   5.288397    -0.17   0.863    -11.27889     9.45125
             |
       _cons |     218398   80556.47     2.71   0.007     60510.27    376285.8
-------------+----------------------------------------------------------------
expde        |
         pde |
         L1. |     .00207     .00763     0.27   0.786    -.0128844    .0170245
         L2. |  -.0019626   .0075491    -0.26   0.795    -.0167586    .0128334
         L3. |   .0024847   .0076125     0.33   0.744    -.0124356    .0174051
             |
       expde |
         L1. |   .2446057   .1964613     1.25   0.213    -.1404515    .6296628
         L2. |   .1155666   .2074249     0.56   0.577    -.2909787     .522112
         L3. |   .0546772   .2026385     0.27   0.787     -.342487    .4518413
             |
       _cons |   1002.025   3086.728     0.32   0.745     -5047.85      7051.9
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               pde              expde |  1.0325     3    0.793    |
 |               pde                ALL |  1.0325     3    0.793    |
 |--------------------------------------+---------------------------|
 |             expde                pde |  .23623     3    0.972    |
 |             expde                ALL |  .23623     3    0.972    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------

-----------
pde             long    %8.0g                 PDE

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    2.08
       Model |  6026402.45     4  1506600.61           Prob > F      =  0.1212
    Residual |  14468697.7    20  723434.885           R-squared     =  0.2940
-------------+------------------------------           Adj R-squared =  0.1528
       Total |  20495100.2    24  853962.507           Root MSE      =  850.55

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pde |
         --. |  -.0180499   .0088362    -2.04   0.054    -.0364818     .000382
         L1. |   .0038135   .0110037     0.35   0.733    -.0191397    .0267667
         L2. |  -.0032409   .0109906    -0.29   0.771    -.0261669    .0196851
         L3. |   .0051142   .0085262     0.60   0.555    -.0126712    .0228995
             |
       _cons |   4699.345   891.1253     5.27   0.000     2840.491      6558.2
------------------------------------------------------------------------------
```

```
 ( 1)  L.pde = 0
 ( 2)  L2.pde = 0
 ( 3)  L3.pde = 0

       F(  3,    20) =    0.22
            Prob > F =    0.8800

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.92
       Model |  8.1785e+09     4  2.0446e+09           Prob > F      =  0.1465
    Residual |  2.1302e+10    20  1.0651e+09           R-squared     =  0.2774
-------------+------------------------------           Adj R-squared =  0.1329
       Total |  2.9481e+10    24  1.2284e+09           Root MSE      =   32636

------------------------------------------------------------------------------
         pde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -18.60785   8.354535    -2.23   0.038    -36.03511   -1.180599
         L1. |  -.9076809   9.557552    -0.09   0.925    -20.84439    19.02902
         L2. |  -3.076007   9.403612    -0.33   0.747     -22.6916    16.53958
         L3. |   2.940544   8.709649     0.34   0.739    -15.22746    21.10855
             |
       _cons |   217891.9   29605.09     7.36   0.000     156136.8    279647.1
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.06
            Prob > F =    0.9785

Vector autoregression

Sample:  6344q1 - 6350q1                           No. of obs      =        25
Log likelihood = -475.4602                         AIC             =  39.15682
FPE            =  3.58e+14                         HQIC            =  39.34613
Det(Sigma_ml)  =  1.13e+14                         SBIC            =  39.83939

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
pde                  7     20194.9   0.7510   75.3981   0.0000
expde                7     904.209   0.2819   9.816114  0.1326
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
pde          |
         pde |
         L1. |   .7919493   .2238716     3.54   0.000      .353169     1.23073
         L2. |  -.1376259   .2846544    -0.48   0.629    -.6955382    .4202864
         L3. |   .2929689   .2154514     1.36   0.174    -.1293081     .715246
             |
       expde |
         L1. |   6.204882   5.491833     1.13   0.259    -4.558912    16.96868
         L2. |   -2.63387   6.347895    -0.41   0.678    -15.07552    9.807776
         L3. |   11.21848   5.678138     1.98   0.048     .0895327    22.34743
             |
       _cons |  -26152.81   31162.29    -0.84   0.401    -87229.78    34924.16
-------------+----------------------------------------------------------------
expde        |
         pde |
         L1. |  -.0003077   .0100237    -0.03   0.976    -.0199537    .0193383
         L2. |   -.004632   .0127451    -0.36   0.716     -.029612     .020348
         L3. |   .0000417   .0096466     0.00   0.997    -.0188654    .0189487
             |
       expde |
         L1. |   .4763491   .2458919     1.94   0.053    -.0055902    .9582885
         L2. |  -.0169444   .2842214    -0.06   0.952    -.5740081    .5401193
         L3. |   -.153813   .2542336    -0.61   0.545    -.6521017    .3444757
             |
```

```
     _cons |   2632.743   1395.264    1.89   0.059   -101.9241    5367.41
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               pde              expde |  6.5542     3    0.088    |
 |               pde                ALL |  6.5542     3    0.088    |
 |--------------------------------------+---------------------------|
 |             expde                pde |  .92294     3    0.820    |
 |             expde                ALL |  .92294     3    0.820    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------------------------------

-----------
ipd             long    %8.0g                 IPD

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.31
       Model |  3326605.31     4  831651.327           Prob > F      =  0.3013
    Residual |  12727710.5    20  636385.523           R-squared     =  0.2072
-------------+------------------------------           Adj R-squared =  0.0487
       Total |  16054315.8    24  668929.823           Root MSE      =  797.74

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ipd |
         --. |   .0552668   .0373034     1.48   0.154    -.0225468    .1330804
         L1. |   .0533458    .037417     1.43   0.169    -.0247047    .1313963
         L2. |   .0384718   .0372492     1.03   0.314    -.0392286    .1161723
         L3. |   .0329593   .0383032     0.86   0.400    -.0469398    .1128584
             |
       _cons |  -6390.546   4530.448    -1.41   0.174     -15840.9    3059.802
------------------------------------------------------------------------------

 ( 1)  L.ipd = 0
 ( 2)  L2.ipd = 0
 ( 3)  L3.ipd = 0

       F(  3,    20) =    1.19
            Prob > F =    0.3384

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.81
       Model |  67846161.4     4  16961540.3           Prob > F      =  0.5358
    Residual |   420872796    20  21043639.8           R-squared     =  0.1388
-------------+------------------------------           Adj R-squared = -0.0334
       Total |   488718958    24  20363289.9           Root MSE      =  4587.3

------------------------------------------------------------------------------
         ipd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   .3741206    1.52004     0.25   0.808    -2.796627    3.544868
         L1. |   .4481412   1.431506     0.31   0.757    -2.537927     3.43421
         L2. |  -.3337836   1.405282    -0.24   0.815    -3.265151    2.597584
         L3. |   1.543796   1.444858     1.07   0.298    -1.470126    4.557717
             |
       _cons |   48230.06   4766.115    10.12   0.000     38288.11       58172
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.57
            Prob > F =    0.6430
```

```
Vector autoregression

Sample:  6344q1 - 6350q1                     No. of obs     =       25
Log likelihood = -436.8413                   AIC            =  36.0673
FPE          =  1.63e+13                     HQIC           =  36.25662
Det(Sigma_ml)  =  5.16e+12                   SBIC           =  36.74987

Equation         Parms     RMSE    R-sq     chi2    P>chi2
----------------------------------------------------------------
ipd               7    4496.72  0.2553  8.568774  0.1993
expde             7    703.315  0.4454  20.07742  0.0027
----------------------------------------------------------------

------------------------------------------------------------------------------
             |     Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ipd          |
         ipd |
         L1. |  -.0748003   .1907953    -0.39   0.695    -.4487522    .2991515
         L2. |  -.3331001   .1781664    -1.87   0.062    -.6822998    .0160995
         L3. |  -.1395682    .189091    -0.74   0.460    -.5101799    .2310434
             |
       expde |
         L1. |   .8215672   1.199303     0.69   0.493    -1.529024    3.172158
         L2. |   .1570492   1.159753     0.14   0.892    -2.116026    2.430124
         L3. |   1.732749   1.123167     1.54   0.123     -.468618    3.934115
             |
       _cons |   76032.97   18495.07     4.11   0.000     39783.31    112282.6
-------------+----------------------------------------------------------------
expde        |
         ipd |
         L1. |   .0224591   .0298416     0.75   0.452    -.0360293    .0809476
         L2. |   .0017101   .0278664     0.06   0.951    -.0529069    .0563272
         L3. |   .0051072    .029575     0.17   0.863    -.0528589    .0630732
             |
       expde |
         L1. |   .1153695   .1875787     0.62   0.539    -.2522779     .483017
         L2. |   .2333769   .1813928     1.29   0.198    -.1221465    .5889003
         L3. |   .3417291   .1756705     1.95   0.052    -.0025788    .6860369
             |
       _cons |  -397.2094   2892.747    -0.14   0.891     -6066.89    5272.471
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               ipd              expde |  6.4122     3    0.093    |
 |               ipd                ALL |  6.4122     3    0.093    |
 |--------------------------------------+---------------------------|
 |             expde                ipd |  .57279     3    0.903    |
 |             expde                ALL |  .57279     3    0.903    |
 +------------------------------------------------------------------+

              storage  display     value
variable name   type   format      label      variable label
------------------------------------------------------------------------------------------------------------------------

-----------
ipd             long   %8.0g                  IPD

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    5.14
       Model |  3115517.16     4  778879.29            Prob > F      =  0.0051
    Residual |  3028716.84    20  151435.842           R-squared     =  0.5071
-------------+------------------------------           Adj R-squared =  0.4085
       Total |     6144234    24  256009.75            Root MSE      =  389.15

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ipd |
         --. |   .0055344   .0087777     0.63   0.536    -.0127756    .0238445
```

```
         L1. |   .0208832   .0101559    2.06   0.053    -.0003017    .0420681
         L2. |   .0059391   .0099996    0.59   0.559    -.0149197    .0267978
         L3. |   .0057688    .009123    0.63   0.534    -.0132615    .0247992
             |
       _cons |  -1199.311    904.659   -1.33   0.200    -3086.396    687.7749
------------------------------------------------------------------------------

 ( 1)  L.ipd = 0
 ( 2)  L2.ipd = 0
 ( 3)  L3.ipd = 0

       F(  3,    20) =    3.55
            Prob > F =    0.0331

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    5.67
       Model |  1.7785e+09     4  444621882            Prob > F      =  0.0032
    Residual |  1.5674e+09    20  78369333.7           R-squared     =  0.5315
-------------+------------------------------           Adj R-squared =  0.4379
       Total |  3.3459e+09    24  139411425            Root MSE      =  8852.6

------------------------------------------------------------------------------
         ipd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   1.780787   4.571612    0.39   0.701    -7.755428      11.317
         L1. |   2.014669   4.271875    0.47   0.642    -6.896306    10.92565
         L2. |   6.295378   4.341468    1.45   0.163    -2.760766    15.35152
         L3. |   11.02005   4.276471    2.58   0.018     2.099489    19.94062
             |
       _cons |   48167.42   11611.45    4.15   0.000     23946.35    72388.49
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    4.08
            Prob > F =    0.0206

Vector autoregression

Sample:  6344q1 - 6350q1                           No. of obs      =        25
Log likelihood = -437.9446                         AIC             =  36.15557
FPE            =  1.78e+13                         HQIC            =  36.34489
Det(Sigma_ml)  =  5.63e+12                         SBIC            =  36.83814

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ipd                  7      8382.9   0.6219   41.12842   0.0000
expde                7     393.347   0.5467   30.15496   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ipd          |
         ipd |
         L1. |   .3512471   .1750087    2.01   0.045     .0082363    .6942579
         L2. |  -.3020127   .1923465   -1.57   0.116    -.6790048    .0749795
         L3. |  -.0422696   .1927953   -0.22   0.826    -.4201416    .3356023
             |
       expde |
         L1. |   3.884102   4.028046    0.96   0.335    -4.010722    11.77893
         L2. |   7.073468   4.012835    1.76   0.078    -.7915444    14.93848
         L3. |   9.671178   3.420324    2.83   0.005     2.967466    16.37489
             |
       _cons |   48437.39   17036.78    2.84   0.004     15045.91    81828.87
-------------+----------------------------------------------------------------
expde        |
         ipd |
         L1. |     .01881   .0082118    2.29   0.022     .0027151    .0349049
         L2. |   .0068188   .0090254    0.76   0.450    -.0108706    .0245082
```

```
         L3. |    .001338   .0090464     0.15   0.882    -.0163927    .0190687
             |
       expde |
         L1. |  -.0980346   .1890059    -0.52   0.604    -.4684793    .2724101
         L2. |   .1595137   .1882921     0.85   0.397    -.2095322    .5285595
         L3. |   .2312445   .1604901     1.44   0.150    -.0833103    .5457993
             |
       _cons |  -793.6993    799.408    -0.99   0.321     -2360.51    773.1117
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               ipd              expde |  13.846     3    0.003    |
 |               ipd                ALL |  13.846     3    0.003    |
 |--------------------------------------+---------------------------|
 |             expde                ipd |  8.6608     3    0.034    |
 |             expde                ALL |  8.6608     3    0.034    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------------------------------------------

-----------
ipd             long    %8.0g                 IPD

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.04
       Model |  109128.624     4  27282.1561           Prob > F      =  0.9967
    Residual |  13690817.1    20  684540.857           R-squared     =  0.0079
-------------+------------------------------           Adj R-squared = -0.1905
       Total |  13799945.8    24  574997.74            Root MSE      =  827.37

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ipd |
         --. |   .0010686   .0122914     0.09   0.932    -.0245708     .026708
         L1. |   .0027689   .0119596     0.23   0.819    -.0221784    .0277162
         L2. |  -.0033782   .0119201    -0.28   0.780    -.0282431    .0214866
         L3. |  -.0010985   .0120289    -0.09   0.928    -.0261903    .0239933
             |
       _cons |   2770.421   4733.008     0.59   0.565    -7102.461     12643.3
------------------------------------------------------------------------------

 ( 1)  L.ipd = 0
 ( 2)  L2.ipd = 0
 ( 3)  L3.ipd = 0

       F(  3,    20) =    0.05
            Prob > F =    0.9846

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.22
       Model |   196118545     4  49029636.2           Prob > F      =  0.9261
    Residual |  4.5270e+09    20   226349572           R-squared     =  0.0415
-------------+------------------------------           Adj R-squared = -0.1502
       Total |  4.7231e+09    24   196796249           Root MSE      =   15045

------------------------------------------------------------------------------
         ipd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   .0846997   4.276218     0.02   0.984    -8.835335    9.004735
         L1. |   3.324155   4.335394     0.77   0.452    -5.719318    12.36763
         L2. |  -2.713179   4.418775    -0.61   0.546    -11.93058    6.504225
         L3. |  -.9092963   4.270735    -0.21   0.834    -9.817894    7.999301
             |
       _cons |   174818.4   16098.02    10.86   0.000     141238.5    208398.3
------------------------------------------------------------------------------
```

```
 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.29
            Prob > F =    0.8350

Vector autoregression

Sample:  6344q1 - 6350q1                      No. of obs     =        25
Log likelihood = -471.9395                    AIC            =  38.87516
FPE            =  2.70e+14                    HQIC           =  39.06448
Det(Sigma_ml)  =  8.55e+13                    SBIC           =  39.55773

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ipd                  7     15546.5   0.0789   2.141375   0.9062
expde                7     826.053   0.1100   3.088547   0.7977
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ipd          |
         ipd |
         L1. |  -.0912375   .1938148    -0.47   0.638    -.4711076    .2886325
         L2. |  -.0567839    .190541    -0.30   0.766    -.4302374    .3166696
         L3. |  -.1672922   .1909356    -0.88   0.381    -.5415191    .2069347
             |
       expde |
         L1. |   3.031105   3.711465     0.82   0.414    -4.243233    10.30544
         L2. |  -2.470105   3.902532    -0.63   0.527    -10.11893    5.178716
         L3. |  -1.440882   3.825428    -0.38   0.706    -8.938584     6.05682
             |
       _cons |   231727.3   63331.24     3.66   0.000     107600.3    355854.2
-------------+----------------------------------------------------------------
expde        |
         ipd |
         L1. |   .0026938   .0102982     0.26   0.794    -.0174904     .022878
         L2. |  -.0033187   .0101243    -0.33   0.743     -.023162    .0165245
         L3. |   .0008338   .0101453     0.08   0.934    -.0190505    .0207181
             |
       expde |
         L1. |    .243289   .1972065     1.23   0.217    -.1432287    .6298068
         L2. |   .1155114   .2073588     0.56   0.577    -.2909043    .5219272
         L3. |   .0527631   .2032619     0.26   0.795     -.345623    .4511491
             |
       _cons |   1565.789   3365.069     0.47   0.642    -5029.625    8161.202
------------------------------------------------------------------------------

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |               ipd              expde |  1.0375     3    0.792    |
  |               ipd                ALL |  1.0375     3    0.792    |
  |--------------------------------------+---------------------------|
  |             expde                ipd |  .19485     3    0.978    |
  |             expde                ALL |  .19485     3    0.978    |
  +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------------

-----------
ipd             long    %8.0g                 IPD

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.67
       Model |  2416391.73     4  604097.933           Prob > F      =  0.6215
    Residual |  18078708.4    20  903935.421           R-squared     =  0.1179
-------------+------------------------------           Adj R-squared = -0.0585
```

```
     Total |  20495100.2    24  853962.507         Root MSE      =  950.76

------------------------------------------------------------------------------
     expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       ipd |
       --. |  -.0253634   .0258668    -0.98   0.339    -.0793206    .0285937
       L1. |   -.020774   .0265652    -0.78   0.443    -.0761879      .03464
       L2. |  -.0050939    .027554    -0.18   0.855    -.0625706    .0523827
       L3. |  -.0074462   .0274595    -0.27   0.789    -.0647258    .0498334
           |
     _cons |   7495.547   3385.776     2.21   0.039     432.9411    14558.15
------------------------------------------------------------------------------

 ( 1)  L.ipd = 0
 ( 2)  L2.ipd = 0
 ( 3)  L3.ipd = 0

     F(  3,    20) =    0.28
          Prob > F =    0.8360

    Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.03
     Model |   262781029     4  65695257.3           Prob > F      =  0.4166
  Residual |  1.2770e+09    20  63847943.6           R-squared     =  0.1707
-------------+------------------------------           Adj R-squared =  0.0048
     Total |  1.5397e+09    24  64155829.2           Root MSE      =  7990.5

------------------------------------------------------------------------------
       ipd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     expde |
       --. |  -2.481083   2.045486    -1.21   0.239    -6.747891    1.785726
       L1. |   1.489534   2.340027     0.64   0.532    -3.391677    6.370745
       L2. |  -2.981378   2.302337    -1.29   0.210    -7.783969    1.821214
       L3. |   2.299211    2.13243     1.08   0.294    -2.148961    6.747383
           |
     _cons |   87395.82   7248.374    12.06   0.000     72275.97    102515.7
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

     F(  3,    20) =    0.73
          Prob > F =    0.5479

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -456.7365                      AIC             =  37.65892
FPE            =  8.01e+13                      HQIC            =  37.84824
Det(Sigma_ml)  =  2.53e+13                      SBIC            =  38.34149

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ipd                  7     7941.25   0.2628   8.910689   0.1787
expde                7     896.779   0.2937   10.39542   0.1090
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ipd          |
       ipd |
       L1. |   .3341672    .188508     1.77   0.076    -.0353016    .7036361
       L2. |  -.1268601   .1992026    -0.64   0.524    -.5172901    .2635699
       L3. |   .2609919   .1923667     1.36   0.175      -.11604    .6380238
           |
     expde |
       L1. |   .8697907   1.805986     0.48   0.630    -2.669877    4.409459
       L2. |  -3.430398     1.9838    -1.73   0.084    -7.318574    .4577794
       L3. |   3.486723   1.830092     1.91   0.057     -.100191    7.073637
```

```
         |
   _cons |   41779.01   25370.17     1.65   0.100    -7945.604    91503.63
-------------+----------------------------------------------------------------
expde        |
         ipd |
         L1. |  -.0214886   .0212876    -1.01   0.313    -.0632114    .0202343
         L2. |   .0056103   .0224953     0.25   0.803    -.0384796    .0497002
         L3. |  -.0115629   .0217233    -0.53   0.595    -.0541398     .031014
             |
       expde |
         L1. |   .4708506   .2039438     2.31   0.021      .071128    .8705731
         L2. |   .0886886   .2240237     0.40   0.692    -.3503899     .527767
         L3. |  -.1882237    .206666    -0.91   0.362    -.5932815    .2168342
             |
       _cons |   3942.824   2864.966     1.38   0.169    -1672.407    9558.054
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               ipd              expde |  4.7538     3    0.191    |
 |               ipd                ALL |  4.7538     3    0.191    |
 |--------------------------------------+---------------------------|
 |             expde                ipd |  1.3543     3    0.716    |
 |             expde                ALL |  1.3543     3    0.716    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------

-----------
ips             long    %8.0g                 IPS

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    2.20
       Model |  4911846.44     4  1227961.61           Prob > F      =  0.1053
    Residual |  11142469.3    20  557123.466           R-squared     =  0.3060
-------------+------------------------------           Adj R-squared =  0.1671
       Total |  16054315.8    24  668929.823           Root MSE      =  746.41

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ips |
         --. |  -.0592684   .1150238    -0.52   0.612    -.2992038    .1806669
         L1. |  -.1140903   .1255989    -0.91   0.374    -.3760851    .1479044
         L2. |  -.1217724   .1260807    -0.97   0.346    -.3847721    .1412273
         L3. |  -.1366715   .1215202    -1.12   0.274    -.3901582    .1168151
             |
       _cons |   7653.707   1419.503     5.39   0.000     4692.677    10614.74
------------------------------------------------------------------------------

 ( 1)  L.ips = 0
 ( 2)  L2.ips = 0
 ( 3)  L3.ips = 0

       F(  3,    20) =    1.86
            Prob > F =    0.1686

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.59
       Model |  13525665.3     4  3381416.32           Prob > F      =  0.2158
    Residual |  42541363.3    20  2127068.17           R-squared     =  0.2412
-------------+------------------------------           Adj R-squared =  0.0895
       Total |  56067028.6    24  2336126.19           Root MSE      =  1458.4

------------------------------------------------------------------------------
         ips |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -.0687675   .4832649    -0.14   0.888     -1.07684    .9393055
```

```
       L1. |  -.2419468   .4551173    -0.53   0.601    -1.191305    .7074112
       L2. |  -.5197154   .4467801    -1.16   0.258    -1.451682    .4122515
       L3. |   -.227928   .4593625    -0.50   0.625    -1.186141    .7302853
           |
     _cons |   12884.75   1515.287     8.50   0.000     9723.917    16045.58
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

     F(  3,    20) =    1.13
          Prob > F =    0.3592

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -408.1803                      AIC             =  33.77442
FPE            =  1.65e+12                      HQIC            =  33.96374
Det(Sigma_ml)  =  5.21e+11                      SBIC            =  34.45699

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ips                   7     1455.38   0.3200   11.76376   0.0675
expde                 7     688.885   0.4679   21.98573   0.0012
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ips          |
         ips |
         L1. |   .3262004   .2043117     1.60   0.110    -.0742431    .7266439
         L2. |   .0207885   .2136138     0.10   0.922    -.3978868    .4394638
         L3. |   .0183902   .2158093     0.09   0.932    -.4045882    .4413687
             |
       expde |
         L1. |  -.1681555   .4022233    -0.42   0.676    -.9564986    .6201876
         L2. |  -.4365416   .3761173    -1.16   0.246    -1.173718    .3006348
         L3. |  -.0881979   .3756879    -0.23   0.814    -.8245327    .6481368
             |
       _cons |    8172.55   4053.477     2.02   0.044     227.8803    16117.22
-------------+----------------------------------------------------------------
expde        |
         ips |
         L1. |  -.0452851    .096708    -0.47   0.640    -.2348293     .144259
         L2. |  -.0780901    .101111    -0.77   0.440     -.276264    .1200838
         L3. |  -.0522271   .1021502    -0.51   0.609    -.2524378    .1479836
             |
       expde |
         L1. |   .0652661   .1903866     0.34   0.732    -.3078847    .4384169
         L2. |    .208454   .1780297     1.17   0.242    -.1404777    .5573858
         L3. |   .2980839   .1778264     1.68   0.094    -.0504495    .6466172
             |
       _cons |   3306.068   1918.655     1.72   0.085    -454.4266    7066.562
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               ips              expde |  2.6114     3    0.455    |
 |               ips                ALL |  2.6114     3    0.455    |
 |--------------------------------------+---------------------------|
 |             expde                ips |  1.6554     3    0.647    |
 |             expde                ALL |  1.6554     3    0.647    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------------

-----------
```

```
ips            long    %8.0g               IPS

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    2.24
      Model |  1903851.51     4  475962.879           Prob > F      =  0.1005
   Residual |  4240382.49    20  212019.124           R-squared     =  0.3099
-------------+------------------------------           Adj R-squared =  0.1718
      Total |    6144234    24   256009.75           Root MSE      =  460.46

------------------------------------------------------------------------------
      expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        ips |
         --. |   .1692164   .0748064     2.26   0.035     .013173    .3252599
         L1. |   .0456538   .0779345     0.59   0.565   -.1169147    .2082223
         L2. |   .1107036   .0784843     1.41   0.174   -.0530117    .2744189
         L3. |  -.0138737   .0753087    -0.18   0.856   -.1709649    .1432175
             |
      _cons |  -1440.724   1749.029    -0.82   0.420   -5089.135    2207.687
------------------------------------------------------------------------------

 ( 1)  L.ips = 0
 ( 2)  L2.ips = 0
 ( 3)  L3.ips = 0

       F(  3,    20) =    1.14
            Prob > F =    0.3581

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    2.49
      Model |  14866402.6     4  3716600.66           Prob > F      =  0.0762
   Residual |  29885096.3    20  1494254.82           R-squared     =  0.3322
-------------+------------------------------           Adj R-squared =  0.1986
      Total |    44751499    24  1864645.79           Root MSE      =  1222.4

------------------------------------------------------------------------------
        ips |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      expde |
         --. |    .627196   .6312605     0.99   0.332   -.6895902    1.943982
         L1. |  -.1906047    .589872    -0.32   0.750   -1.421056    1.039847
         L2. |  -.0311321   .5994817    -0.05   0.959   -1.281629    1.219365
         L3. |   1.183128   .5905067     2.00   0.059   -.0486471    2.414904
             |
      _cons |    8903.14   1603.341     5.55   0.000     5558.63    12247.65
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    1.40
            Prob > F =    0.2725

Vector autoregression

Sample:  6344q1 - 6350q1                          No. of obs      =        25
Log likelihood = -388.9457                        AIC             =  32.23565
FPE            =  3.53e+11                        HQIC            =  32.42497
Det(Sigma_ml)  =  1.12e+11                        SBIC            =  32.91822

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ips                  7     1106.56   0.5075     25.76   0.0002
expde                7     422.177   0.4779   22.8792   0.0008
----------------------------------------------------------------




------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
ips          |
         ips |
         L1. |   .1891853   .1660193     1.14   0.254    -.1362065    .5145771
         L2. |  -.2936647    .160778    -1.83   0.068    -.6087838    .0214544
         L3. |  -.2716117   .1596956    -1.70   0.089    -.5846094     .041386
             |
       expde |
         L1. |   -.171992   .4847193    -0.35   0.723    -1.122024    .7780404
         L2. |    .495262   .4537461     1.09   0.275     -.394064    1.384588
         L3. |   1.499327   .4271695     3.51   0.000     .6620897    2.336564
             |
       _cons |   13182.53   2980.916     4.42   0.000     7340.045    19025.02
-------------+----------------------------------------------------------------
expde        |
         ips |
         L1. |    .035156   .0633397     0.56   0.579    -.0889876    .1592995
         L2. |   .0346557     .06134     0.56   0.572    -.0855685      .15488
         L3. |  -.1000226   .0609271    -1.64   0.101    -.2194375    .0193923
             |
       expde |
         L1. |   .0575636   .1849302     0.31   0.756    -.3048929    .4200201
         L2. |   .3417032   .1731133     1.97   0.048     .0024074     .680999
         L3. |   .4037325   .1629738     2.48   0.013     .0843097    .7231552
             |
       _cons |   988.6007   1137.279     0.87   0.385    -1240.426    3217.628
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               ips              expde |  17.975     3    0.000    |
 |               ips                ALL |  17.975     3    0.000    |
 |--------------------------------------+---------------------------|
 |             expde                ips |  4.2204     3    0.239    |
 |             expde                ALL |  4.2204     3    0.239    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------------

-----------
ips             long    %8.0g                 IPS

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.86
       Model |  2025551.74     4  506387.934           Prob > F      =  0.5046
    Residual |    11774394    20  588719.701           R-squared     =  0.1468
-------------+------------------------------           Adj R-squared = -0.0239
       Total |  13799945.8    24   574997.74           Root MSE      =  767.28

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ips |
         --. |   .0133429   .0390318     0.34   0.736    -.0680761    .0947619
         L1. |  -.0147297    .044982    -0.33   0.747    -.1085604    .0791011
         L2. |   .0137483   .0449744     0.31   0.763    -.0800665    .1075632
         L3. |  -.0515837    .038686    -1.33   0.197    -.1322812    .0291139
             |
       _cons |     3941.3   884.6189     4.46   0.000     2096.017    5786.583
------------------------------------------------------------------------------

 ( 1)  L.ips = 0
 ( 2)  L2.ips = 0
 ( 3)  L3.ips = 0

       F(  3,    20) =    0.94
            Prob > F =    0.4380

      Source |       SS       df       MS              Number of obs =      25
```

```
-------------+------------------------------           F(  4,    20) =    0.36
       Model |  64549285.6     4  16137321.4           Prob > F      =  0.8353
    Residual |   901028926    20  45051446.3           R-squared     =  0.0669
-------------+------------------------------           Adj R-squared = -0.1198
       Total |   965578211    24  40232425.5           Root MSE      =    6712

------------------------------------------------------------------------------
         ips |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -.9534289   1.907763    -0.50   0.623    -4.932953    3.026095
         L1. |  -.1248205   1.934163    -0.06   0.949    -4.159414    3.909773
         L2. |  -1.001482   1.971362    -0.51   0.617    -5.113672    3.110708
         L3. |  -1.109211   1.905317    -0.58   0.567    -5.083632     2.86521
             |
       _cons |   38406.69   7181.862     5.35   0.000     23425.59    53387.79
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.29
            Prob > F =    0.8304

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -439.8774                      AIC             =  36.31019
FPE            =  2.08e+13                      HQIC            =  36.49951
Det(Sigma_ml)  =  6.58e+12                      SBIC            =  36.99277

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ips                  7     4537.12   0.6163   40.14705   0.0000
expde                7     786.972   0.1922   5.947557   0.4291
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ips          |
         ips |
         L1. |   .5892647   .1990961     2.96   0.003     .1990436    .9794858
         L2. |   .1978028   .2271874     0.87   0.384    -.2474762    .6430819
         L3. |   .0168472   .1983117     0.08   0.932    -.3718366    .4055309
             |
       expde |
         L1. |   .8192474   1.108672     0.74   0.460     -1.35371    2.992204
         L2. |  -.9177418   1.146826    -0.80   0.424     -3.16548    1.329997
         L3. |  -.2403024   1.120344    -0.21   0.830    -2.436137    1.955532
             |
       _cons |   6015.577   6787.277     0.89   0.375    -7287.242     19318.4
-------------+----------------------------------------------------------------
expde        |
         ips |
         L1. |  -.0099916   .0345336    -0.29   0.772    -.0776762     .057693
         L2. |   .0215569   .0394061     0.55   0.584    -.0556776    .0987914
         L3. |  -.0446777   .0343975    -1.30   0.194    -.1120956    .0227403
             |
       expde |
         L1. |    .196443   .1923013     1.02   0.307    -.1804606    .5733466
         L2. |   .0842935   .1989193     0.42   0.672    -.3055811    .4741682
         L3. |  -.0056386   .1943259    -0.03   0.977    -.3865104    .3752332
             |
       _cons |    3018.04   1177.266     2.56   0.010     710.6404     5325.44
------------------------------------------------------------------------------

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |               ips              expde |  1.0722     3    0.784    |
```

```
 |           ips           ALL |  1.0722    3    0.784    |
 |--------------------------------------+---------------------------|
 |          expde           ips |  2.7593    3    0.430    |
 |          expde           ALL |  2.7593    3    0.430    |
 +------------------------------------------------------------------+

          storage   display    value
variable name   type    format     label     variable label
------------------------------------------------------------------------------------------------------------------------------------

-----------
ips           long    %8.0g              IPS

     Source |       SS       df       MS            Number of obs =      25
-------------+------------------------------           F(  4,    20) =     3.38
      Model |  8266201.49     4  2066550.37          Prob > F      =  0.0288
   Residual |  12228898.7    20  611444.934          R-squared     =  0.4033
-------------+------------------------------           Adj R-squared =  0.2840
      Total |  20495100.2    24  853962.507          Root MSE      =  781.95

------------------------------------------------------------------------------
      expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        ips |
        --. |   .0226598   .0519913     0.44   0.668    -.0857921    .1311117
        L1. |    -.01867   .0629467    -0.30   0.770    -.1499745    .1126345
        L2. |   .0119215    .063054     0.19   0.852    -.1196068    .1434497
        L3. |  -.1462722   .0523615    -2.79   0.011    -.2554964    -.037048
            |
      _cons |   4469.683   729.3837     6.13   0.000     2948.215     5991.15
------------------------------------------------------------------------------

 ( 1)  L.ips = 0
 ( 2)  L2.ips = 0
 ( 3)  L3.ips = 0

       F(  3,    20) =     4.47
            Prob > F =    0.0147

     Source |       SS       df       MS            Number of obs =      25
-------------+------------------------------           F(  4,    20) =     0.13
      Model |  10142042.8     4  2535510.69          Prob > F      =  0.9717
   Residual |   405017486    20  20250874.3          R-squared     =  0.0244
-------------+------------------------------           Adj R-squared = -0.1707
      Total |   415159529    24  17298313.7          Root MSE      =  4500.1

------------------------------------------------------------------------------
        ips |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      expde |
        --. |   -.425886    1.15198    -0.37   0.715    -2.828874    1.977102
        L1. |   .5285318    1.31786     0.40   0.693    -2.220476     3.27754
        L2. |  -.3087772   1.296634    -0.24   0.814    -3.013508    2.395954
        L3. |   .5834468   1.200945     0.49   0.632    -1.921682    3.088575
            |
      _cons |   13155.49   4082.151     3.22   0.004     4640.272    21670.71
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =     0.15
            Prob > F =    0.9315

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood =   -432.58                      AIC             =   35.7264
FPE            =  1.16e+13                      HQIC            =  35.91571
Det(Sigma_ml)  =  3.67e+12                      SBIC            =  36.40897

Equation           Parms      RMSE     R-sq      chi2     P>chi2
```

```
----------------------------------------------------------------
ips              7    3471.45   0.4775   22.84755   0.0008
expde             7    770.242   0.4790   22.98031   0.0008
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ips          |
         ips |
         L1. |   .7025707   .1986297     3.54   0.000     .3132637    1.091878
         L2. |   .0647117   .2421612     0.27   0.789    -.4099154    .5393388
         L3. |  -.1607235   .2109647    -0.76   0.446    -.5742067    .2527597
             |
       expde |
         L1. |   .2881927   .8285892     0.35   0.728    -1.335812    1.912198
         L2. |  -.7641237   .8679677    -0.88   0.379    -2.465309    .9370618
         L3. |   .6476522   .7918688     0.82   0.413    -.9043821    2.199686
             |
       _cons |   5092.243   3823.487     1.33   0.183    -2401.653    12586.14
-------------+----------------------------------------------------------------
expde        |
         ips |
         L1. |   -.020289   .0440717    -0.46   0.645     -.106668      .06609
         L2. |   .0222247   .0537304     0.41   0.679     -.083085    .1275344
         L3. |  -.1200958   .0468086    -2.57   0.010     -.211839   -.0283527
             |
       expde |
         L1. |   .3393369   .1838464     1.85   0.065    -.0209954    .6996692
         L2. |   .0006267   .1925837     0.00   0.997    -.3768303    .3780837
         L3. |  -.0602539   .1756989    -0.34   0.732    -.4046174    .2841096
             |
       _cons |   3575.982   848.3507     4.22   0.000     1913.246    5238.719
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               ips              expde |   1.07     3    0.784     |
 |               ips                ALL |   1.07     3    0.784     |
 |--------------------------------------+---------------------------|
 |             expde                ips |  10.725    3    0.013     |
 |             expde                ALL |  10.725    3    0.013     |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------------

-----------
opd             long    %8.0g                 OPD

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    4.40
       Model |   7512594.3     4  1878148.58           Prob > F      =  0.0103
    Residual |  8541721.46    20  427086.073           R-squared     =  0.4679
-------------+------------------------------           Adj R-squared =  0.3615
       Total |  16054315.8    24  668929.823           Root MSE      =  653.52

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         opd |
         --. |  -.0151778   .0056447    -2.69   0.014    -.0269523   -.0034033
         L1. |  -.0037782   .0061023    -0.62   0.543    -.0165074    .0089511
         L2. |  -.0023247   .0060245    -0.39   0.704    -.0148915     .010242
         L3. |  -.0032144   .0054228    -0.59   0.560    -.0145262    .0080973
             |
       _cons |   6719.093   840.9647     7.99   0.000     4964.871    8473.314
------------------------------------------------------------------------------

 ( 1)  L.opd = 0
```

```
 ( 2)  L2.opd = 0
 ( 3)  L3.opd = 0

       F(  3,    20) =    0.68
            Prob > F =    0.5761

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    4.13
       Model |  8.4963e+09     4  2.1241e+09           Prob > F      =  0.0134
    Residual |  1.0277e+10    20   513848995           R-squared     =  0.4526
-------------+------------------------------           Adj R-squared =  0.3431
       Total |  1.8773e+10    24   782220502           Root MSE      =   22668

------------------------------------------------------------------------------
         opd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -17.97947   7.511252    -2.39   0.027    -33.64766   -2.311268
         L1. |  -6.962228   7.073761    -0.98   0.337    -21.71783    7.793379
         L2. |  -1.952959   6.944178    -0.28   0.781    -16.43826    12.53234
         L3. |   .9549247   7.139743     0.13   0.895    -13.93832    15.84817
             |
       _cons |   220086.8   23551.68     9.34   0.000     170958.9    269214.7
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.47
            Prob > F =    0.7058

Vector autoregression

Sample:  6344q1 - 6350q1                          No. of obs      =        25
Log likelihood = -477.2288                        AIC             =   39.2983
FPE            =  4.13e+14                        HQIC            =  39.48762
Det(Sigma_ml)  =  1.31e+14                        SBIC            =  39.98087

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
opd                  7     25747.4   0.3644   14.33168   0.0261
expde                7     686.763   0.4712   22.27657   0.0011
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
opd          |
         opd |
         L1. |   .2964123   .2213949     1.34   0.181    -.1375137    .7303383
         L2. |  -.2690662   .2230473    -1.21   0.228    -.7062309    .1680985
         L3. |   .0686188   .2160683     0.32   0.751    -.3548673    .4921049
             |
       expde |
         L1. |  -5.667301   7.773437    -0.73   0.466    -20.90296    9.568355
         L2. |  -8.721351   7.566959    -1.15   0.249    -23.55232    6.109615
         L3. |  -5.029786   7.760536    -0.65   0.517    -20.24016    10.18058
             |
       _cons |   182695.7   80054.37     2.28   0.022     25792.03    339599.4
-------------+----------------------------------------------------------------
expde        |
         opd |
         L1. |  -.0043261   .0059053    -0.73   0.464    -.0159002    .0072481
         L2. |   .0058147   .0059494     0.98   0.328    -.0058459    .0174752
         L3. |   .0026904   .0057632     0.47   0.641    -.0086053    .0139861
             |
       expde |
         L1. |   .0787733   .2073419     0.38   0.704    -.3276093    .4851559
         L2. |   .3570076   .2018345     1.77   0.077    -.0385806    .7525959
         L3. |   .4252074   .2069978     2.05   0.040     .0194992    .8309155
             |
       _cons |   67.14009     2135.3     0.03   0.975    -4117.972    4252.252
```

```
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               opd              expde |  3.0829     3    0.379    |
 |               opd                ALL |  3.0829     3    0.379    |
 |--------------------------------------+---------------------------|
 |             expde                opd |  1.8204     3    0.611    |
 |             expde                ALL |  1.8204     3    0.611    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------------------------------------

-----------
opd             long    %8.0g                 OPD

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    3.28
       Model |  2435158.08     4  608789.52           Prob > F      =  0.0319
    Residual |  3709075.92    20  185453.796           R-squared     =  0.3963
-------------+------------------------------           Adj R-squared =  0.2756
       Total |     6144234    24  256009.75           Root MSE      =  430.64

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         opd |
         --. |  -.0013126   .0128796    -0.10   0.920    -.028179    .0255539
         L1. |   .0086297   .0144908     0.60   0.558   -.0215976     .038857
         L2. |   .0224696   .0148075     1.52   0.145   -.0084182    .0533574
         L3. |  -.0038036   .0135287    -0.28   0.781   -.0320239    .0244166
             |
       _cons |    453.296   626.4737     0.72   0.478   -853.5052    1760.097
------------------------------------------------------------------------------

 ( 1)  L.opd = 0
 ( 2)  L2.opd = 0
 ( 3)  L3.opd = 0

       F(  3,    20) =    1.74
            Prob > F =    0.1920

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    4.48
       Model |  1.7901e+09     4  447537019           Prob > F      =  0.0096
    Residual |  1.9996e+09    20  99978781.9           R-squared     =  0.4724
-------------+------------------------------           Adj R-squared =  0.3668
       Total |  3.7897e+09    24  157905155           Root MSE      =  9998.9

------------------------------------------------------------------------------
         opd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   2.659304   5.163571     0.52   0.612   -8.111717    13.43032
         L1. |   4.426351   4.825023     0.92   0.370   -5.638471    14.49117
         L2. |   6.946577   4.903628     1.42   0.172   -3.282211    17.17537
         L3. |   8.144582   4.830214     1.69   0.107   -1.931069    18.22023
             |
       _cons |   26925.83   13114.98     2.05   0.053   -431.5281    54283.19
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    2.95
            Prob > F =    0.0577

Vector autoregression
```

```
Sample:  6344q1 - 6350q1                     No. of obs      =       25
Log likelihood = -434.4601                   AIC             =  35.87681
FPE            =  1.35e+13                   HQIC            =  36.06612
Det(Sigma_ml)  =  4.26e+12                   SBIC            =  36.55938

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
opd                  7     7176.76   0.7554   77.19231   0.0000
expde                7     410.222   0.5070   25.71041   0.0003
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
opd          |
         opd |
         L1. |   .4832149    .182774     2.64   0.008     .1249844    .8414454
         L2. |   .1233258   .2105588     0.59   0.558     -.289362    .5360135
         L3. |   .1697575   .2025909     0.84   0.402    -.2273134    .5668285
             |
       expde |
         L1. |  -.8532218   3.283501    -0.26   0.795    -7.288765    5.582321
         L2. |   1.820704   3.050129     0.60   0.551    -4.157439    7.798846
         L3. |   5.812957    2.81288     2.07   0.039     .2998126     11.3261
             |
       _cons |   3009.412   9096.465     0.33   0.741    -14819.33    20838.16
-------------+----------------------------------------------------------------
expde        |
         opd |
         L1. |   .0038657   .0104473     0.37   0.711    -.0166107    .0243421
         L2. |   .0200186   .0120355     1.66   0.096    -.0035705    .0436078
         L3. |  -.0089806   .0115801    -0.78   0.438    -.0316771    .0137159
             |
       expde |
         L1. |  -.0036179   .1876842    -0.02   0.985    -.3714722    .3642364
         L2. |   .2482119   .1743447     1.42   0.155    -.0934975    .5899213
         L3. |   .2631064   .1607837     1.64   0.102    -.0520237    .5782366
             |
       _cons |   122.6217   519.9521     0.24   0.814    -896.4657    1141.709
------------------------------------------------------------------------------

  Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |               opd              expde |  5.1466     3    0.161    |
  |               opd                ALL |  5.1466     3    0.161    |
  |--------------------------------------+---------------------------|
  |             expde                opd |  5.9483     3    0.114    |
  |             expde                ALL |  5.9483     3    0.114    |
  +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------

-----------
opd             long    %8.0g                 OPD

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.34
       Model |  879241.227     4  219810.307           Prob > F      =  0.8476
    Residual |  12920704.5    20  646035.227           R-squared     =  0.0637
-------------+------------------------------           Adj R-squared = -0.1235
       Total |  13799945.8    24   574997.74           Root MSE      =  803.76

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         opd |
         --. |  -.0021005   .0143428    -0.15   0.885    -.0320191    .0278182
         L1. |    .005464    .013483     0.41   0.690    -.0226611    .0335891
```

```
        L2. |   .0008821   .0133841    0.07   0.948    -.0270366    .0288009
        L3. |   .0083994   .0123683    0.68   0.505    -.0174004    .0341991
            |
      _cons |   1056.391   1685.879    0.63   0.538    -2460.291    4573.072
------------------------------------------------------------------------------

 ( 1)  L.opd = 0
 ( 2)  L2.opd = 0
 ( 3)  L3.opd = 0

       F(  3,    20) =    0.31
            Prob > F =    0.8196

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.40
       Model |  441872615     4  110468154           Prob > F      =  0.8079
    Residual |  5.5558e+09    20  277790383           R-squared     =  0.0737
-------------+------------------------------           Adj R-squared = -0.1116
       Total |  5.9977e+09    24  249903345           Root MSE      =   16667

------------------------------------------------------------------------------
         opd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   1.531371   4.737275     0.32   0.750    -8.350412    11.41315
         L1. |    4.22985   4.802831     0.88   0.389     -5.78868    14.24838
         L2. |  -.2125099   4.895203    -0.04   0.966    -10.42372    9.998704
         L3. |   1.863639   4.731201     0.39   0.698    -8.005473    11.73275
             |
       _cons |   111461.2   17833.69     6.25   0.000     74260.79    148661.7
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.38
            Prob > F =    0.7667

Vector autoregression

Sample:  6344q1 - 6350q1                        No. of obs      =        25
Log likelihood = -467.0709                      AIC             =  38.48568
FPE            =  1.83e+14                      HQIC            =  38.67499
Det(Sigma_ml)  =  5.79e+13                      SBIC            =  39.16825

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
opd                   7     12934.9   0.4979   24.78814   0.0004
expde                 7     817.987   0.1273   3.645199   0.7246
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
opd          |
         opd |
         L1. |    .431409   .1695093     2.55   0.011     .0991768    .7636411
         L2. |  -.1782353   .1830713    -0.97   0.330    -.5370484    .1805778
         L3. |   .4447464   .1464675     3.04   0.002     .1576753    .7318174
             |
       expde |
         L1. |   2.225218    3.12555     0.71   0.476    -3.900747    8.351182
         L2. |  -2.823126    3.27478    -0.86   0.389    -9.241577    3.595325
         L3. |   .8408896   3.193075     0.26   0.792    -5.417422    7.099201
             |
       _cons |   41036.91   21805.12     1.88   0.060     -1700.35    83774.17
-------------+----------------------------------------------------------------
expde        |
         opd |
         L1. |   .0027351   .0107196     0.26   0.799    -.0182748    .0237451
         L2. |   .0007472   .0115772     0.06   0.949    -.0219438    .0234381
         L3. |   .0051745   .0092624     0.56   0.576    -.0129796    .0233285
```

```
         |
     expde |
       L1. |   .2094123   .1976562     1.06   0.289    -.1779868    .5968113
       L2. |   .1042678   .2070934     0.50   0.615    -.3016278    .5101633
       L3. |   .0138123   .2019264     0.07   0.945    -.3819563    .4095808
         |
     _cons |    715.047   1378.931     0.52   0.604    -1987.609    3417.703
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               opd              expde |  1.0693     3    0.784    |
 |               opd                ALL |  1.0693     3    0.784    |
 |--------------------------------------+---------------------------|
 |             expde                opd |  .69416     3    0.875    |
 |             expde                ALL |  .69416     3    0.875    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------------

-----------
opd             long    %8.0g                 OPD

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    2.19
       Model |   6252147.5     4  1563036.87           Prob > F      =  0.1064
    Residual |  14242952.7    20  712147.633           R-squared     =  0.3051
-------------+------------------------------           Adj R-squared =  0.1661
       Total |  20495100.2    24  853962.507           Root MSE      =  843.89

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         opd |
         --. |  -.0074577   .0035945    -2.07   0.051    -.0149556    .0000402
         L1. |     .00328    .004651     0.71   0.489    -.0064219    .0129818
         L2. |  -.0030798   .0046862    -0.66   0.519    -.0128552    .0066955
         L3. |   .0025385   .0035409     0.72   0.482    -.0048477    .0099247
           |
       _cons |    3734.61   487.6453     7.66   0.000     2717.399     4751.82
------------------------------------------------------------------------------

 ( 1)  L.opd = 0
 ( 2)  L2.opd = 0
 ( 3)  L3.opd = 0

       F(  3,    20) =    0.38
            Prob > F =    0.7688

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.84
       Model |  5.3576e+10     4  1.3394e+10           Prob > F      =  0.1603
    Residual |  1.4539e+11    20  7.2695e+09           R-squared     =  0.2693
-------------+------------------------------           Adj R-squared =  0.1231
       Total |  1.9897e+11    24  8.2902e+09           Root MSE      =   85261

------------------------------------------------------------------------------
         opd |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |  -47.49781   21.82604    -2.18   0.042    -93.02613   -1.969497
         L1. |   -7.41638   24.96889    -0.30   0.770    -59.50058    44.66782
         L2. |   1.028105   24.56673     0.04   0.967     -50.2172    52.27341
         L3. |    3.14452   22.75377     0.14   0.891      -44.319    50.60804
           |
       _cons |   364149.6   77342.65     4.71   0.000     202815.6    525483.5
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
```

```
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.03
            Prob > F =    0.9911

Vector autoregression

Sample:  6344q1 - 6350q1                     No. of obs     =       25
Log likelihood = -496.3259                   AIC            =  40.82607
FPE            =  1.90e+15                   HQIC           =  41.01539
Det(Sigma_ml)  =  6.01e+14                   SBIC           =  41.50864

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
opd                  7     49702.3   0.7765   86.86482   0.0000
expde                7     883.064   0.3151   11.50337   0.0740
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
opd          |
         opd |
         L1. |   .7667413   .2545115     3.01   0.003     .2679078    1.265575
         L2. |   .2306004   .3310062     0.70   0.486    -.4181598    .8793606
         L3. |  -.0300693   .2436097    -0.12   0.902    -.5075356     .447397
             |
       expde |
         L1. |   11.23715   14.44951     0.78   0.437    -17.08338    39.55768
         L2. |   18.91673   17.17316     1.10   0.271    -14.74205    52.57551
         L3. |   8.003093   15.49216     0.52   0.605    -22.36099    38.36718
             |
       _cons |  -82910.83   58460.61    -1.42   0.156    -197491.5    31669.86
-------------+----------------------------------------------------------------
expde        |
         opd |
         L1. |   .0034185   .0045219     0.76   0.450    -.0054443    .0122814
         L2. |  -.0072277    .005881    -1.23   0.219    -.0187543    .0042988
         L3. |    .002006   .0043282     0.46   0.643    -.0064772    .0104891
             |
       expde |
         L1. |   .6051059   .2567256     2.36   0.018     .1019329    1.108279
         L2. |  -.2169586   .3051169    -0.71   0.477    -.8149768    .3810595
         L3. |   -.130063   .2752504    -0.47   0.637     -.669544    .4094179
             |
       _cons |    2338.93   1038.674     2.25   0.024      303.166    4374.694
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |               opd              expde |  5.9897     3    0.112    |
 |               opd                ALL |  5.9897     3    0.112    |
 |--------------------------------------+---------------------------|
 |             expde                opd |  2.1792     3    0.536    |
 |             expde                ALL |  2.1792     3    0.536    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
-------------------------------------------------------------------------------------------------------------------------------------

-----------
ch              int     %8.0g                 CH

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    1.10
       Model |  2903438.18     4  725859.544           Prob > F      =  0.3820
    Residual |  13150877.6    20  657543.879           R-squared     =  0.1809
-------------+------------------------------           Adj R-squared =  0.0170
       Total |  16054315.8    24  668929.823           Root MSE      =  810.89
```

```
------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ch |
         --. |   .2416431   .2271851     1.06   0.300    -.2322568    .7155429
         L1. |  -.0318181   .2467104    -0.13   0.899    -.5464471    .4828108
         L2. |  -.1916509   .2483865    -0.77   0.449    -.7097761    .3264743
         L3. |  -.2577742   .2261265    -1.14   0.268    -.7294659    .2139174
             |
       _cons |   4613.309   1003.976     4.60   0.000     2519.052    6707.566
------------------------------------------------------------------------------

 ( 1)  L.ch = 0
 ( 2)  L2.ch = 0
 ( 3)  L3.ch = 0

       F(  3,    20) =    1.47
            Prob > F =    0.2526

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.03
       Model |  149904.186     4  37476.0466           Prob > F      =  0.9976
    Residual |  21951096.8    20  1097554.84           R-squared     =  0.0068
-------------+------------------------------           Adj R-squared = -0.1919
       Total |    22101001    24   920875.04           Root MSE      =  1047.6

------------------------------------------------------------------------------
          ch |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   .0187759   .3471424     0.05   0.957    -.7053505    .7429023
         L1. |   .0487486   .3269232     0.15   0.883    -.6332012    .7306985
         L2. |   .0668467   .3209344     0.21   0.837    -.6026106    .7363041
         L3. |  -.1041421   .3299726    -0.32   0.756    -.7924529    .5841688
             |
       _cons |     4561.2   1088.472     4.19   0.000     2290.688    6831.713
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.04
            Prob > F =    0.9871

Vector autoregression

Sample:  6344q1 - 6350q1                           No. of obs      =        25
Log likelihood =  -393.656                         AIC             =  32.61248
FPE            =  5.15e+11                         HQIC            =   32.8018
Det(Sigma_ml)  =  1.63e+11                         SBIC            =  33.29505

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ch                    7     824.383   0.4465   20.16702   0.0026
expde                 7     691.686   0.4636   21.60592   0.0014
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ch           |
          ch |
         L1. |   .4239005   .1958184     2.16   0.030     .0401036    .8076975
         L2. |   .2354515   .2107907     1.12   0.264    -.1776908    .6485937
         L3. |   .0986937   .2054673     0.48   0.631    -.3040149    .5014023
             |
       expde |
         L1. |   .1439261   .2221412     0.65   0.517    -.2914626    .5793149
         L2. |   .0938378    .208989     0.45   0.653    -.3157732    .5034488
         L3. |  -.0385534   .2066817    -0.19   0.852    -.4436422    .3665354
             |
```

```
     _cons |   439.5509   1261.391     0.35   0.727    -2032.73    2911.831
-------------+----------------------------------------------------------------
expde        |
          ch |
         L1. |    .032182   .1642985     0.20   0.845    -.2898371    .3542011
         L2. |  -.1098597   .1768608    -0.62   0.534    -.4565005    .2367812
         L3. |  -.0842235   .1723943    -0.49   0.625    -.4221101    .2536631
             |
       expde |
         L1. |    .091919   .1863843     0.49   0.622    -.2733875    .4572254
         L2. |   .2411948   .1753491     1.38   0.169    -.1024832    .5848727
         L3. |     .33742   .1734132     1.95   0.052    -.0024637    .6773036
             |
       _cons |   2036.408   1058.351     1.92   0.054    -37.92207    4110.738
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |                ch              expde |  1.036     3    0.793     |
 |                ch                ALL |  1.036     3    0.793     |
 |--------------------------------------+---------------------------|
 |             expde                 ch | 1.4399     3    0.696     |
 |             expde                ALL | 1.4399     3    0.696     |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
-----------------------------------------------------------------------------------------------------------------------------

-----------
ch              int     %8.0g                 CH

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    6.88
       Model |  3558390.93     4  889597.734           Prob > F      =  0.0012
    Residual |  2585843.07    20  129292.153           R-squared     =  0.5791
-------------+------------------------------           Adj R-squared =  0.4950
       Total |     6144234    24   256009.75           Root MSE      =  359.57

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ch |
         --. |   .1635842   .0513059     3.19   0.005     .0565619    .2706065
         L1. |   .0202707   .0572845     0.35   0.727    -.0992227    .1397641
         L2. |   .0770422   .0566452     1.36   0.189    -.0411177    .1952021
         L3. |  -.0357567   .0554536    -0.64   0.526    -.1514309    .0799174
             |
       _cons |   524.7774   460.3079     1.14   0.268    -435.4082    1484.963
------------------------------------------------------------------------------

 ( 1)  L.ch = 0
 ( 2)  L2.ch = 0
 ( 3)  L3.ch = 0

       F(  3,    20) =    1.13
            Prob > F =    0.3616

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    5.97
       Model |  48599266.1     4  12149816.5           Prob > F      =  0.0025
    Residual |  40731343.9    20  2036567.19           R-squared     =  0.5440
-------------+------------------------------           Adj R-squared =  0.4528
       Total |    89330610    24  3722108.75           Root MSE      =  1427.1

------------------------------------------------------------------------------
          ch |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   2.449187   .7369629     3.32   0.003     .9119093    3.986465
         L1. |   .1151435   .6886441     0.17   0.869    -1.321343     1.55163
```

```
         L2. |  -.3754991   .6998628   -0.54   0.598   -1.835387    1.084389
         L3. |   .7160172   .6893851    1.04   0.311   -.7220148    2.154049
             |
       _cons |    1650.98   1871.815    0.88   0.388   -2253.558    5555.518
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.53
            Prob > F =    0.6684

Vector autoregression

Sample:  6344q1 - 6350q1                      No. of obs      =        25
Log likelihood = -388.2498                    AIC             =  32.17999
FPE            =  3.34e+11                    HQIC            =   32.3693
Det(Sigma_ml)  =  1.06e+11                    SBIC            =  32.86256

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ch                   7     1365.52   0.6243   41.53848   0.0000
expde                7     361.311   0.6176   40.36898   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ch           |
          ch |
         L1. |   .8228774   .1865031    4.41   0.000      .457338    1.188417
         L2. |  -.0821484   .2139753   -0.38   0.701   -.5015322    .3372354
         L3. |   .1679018   .1931381    0.87   0.385   -.2106418    .5464455
             |
       expde |
         L1. |  -1.774199   .7370936   -2.41   0.016   -3.218876   -.3295224
         L2. |   .1467648   .6603718    0.22   0.824    -1.14754     1.44107
         L3. |   1.886417   .5983057    3.15   0.002    .7137594    3.059075
             |
       _cons |   556.0647   1594.256    0.35   0.727   -2568.619    3680.749
-------------+----------------------------------------------------------------
expde        |
          ch |
         L1. |   .1634247   .0493481    3.31   0.001    .0667042    .2601452
         L2. |   .0350367   .0566171    0.62   0.536   -.0759309    .1460042
         L3. |  -.0625496   .0511037   -1.22   0.221    -.162711    .0376118
             |
       expde |
         L1. |  -.3578527   .1950325   -1.83   0.067   -.7401094     .024404
         L2. |     .27783   .1747322    1.59   0.112   -.0646387    .6202988
         L3. |   .5539054   .1583097    3.50   0.000    .2436242    .8641866
             |
       _cons |   231.7303   421.8347    0.55   0.583   -595.0506    1058.511
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |                ch              expde |  11.586     3    0.009    |
 |                ch                ALL |  11.586     3    0.009    |
 |--------------------------------------+---------------------------|
 |             expde                 ch |  14.894     3    0.002    |
 |             expde                ALL |  14.894     3    0.002    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
------------------------------------------------------------------------------------------------------------------------------

-----------
ch              int     %8.0g                 CH
```

```
     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.90
      Model |  2104030.36     4  526007.589           Prob > F      =  0.4828
   Residual |  11695915.4    20  584795.77            R-squared     =  0.1525
-------------+------------------------------           Adj R-squared = -0.0170
      Total |  13799945.8    24  574997.74            Root MSE      =  764.72

------------------------------------------------------------------------------
      expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ch |
        --. |  -.0441118   .0366505    -1.20   0.243    -.1205634    .0323399
        L1. |  -.0033435   .0449045    -0.07   0.941    -.0970126    .0903255
        L2. |  -.0067618   .0456802    -0.15   0.884    -.1020491    .0885255
        L3. |   .0131849   .0364126     0.36   0.721    -.0627705    .0891403
            |
      _cons |   3404.223   541.3938     6.29   0.000     2274.895     4533.55
------------------------------------------------------------------------------

 ( 1)  L.ch = 0
 ( 2)  L2.ch = 0
 ( 3)  L3.ch = 0

       F(  3,    20) =    0.05
            Prob > F =    0.9862

     Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    2.13
      Model |   311262669     4  77815667.2           Prob > F      =  0.1150
   Residual |   731616521    20  36580826.1           R-squared     =  0.2985
-------------+------------------------------           Adj R-squared =  0.1582
      Total |  1.0429e+09    24  43453299.6           Root MSE      =  6048.2

------------------------------------------------------------------------------
         ch |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      expde |
        --. |  -2.299111   1.719083    -1.34   0.196    -5.885055    1.286833
        L1. |  -1.362911   1.742872    -0.78   0.443    -4.998478    2.272656
        L2. |  -2.085435   1.776392    -1.17   0.254    -5.790924    1.620055
        L3. |  -1.413528   1.716878    -0.82   0.420    -4.994874    2.167817
            |
      _cons |   36907.64   6471.566     5.70   0.000     23408.19    50407.09
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    1.44
            Prob > F =    0.2598

Vector autoregression

Sample:  6344q1 - 6350q1                           No. of obs      =        25
Log likelihood = -441.5827                         AIC             =  36.44661
FPE            =  2.38e+13                         HQIC            =  36.63593
Det(Sigma_ml)  =  7.54e+12                         SBIC            =  37.12919

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ch                   7     4819.56   0.5991   37.35731   0.0000
expde                7     815.894   0.1317   3.792347   0.7048
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ch           |
          ch |
         L1. |   .7108323   .2070864     3.43   0.001     .3049505    1.116714
         L2. |  -.0813242   .2489422    -0.33   0.744    -.5692419    .4065935
```

```
       L3. |   .0909701   .1987124    0.46   0.647    -.298499    .4804391
           |
     expde |
       L1. |  -.1387256   1.207778   -0.11   0.909   -2.505926    2.228475
       L2. |  -1.183943   1.246097   -0.95   0.342   -3.626248    1.258362
       L3. |   .4761063   1.254372    0.38   0.704   -1.982418    2.934631
           |
     _cons |   6954.025   7097.196    0.98   0.327   -6956.223    20864.27
-------------+----------------------------------------------------------------
expde        |
        ch |
       L1. |  -.0248956   .0350573   -0.71   0.478   -.0936066    .0438154
       L2. |  -.0019102    .042143   -0.05   0.964    -.084509    .0806885
       L3. |   .0090285   .0336397    0.27   0.788   -.0569041     .074961
           |
     expde |
       L1. |   .1814178   .2044625    0.89   0.375   -.2193214     .582157
       L2. |   .0956189   .2109496    0.45   0.650   -.3178346    .5090725
       L3. |  -.0063992   .2123505   -0.03   0.976   -.4225985    .4098001
           |
     _cons |   2287.902   1201.472    1.90   0.057   -66.94013    4642.743
------------------------------------------------------------------------------

  Granger causality Wald tests
 +------------------------------------------------------------------+
 |          Equation           Excluded |   chi2     df Prob > chi2 |
 |--------------------------------------+---------------------------|
 |                ch              expde |  1.0314     3    0.794    |
 |                ch                ALL |  1.0314     3    0.794    |
 |--------------------------------------+---------------------------|
 |             expde                 ch |  .82615     3    0.843    |
 |             expde                ALL |  .82615     3    0.843    |
 +------------------------------------------------------------------+

              storage   display    value
variable name   type    format     label      variable label
--------------------------------------------------------------------------------------------------------------------------------

-----------
ch              int     %8.0g                 CH

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.18
       Model |   709932.03     4  177483.008           Prob > F      =  0.9464
    Residual |  19785168.1    20  989258.406           R-squared     =  0.0346
-------------+------------------------------           Adj R-squared = -0.1584
       Total |  20495100.2    24  853962.507           Root MSE      =  994.61

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ch |
         --. |   .0076194   .0853872     0.09   0.930    -.1704952    .1857339
         L1. |    .017219   .1017114     0.17   0.867    -.1949472    .2293852
         L2. |   .0035766   .1014481     0.04   0.972    -.2080405    .2151936
         L3. |   .0139193   .0826777     0.17   0.868    -.1585433    .1863819
             |
       _cons |   2174.735   571.5999     3.80   0.001     982.3983    3367.071
------------------------------------------------------------------------------

 ( 1)  L.ch = 0
 ( 2)  L2.ch = 0
 ( 3)  L3.ch = 0

       F(  3,    20) =    0.06
            Prob > F =    0.9819

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(  4,    20) =    0.79
       Model |  60855458.2     4  15213864.6           Prob > F      =  0.5455
    Residual |   385281730    20  19264086.5           R-squared     =  0.1364
-------------+------------------------------           Adj R-squared = -0.0363
       Total |   446137188    24  18589049.5           Root MSE      =  4389.1
```

```
------------------------------------------------------------------------------
          ch |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       expde |
         --. |   .2062055   1.123563     0.18   0.856    -2.137505    2.549916
         L1. |   1.034358   1.285351     0.80   0.430    -1.646836    3.715553
         L2. |    .382163   1.264648     0.30   0.766    -2.255847    3.020173
         L3. |   .9231968    1.17132     0.79   0.440    -1.520134    3.366528
             |
       _cons |   3579.322   3981.451     0.90   0.379    -4725.839    11884.48
------------------------------------------------------------------------------

 ( 1)  L.expde = 0
 ( 2)  L2.expde = 0
 ( 3)  L3.expde = 0

       F(  3,    20) =    0.85
            Prob > F =    0.4836

Vector autoregression

Sample:  6344q1 - 6350q1                       No. of obs      =        25
Log likelihood = -429.7443                     AIC             =  35.49954
FPE            =  9.24e+12                     HQIC            =  35.68886
Det(Sigma_ml)  =  2.92e+12                     SBIC            =  36.18211

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ch                   7     2607.77   0.7256   66.11678   0.0000
expde                7     914.388   0.2657   9.04527   0.1710
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ch           |
          ch |
         L1. |   .7639527   .1947643     3.92   0.000     .3822217    1.145684
         L2. |  -.1258451   .2402423    -0.52   0.600    -.5967114    .3450212
         L3. |   .1921789    .182191     1.05   0.292     -.164909    .5492667
             |
       expde |
         L1. |   .8988297   .5885081     1.53   0.127    -.2546249    2.052284
         L2. |  -.7675224   .6781615    -1.13   0.258    -2.096695    .5616497
         L3. |   .3657121   .6267263     0.58   0.560    -.8626489    1.594073
             |
       _cons |   43.77182   1907.157     0.02   0.982    -3694.187     3781.73
-------------+----------------------------------------------------------------
expde        |
          ch |
         L1. |   .0116818   .0682922     0.17   0.864    -.1221684     .145532
         L2. |   .0128674   .0842386     0.15   0.879    -.1522372     .177972
         L3. |  -.0011141   .0638835    -0.02   0.986    -.1263234    .1240952
             |
       expde |
         L1. |   .5016689   .2063545     2.43   0.015     .0972215    .9061164
         L2. |   .0482935   .2377906     0.20   0.839    -.4177676    .5143546
         L3. |  -.1690912   .2197554    -0.77   0.442    -.5998038    .2616215
             |
       _cons |   1392.189   668.7257     2.08   0.037     81.51116    2702.868
------------------------------------------------------------------------------

  Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |                ch              expde |  2.7111     3    0.438    |
  |                ch                ALL |  2.7111     3    0.438    |
  |--------------------------------------+---------------------------|
  |             expde                 ch |  .34899     3    0.951    |
  |             expde                ALL |  .34899     3    0.951    |
  +------------------------------------------------------------------+
```

```
end of do-file

. tsline expde alos

. tsline expde alos if hospital==1

. tsline expde, over( hospital)
option over() not allowed
r(198);

. tsline expde, by( hospital)

. tsline bur, by( hospital)

. tsline alos , by( hospital)

. tsline csr, by( hospital)

-------------------------------------------------------------------------------------------------------------------------------------------
      name:  <unnamed>
       log:  C:\Users\A. Chikobvu\Desktop\gee_autoregressive.log
  log type:  text
 opened on:  20 Jun 2015, 19:45:16

. xtgee expde alos bur pde ipd csr opd opd ch, family(gaussian) link(identity) corr(ar 1)
note: opd omitted because of collinearity

Iteration 1: tolerance = .9459637
Iteration 2: tolerance = 5.2098389
Iteration 3: tolerance = 1.2042245
Iteration 4: tolerance = .19617866
Iteration 5: tolerance = .05950567
Iteration 6: tolerance = .02045388
Iteration 7: tolerance = .00730954
Iteration 8: tolerance = .00264758
Iteration 9: tolerance = .00096361
Iteration 10: tolerance = .00035133
Iteration 11: tolerance = .00012817
Iteration 12: tolerance = .00004677
Iteration 13: tolerance = .00001707
Iteration 14: tolerance = 6.229e-06
Iteration 15: tolerance = 2.273e-06
Iteration 16: tolerance = 8.297e-07

GEE population-averaged model               Number of obs      =       112
Group and time vars:    hospital Quarter     Number of groups   =         4
Link:                          identity      Obs per group: min =        28
Family:                        Gaussian                     avg =      28.0
Correlation:                      AR(1)                     max =        28
                                             Wald chi2(7)       =     26.65
Scale parameter:               507160.9      Prob > chi2        =    0.0004

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        alos |  -17.62753   85.35567    -0.21   0.836    -184.9216    149.6665
         bur |   6.696148   12.25131     0.55   0.585    -17.31599    30.70828
         pde |  -.0003317    .000667    -0.50   0.619    -.0016389    .0009756
         ipd |   .0058226   .0040349     1.44   0.149    -.0020857     .013731
         csr |   52.15711   18.20775     2.86   0.004     16.47057    87.84365
         opd |  -.0056035   .0015506    -3.61   0.000    -.0086426   -.0025644
         opd |          0  (omitted)
          ch |  -.0282467   .0236914    -1.19   0.233    -.0746809    .0181876
       _cons |   582.7407   1185.876     0.49   0.623    -1741.534    2907.016
------------------------------------------------------------------------------

. xtgee expde alos bur pde ipd csr opd opd ch, family(gaussian) link(identity) corr(ar 2)
note: opd omitted because of collinearity

Iteration 1: tolerance = 1.3452634
Iteration 2: tolerance = 2.1973764
Iteration 3: tolerance = .29765663
```

```
Iteration 4: tolerance = .10116483
Iteration 5: tolerance = .04111177
Iteration 6: tolerance = .01782237
Iteration 7: tolerance = .00793741
Iteration 8: tolerance = .00357714
Iteration 9: tolerance = .00162116
Iteration 10: tolerance = .00073645
Iteration 11: tolerance = .00033487
Iteration 12: tolerance = .00015233
Iteration 13: tolerance = .00006931
Iteration 14: tolerance = .00003154
Iteration 15: tolerance = .00001435
Iteration 16: tolerance = 6.530e-06
Iteration 17: tolerance = 2.972e-06
Iteration 18: tolerance = 1.352e-06
Iteration 19: tolerance = 6.154e-07

GEE population-averaged model              Number of obs      =       112
Group and time vars:    hospital Quarter   Number of groups   =         4
Link:                         identity     Obs per group: min =        28
Family:                       Gaussian                    avg =      28.0
Correlation:                     AR(2)                    max =        28
                                           Wald chi2(7)       =     19.26
Scale parameter:              552342.2     Prob > chi2        =    0.0074

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        alos |   -100.468   87.94524    -1.14   0.253    -272.8376    71.90147
         bur |   11.10912   11.63415     0.95   0.340     -11.6934    33.91163
         pde |  -.0001263   .0006403    -0.20   0.844    -.0013812    .0011287
         ipd |   .0033091   .0048391     0.68   0.494    -.0061754    .0127935
         csr |    32.4433   19.66596     1.65   0.099    -6.101281    70.98787
         opd |  -.0065827   .0017813    -3.70   0.000    -.0100741   -.0030914
         opd |          0  (omitted)
          ch |  -.0372561   .0252524    -1.48   0.140    -.0867498    .0122377
       _cons |   2116.356   1246.644     1.70   0.090    -327.0199    4559.733
------------------------------------------------------------------------------

. xtgee expde alos bur pde ipd csr opd opd ch, family(gaussian) link(identity) corr(ar 3)
note: opd omitted because of collinearity

Iteration 1: tolerance = 1.4930053
Iteration 2: tolerance = 1.7651638
Iteration 3: tolerance = .28259384
Iteration 4: tolerance = .09322963
Iteration 5: tolerance = .03595338
Iteration 6: tolerance = .01471338
Iteration 7: tolerance = .00613181
Iteration 8: tolerance = .00257424
Iteration 9: tolerance = .00108394
Iteration 10: tolerance = .00045697
Iteration 11: tolerance = .00019275
Iteration 12: tolerance = .00008132
Iteration 13: tolerance = .00003431
Iteration 14: tolerance = .00001448
Iteration 15: tolerance = 6.108e-06
Iteration 16: tolerance = 2.577e-06
Iteration 17: tolerance = 1.087e-06
Iteration 18: tolerance = 4.588e-07

GEE population-averaged model              Number of obs      =       112
Group and time vars:    hospital Quarter   Number of groups   =         4
Link:                         identity     Obs per group: min =        28
Family:                       Gaussian                    avg =      28.0
Correlation:                     AR(3)                    max =        28
                                           Wald chi2(7)       =     22.04
Scale parameter:              585866.2     Prob > chi2        =    0.0025

------------------------------------------------------------------------------
       expde |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        alos |    -139.09   86.83062    -1.60   0.109    -309.2749     31.0949
```

```
bur |   6.768694   11.88306     0.57   0.569    -16.52168    30.05907
pde |  -.0001277   .0006344    -0.20   0.840    -.0013711    .0011156
ipd |    .004496   .0053175     0.85   0.398    -.0059261    .0149181
csr |   33.84131   20.70598     1.63   0.102    -6.741672     74.4243
opd |  -.0074291   .0018605    -3.99   0.000    -.0110756   -.0037825
opd |          0  (omitted)
 ch |  -.0454493   .0256111    -1.77   0.076    -.0956462    .0047475
_cons |   2728.435   1266.486     2.15   0.031     246.1676    5210.702
------------------------------------------------------------------------------

. log close
```

LAG SELECTION

```
-----------------------------------------------------------------------------------------------------------------------------------

. foreach var of varlist alos bur csr pde ipd ips opd ch{
  2. varsoc expde `var' if hospital==1,maxlag(10)
  3. }

  Selection-order criteria
  Sample:  11 - 28                        Number of obs     =       18
 +---------------------------------------------------------------------------+
 |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
 |----+----------------------------------------------------------------------|
 |  0 | -169.239                       628474   19.0266   19.0402   19.1255  |
 |  1 | -156.146  26.186    4  0.000   230215   18.0162   18.0572    18.313  |
 |  2 | -154.956  2.3807    4  0.666   322110   18.3284   18.3966   18.8231  |
 |  3 | -152.655  4.6016    4  0.331   411630   18.5172   18.6127   19.2097  |
 |  4 | -151.355  2.6009    4  0.627   620727   18.8172   18.9399   19.7075  |
 |  5 | -148.185  6.3384    4  0.175   832394   18.9095   19.0595   19.9977  |
 |  6 | -144.249  7.8731    4  0.096  1.2e+06   18.9165   19.0939   20.2026  |
 |  7 | -126.453  35.591    4  0.000   524602   17.3837   17.5883   18.8676  |
 |  8 |  206.799   666.5    4  0.000  4.4e-10* -19.1999   -18.968  -17.5181  |
 |  9 |  1012.85  1612.1    4  0.000        .  -108.539  -108.293  -106.758  |
 | 10 |  1022.94  20.184*   4  0.000        .   -109.66* -109.414* -107.879* |
 +---------------------------------------------------------------------------+
  Endogenous:  expde alos
   Exogenous:  _cons

  Selection-order criteria
  Sample:  11 - 28                        Number of obs     =       18
 +---------------------------------------------------------------------------+
 |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
 |----+----------------------------------------------------------------------|
 |  0 | -186.672                      4.4e+06   20.9636   20.9772   21.0625  |
 |  1 | -182.718  7.9086    4  0.095  4.4e+06   20.9687   21.0096   21.2655  |
 |  2 | -175.581  14.275    4  0.006  3.2e+06   20.6201   20.6883   21.1147  |
 |  3 | -171.029  9.1035    4  0.059  3.2e+06   20.5587   20.6542   21.2513  |
 |  4 | -166.412  9.2343    4  0.056  3.3e+06   20.4902   20.6129   21.3806  |
 |  5 | -165.333  2.1582    4  0.707  5.6e+06   20.8147   20.9648    21.903  |
 |  6 | -156.319  18.028    4  0.001  4.6e+06   20.2576    20.435   21.5437  |
 |  7 | -127.543   57.55*   4  0.000   592158   17.5048   17.7094   18.9888  |
 |  8 |        .       .    4      .  -7.8e-10*        .         .         .  |
 |  9 |  983.646       .    4      .        .  -105.294* -105.048* -103.513* |
 | 10 |   983.31 -.67247    4      .        .  -105.257  -105.011  -103.476  |
 +---------------------------------------------------------------------------+
  Endogenous:  expde bur
   Exogenous:  _cons
```

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-190.916				7.0e+06	21.4351	21.4487	21.534
1	-190.077	1.6768	4	0.795	1.0e+07	21.7864	21.8273	22.0832
2	-188.303	3.5492	4	0.470	1.3e+07	22.0336	22.1019	22.5283
3	-184.215	8.1749	4	0.085	1.4e+07	22.0239	22.1194	22.7164
4	-182.081	4.2693	4	0.371	1.9e+07	22.2312	22.354	23.1216
5	-174.273	15.615	4	0.004	1.5e+07	21.8081	21.9582	22.8963
6	-172.146	4.2534	4	0.373	2.7e+07	22.0163	22.1936	23.3023
7	-155.101	34.091	4	0.000	1.3e+07	20.5668	20.7714	22.0507
8	225.662	761.53	4	0.000	5.4e-11*	-21.2958	-21.0639	-19.614
9	938.391	1425.5	4	0.000	.	-100.266	-100.02	-98.4849
10	1017.67	158.56*	4	0.000	.	-109.074*	-108.829*	-107.294*

Endogenous: expde csr
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-329.266				3.3e+13	36.8073	36.821	36.9063
1	-324.689	9.1534	4	0.057	3.1e+13	36.7433	36.7842	37.0401
2	-324.382	.61441	4	0.961	4.8e+13	37.1536	37.2218	37.6482
3	-322.942	2.8813	4	0.578	6.8e+13	37.438	37.5334	38.1305
4	-320.965	3.9531	4	0.412	9.5e+13	37.6628	37.7856	38.5532
5	-320.332	1.2651	4	0.867	1.7e+14	38.0369	38.187	39.1252
6	-312.753	15.159*	4	0.004	1.6e+14	37.6392	37.8166	38.9253
7	-309.626	6.2544	4	0.181	3.6e+14	37.7362	37.9408	39.2202
8	.	.	4	.	-.019626*	.	.	.
9	887.009	.	4	.	.	-94.5566*	-94.3111*	-92.7759*
10	874.587	-24.845	4	.	.	-93.1763	-92.9308	-91.3956

Endogenous: expde pde
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-304.337				2.1e+12	34.0374	34.051	34.1363
1	-302.908	2.857	4	0.582	2.8e+12	34.3231	34.364	34.6199
2	-297.627	10.562	4	0.032	2.5e+12	34.1808	34.249	34.6754
3	-291.188	12.879	4	0.012	2.0e+12	33.9097	34.0052	34.6022
4	-281.263	19.848	4	0.001	1.2e+12	33.2515	33.3743	34.1419
5	-280.61	1.3069	4	0.860	2.0e+12	33.6233	33.7734	34.7116
6	-278.683	3.8533	4	0.426	3.7e+12	33.8537	34.031	35.1398
7	-264.662	28.043	4	0.000	2.4e+12	32.7402	32.9448	34.2241
8	.	.	4	.	-.001501*	.	.	.
9	847.293	.	4	.	.	-90.1436	-89.8981	-88.3629
10	884.128	73.67*	4	0.000	.	-94.2364*	-93.9909*	-92.4557*

Endogenous: expde ipd
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-297.754				1.0e+12	33.306	33.3196	33.4049
1	-287.326	20.857	4	0.000	4.9e+11	32.5917	32.6327	32.8885
2	-285.958	2.7355	4	0.603	6.8e+11	32.8842	32.9524	33.3789
3	-283.264	5.3886	4	0.250	8.3e+11	33.0293	33.1248	33.7218
4	-280.714	5.0998	4	0.277	1.1e+12	33.1904	33.3132	34.0808
5	-276.202	9.0227	4	0.061	1.3e+12	33.1336	33.2836	34.2218
6	-271.468	9.4692	4	0.050	1.7e+12	33.052	33.2293	34.3381
7	-255.636	31.663*	4	0.000	9.0e+11	31.7374	31.942	33.2213
8	.	.	4	.	-.002347*	.	.	.
9	883.972	.	4	.	.	-94.2191	-93.9736	-92.4384
10	884.397	.849	4	0.932	.	-94.2663*	-94.0208*	-92.4856*

Endogenous: expde ips
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-347.96				2.6e+14	38.8845	38.8981	38.9834
1	-341.842	12.235	4	0.016	2.1e+14	38.6492	38.6901	38.9459
2	-341.101	1.4834	4	0.830	3.1e+14	39.0112	39.0794	39.5058
3	-339.502	3.1983	4	0.525	4.3e+14	39.2779	39.3734	39.9705
4	-336.215	6.5735	4	0.160	5.2e+14	39.3572	39.48	40.2476
5	-332.777	6.8752	4	0.143	6.7e+14	39.4197	39.5697	40.5079
6	-325.902	13.751*	4	0.008	7.0e+14	39.1002	39.2775	40.3863
7	-321.84	8.1236	4	0.087	1.4e+15	39.0933	39.298	40.5773
8	.	.	4	.	-.422138*	.	.	.
9	857.93	.	4	.	.	-91.3256*	-91.0801*	-89.5448*
10	857.908	-.04551	4	.	.	-91.3231	-91.0775	-89.5423

Endogenous: expde opd
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-288.21				3.5e+11	32.2456	32.2592	32.3445
1	-279.017	18.388	4	0.001	2.0e+11	31.6685	31.7094	31.9653
2	-274.612	8.8088	4	0.066	1.9e+11	31.6236	31.6918	32.1182
3	-272.616	3.9925	4	0.407	2.5e+11	31.8462	31.9417	32.5387
4	-271.083	3.0668	4	0.547	3.7e+11	32.1203	32.2431	33.0107
5	-270.916	.33238	4	0.988	7.0e+11	32.5463	32.6963	33.6345
6	-269.132	3.5678	4	0.468	1.3e+12	32.7925	32.9698	34.0786
7	-246.24	45.784	4	0.000	3.2e+11	30.6934	30.898	32.1773
8	.	.	4	.	-5.3e-06*	.	.	.
9	889.926	.	4	.	.	-94.8806	-94.6351	-93.0999
10	900.176	20.501*	4	0.000	.	-96.0196*	-95.7741*	-94.2388*

```
  +---------------------------------------------------------------------------+
   Endogenous:  expde ch
    Exogenous:  _cons

. log close
-------------------------------------------------------------------------------------------------------------------
-----------------------------------------------------------------------------------------------------------------------------------------

. foreach var of varlist alos bur csr pde ipd ips opd ch{
  2. varsoc expde `var' if hospital==2,maxlag(10)
  3. }

   Selection-order criteria
   Sample:  11 - 28                        Number of obs      =       18
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 | -153.365                      107711   17.2627   17.2764   17.3617  |
  |  1 | -147.266  12.198   4  0.016  85821.8   17.0295   17.0704   17.3263  |
  |  2 | -145.224  4.0822   4  0.395   109249   17.2472   17.3154   17.7418  |
  |  3 | -141.238  7.9733   4  0.093   115762   17.2486   17.3441   17.9412  |
  |  4 | -140.005  2.4653   4  0.651   175888   17.5561   17.6789   18.4465  |
  |  5 | -138.592  2.8259   4  0.587   286689   17.8436   17.9936   18.9318  |
  |  6 | -127.107   22.97   4  0.000   179220   17.0119   17.1892    18.298  |
  |  7 | -117.302  19.611   4  0.001   189772   16.3669   16.5715   17.8508  |
  |  8 |  235.356  705.32   4  0.000  1.8e-11* -22.3729   -22.141  -20.6911  |
  |  9 |  1041.94  1613.2*   4  0.000        .  -111.771* -111.526* -109.991* |
  | 10 |  1037.25 -9.3788    4      .        .   -111.25  -111.005   -109.47  |
  +---------------------------------------------------------------------------+
   Endogenous:  expde alos
    Exogenous:  _cons

   Selection-order criteria
   Sample:  11 - 28                        Number of obs      =       18
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 | -191.576                     7.5e+06   21.5084   21.5221   21.6073  |
  |  1 | -181.678  19.795   4  0.001  3.9e+06   20.8532   20.8941   21.1499  |
  |  2 | -179.717  3.9236   4  0.416  5.0e+06   21.0796   21.1478   21.5743  |
  |  3 | -177.106  5.2213   4  0.265  6.2e+06    21.234   21.3295   21.9265  |
  |  4 | -173.707  6.7984   4  0.147  7.4e+06   21.3008   21.4235   22.1911  |
  |  5 | -164.313  18.787   4  0.001  5.0e+06   20.7015   20.8515   21.7897  |
  |  6 | -161.017  6.5926   4  0.159  7.8e+06   20.7796    20.957   22.0657  |
  |  7 |  -116.51  89.013   4  0.000   173792   16.2789   16.4835   17.7629  |
  |  8 |  248.636  730.29   4  0.000  4.2e-12* -23.8485  -23.6166  -22.1667  |
  |  9 |   996.86  1496.4   4  0.000        .  -106.762  -106.517  -104.981  |
  | 10 |  1004.25  14.782*  4  0.005        .  -107.583* -107.338* -105.803* |
  +---------------------------------------------------------------------------+
   Endogenous:  expde bur
    Exogenous:  _cons

   Selection-order criteria
   Sample:  11 - 28                        Number of obs      =       18
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 | -173.497                     1.0e+06   19.4996   19.5133   19.5986  |
  |  1 | -168.836  9.3221   4  0.054   942904   19.4262   19.4671    19.723  |
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
2	-167.576	2.5202	4	0.641	1.3e+06	19.7306	19.7988	20.2253
3	-165.807	3.5377	4	0.472	1.8e+06	19.9785	20.074	20.671
4	-161.668	8.2785	4	0.082	2.0e+06	19.9631	20.0858	20.8534
5	-144.2	34.935	4	0.000	534591	18.4667	18.6167	19.5549
6	-138.682	11.036*	4	0.026	648545	18.298	18.4754	19.5841
7	-137.577	2.211	4	0.697	1.8e+06	18.6196	18.8243	20.1036
8	.	.	4	.	-7.0e-11*	.	.	.
9	997.728	.	4	.	.	-106.859*	-106.613*	-105.078*
10	982.487	-30.483	4	.	.	-105.165	-104.92	-103.384

Endogenous: expde csr
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-328.126				2.9e+13	36.6807	36.6944	36.7796
1	-315.105	26.043	4	0.000	1.1e+13	35.6783	35.7192	35.9751
2	-313.064	4.0808	4	0.395	1.4e+13	35.896	35.9643	36.3907
3	-307.21	11.709	4	0.020	1.2e+13	35.69	35.7855	36.3825
4	-303.517	7.386	4	0.117	1.4e+13	35.7241	35.8469	36.6145
5	-295.363	16.309	4	0.003	1.1e+13	35.2625	35.4126	36.3507
6	-288.54	13.645	4	0.009	1.1e+13	34.9489	35.1263	36.235
7	-279.801	17.48*	4	0.002	1.3e+13	34.4223	34.6269	35.9062
8	.	.	4	.	-.001749*	.	.	.
9	858.043	.	4	.	.	-91.3381	-91.0926	-89.5573
10	859.272	2.4574	4	0.652	.	-91.4746*	-91.2291*	-89.6939*

Endogenous: expde pde
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-321.157				1.3e+13	35.9063	35.9199	36.0052
1	-311.383	19.548	4	0.001	7.1e+12	35.2647	35.3057	35.5615
2	-309.238	4.2892	4	0.368	9.0e+12	35.4709	35.5391	35.9656
3	-306.996	4.4846	4	0.344	1.2e+13	35.6662	35.7617	36.3587
4	-303.223	7.5452	4	0.110	1.3e+13	35.6915	35.8142	36.5818
5	-294.147	18.152	4	0.001	9.2e+12	35.1275	35.2775	36.2157
6	-290.474	7.3466	4	0.119	1.4e+13	35.1638	35.3411	36.4499
7	-246.244	88.46	4	0.000	3.2e+11	30.6938	30.8984	32.1777
8	.	.	4	.	0*	.	.	.
9	881.282	.	4	.	.	-93.9202	-93.6747	-92.1395
10	915.748	68.932*	4	0.000	.	-97.7498*	-97.5042*	-95.969*

Endogenous: expde ipd
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-284.998				2.4e+11	31.8887	31.9023	31.9876

```
| 1 | -283.319 3.3575  4 0.500 3.2e+11  32.1466  32.1875  32.4434 |
| 2 | -280.451 5.7365  4 0.220 3.7e+11  32.2723  32.3405  32.767 |
| 3 | -277.653 5.5957  4 0.231 4.4e+11  32.4059  32.5014  33.0984 |
| 4 | -273.55 8.2064  4 0.084 4.9e+11  32.3944  32.5172  33.2848 |
| 5 | -270.685 5.7292  4 0.220 6.8e+11  32.5206  32.6706  33.6088 |
| 6 | -266.68 8.0111  4 0.091 9.7e+11  32.52  32.6973  33.8061 |
| 7 | -234.358 64.644  4 0.000 8.4e+10  29.3731  29.5777  30.857 |
| 8 | 109.937 688.59  4 0.000 .000021* -8.43745 -8.20555 -6.75563 |
| 9 | 904.033 1588.2*  4 0.000     . -96.4482* -96.2026* -94.6674* |
| 10 | 881.061 -45.945  4    .     . -93.8956 -93.6501 -92.1149 |
+---------------------------------------------------------------------------+
 Endogenous:  expde ips
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                      Number of obs     =     18
+---------------------------------------------------------------------------+
|lag |   LL     LR     df   p     FPE     AIC     HQIC     SBIC   |
|----+----------------------------------------------------------------------|
| 0 | -327.804                2.8e+13  36.6449  36.6586  36.7438 |
| 1 | -316.413 22.782  4 0.000 1.2e+13  35.8237  35.8646  36.1205 |
| 2 | -310.745 11.337  4 0.023 1.1e+13  35.6383  35.7065  36.133 |
| 3 | -308.671 4.1465  4 0.387 1.4e+13  35.8524  35.9479  36.5449 |
| 4 | -304.127 9.0892  4 0.059 1.5e+13  35.7919  35.9146  36.6822 |
| 5 | -299.492 9.2697  4 0.055 1.7e+13  35.7213  35.8714  36.8096 |
| 6 | -297.764 3.4552  4 0.485 3.1e+13  35.9738  36.1512  37.2599 |
| 7 | -263.106 69.316  4 0.000 2.1e+12  32.5674  32.772  34.0513 |
| 8 | 122.422 771.06  4 0.000 5.2e-06* -9.8247  -9.5928 -8.14289 |
| 9 | 830.822 1416.8*  4 0.000     . -88.3136* -88.0681* -86.5328* |
| 10 | 821.624 -18.397  4    .     . -87.2916  -87.046 -85.5108 |
+---------------------------------------------------------------------------+
 Endogenous:  expde opd
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                      Number of obs     =     18
+---------------------------------------------------------------------------+
|lag |   LL     LR     df   p     FPE     AIC     HQIC     SBIC   |
|----+----------------------------------------------------------------------|
| 0 | -292.755                5.7e+11  32.7506  32.7642  32.8495 |
| 1 | -286.569 12.372  4 0.015 4.5e+11  32.5077  32.5486  32.8045 |
| 2 | -286.031 1.0773  4 0.898 6.8e+11  32.8923  32.9605  33.387 |
| 3 | -280.092 11.877  4 0.018 5.8e+11  32.6769  32.7724  33.3694 |
| 4 | -273.769 12.647  4 0.013 5.0e+11  32.4188  32.5415  33.3091 |
| 5 | -272.209 3.1202  4 0.538 8.0e+11  32.6899  32.8399  33.7781 |
| 6 | -258.221 27.977  4 0.000 3.8e+11  31.5801  31.7574  32.8662 |
| 7 | -243.058 30.325  4 0.000 2.2e+11  30.3398  30.5444  31.8237 |
| 8 |      .      .   4    . -1.9e-06*      .       .       . |
| 9 | 861.813      .   4    .      .  -91.757  -91.5115  -89.9763 |
| 10 | 885.763 47.899*  4 0.000     .  -94.4181* -94.1725* -92.6373* |
+---------------------------------------------------------------------------+
 Endogenous:  expde ch
  Exogenous:  _cons

. log close
------------------------------------------------------------------------------------------------------------------------------------------------------
---------------------------------------------------------------------------------------------------------------------------

. foreach var of varlist alos bur csr pde ipd ips opd ch{
```

```
2. varsoc expde `var' if hospital==3,maxlag(10)
3. }

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 | -172.239                      877134   19.3599   19.3736   19.4589  |
|  1 | -163.034  18.411    4  0.001   494872   18.7815   18.8225   19.0783  |
|  2 |  -162.44  1.1872    4  0.880   739880     19.16   19.2282   19.6547  |
|  3 | -159.293  6.2946    4  0.178   860627   19.2548   19.3503   19.9473  |
|  4 | -156.337  5.9117    4  0.206  1.1e+06   19.3708   19.4936   20.2612  |
|  5 | -146.682   19.31    4  0.001   704340   18.7424   18.8925   19.8307  |
|  6 | -143.216  6.9327    4  0.139  1.1e+06   18.8017   18.9791   20.0878  |
|  7 | -126.132  34.168    4  0.000   506188    17.348   17.5526   18.8319  |
|  8 |        .       .    4      . -6.1e-09*        .         .         .  |
|  9 |   1006.4       .    4      .        .  -107.822  -107.576  -106.041  |
| 10 |  1028.15  43.502*   4  0.000        .  -110.239* -109.993* -108.458* |
+---------------------------------------------------------------------------+
 Endogenous:  expde alos
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 | -196.172                     1.3e+07   22.0192   22.0328   22.1181  |
|  1 | -194.838  2.6685    4  0.615  1.7e+07   22.3154   22.3563   22.6121  |
|  2 | -192.143  5.3896    4  0.250  2.0e+07   22.4604   22.5286    22.955  |
|  3 |  -191.37  1.5478    4  0.818  3.0e+07   22.8188   22.9143   23.5113  |
|  4 | -183.225  16.289    4  0.003  2.1e+07   22.3583   22.4811   23.2487  |
|  5 | -178.361  9.7272    4  0.045  2.4e+07   22.2624   22.4124   23.3506  |
|  6 |  -169.37  17.983    4  0.001  2.0e+07   21.7078   21.8851   22.9938  |
|  7 | -163.729  11.281    4  0.024  3.3e+07   21.5255   21.7301   23.0094  |
|  8 |  180.738  688.93    4  0.000  8.0e-09* -16.3042  -16.0723  -14.6224  |
|  9 |  976.748    1592    4  0.000        .  -104.528  -104.282  -102.747  |
| 10 |  982.606  11.716*   4  0.020        .  -105.178* -104.933* -103.398* |
+---------------------------------------------------------------------------+
 Endogenous:  expde bur
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 |  -186.78                     4.4e+06   20.9756   20.9892   21.0745  |
|  1 | -186.245  1.0708    4  0.899  6.5e+06   21.3605   21.4014   21.6573  |
|  2 | -178.098  16.294    4  0.003  4.2e+06   20.8997   20.9679   21.3944  |
|  3 | -170.945  14.304    4  0.006  3.1e+06   20.5495    20.645    21.242  |
|  4 | -165.312  11.267    4  0.024  2.9e+06    20.368   20.4908   21.2584  |
|  5 | -162.158  6.3077    4  0.177  3.9e+06    20.462   20.6121   21.5502  |
|  6 | -153.508    17.3    4  0.002  3.4e+06   19.9453   20.1226   21.2314  |
|  7 | -144.425  18.166    4  0.001  3.9e+06   19.3806   19.5852   20.8645  |
|  8 |  237.619  764.09    4  0.000  1.4e-11* -22.6243  -22.3924  -20.9425  |
|  9 |   992.98  1510.7*   4  0.000        .  -106.331* -106.086*  -104.55* |
| 10 |  986.461 -13.039    4      .        .  -105.607  -105.361  -103.826  |
```

Endogenous: expde csr
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-337.665				8.4e+13	37.7405	37.7542	37.8395
1	-336.193	2.9427	4	0.567	1.1e+14	38.0215	38.0624	38.3183
2	-333.533	5.3209	4	0.256	1.3e+14	38.1703	38.2385	38.665
3	-332.847	1.3719	4	0.849	2.0e+14	38.5386	38.634	39.2311
4	-327.222	11.249	4	0.024	1.9e+14	38.358	38.4808	39.2484
5	-318.051	18.343	4	0.001	1.3e+14	37.7834	37.9335	38.8717
6	-310.113	15.876	4	0.003	1.2e+14	37.3459	37.5232	38.632
7	-308.367	3.4921	4	0.479	3.1e+14	37.5963	37.8009	39.0803
8	39.2497	695.23	4	0.000	.053604*	-.583302	-.351402	1.09851
9	829.036	1579.6	4	0.000	.	-88.1152	-87.8696	-86.3344
10	836.203	14.334*	4	0.006	.	-88.9115*	-88.6659*	-87.1307*

Endogenous: expde pde
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-329.683				3.5e+13	36.8536	36.8673	36.9526
1	-329.037	1.2917	4	0.863	5.1e+13	37.2263	37.2672	37.5231
2	-327.039	3.9961	4	0.407	6.5e+13	37.4488	37.517	37.9434
3	-326.345	1.3875	4	0.846	9.9e+13	37.8161	37.9116	38.5086
4	-321.883	8.9235	4	0.063	1.1e+14	37.7648	37.8876	38.6552
5	-319.061	5.6454	4	0.227	1.5e+14	37.8956	38.0457	38.9838
6	-307.525	23.071	4	0.000	9.1e+13	37.0583	37.2357	38.3444
7	-304.195	6.6601	4	0.155	2.0e+14	37.1328	37.3374	38.6167
8	.	.	4	.	0*	.	.	.
9	827.182	.	4	.	.	-87.9092	-87.6636	-86.1284
10	838.082	21.8*	4	0.000	.	-89.1202*	-88.8747*	-87.3395*

Endogenous: expde ipd
Exogenous: _cons

Selection-order criteria
Sample: 11 - 28 Number of obs = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-323.325				1.7e+13	36.1473	36.1609	36.2462
1	-315.128	16.394	4	0.003	1.1e+13	35.6809	35.7218	35.9777
2	-315.007	.24302	4	0.993	1.7e+13	36.1119	36.1801	36.6065
3	-313.928	2.1583	4	0.707	2.5e+13	36.4364	36.5319	37.1289
4	-310.945	5.9661	4	0.202	3.1e+13	36.5494	36.6722	37.4398
5	-303.617	14.655	4	0.005	2.6e+13	36.1797	36.3297	37.2679
6	-292.862	21.511	4	0.000	1.8e+13	35.4291	35.6064	36.7152
7	-288.931	7.8616	4	0.097	3.6e+13	35.4368	35.6414	36.9207
8	.	.	4	.	0*	.	.	.
9	875.818	.	4	.	.	-93.3132	-93.0676	-91.5324

```
| 10 |  880.624  9.6109*   4  0.048       .  -93.8471* -93.6016* -92.0664* |
+---------------------------------------------------------------------------+
 Endogenous:  expde ips
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 | -340.927                      1.2e+14   38.103   38.1166   38.2019  |
|  1 | -332.812  16.23    4  0.003  7.7e+13   37.6458   37.6867   37.9426  |
|  2 |  -332.27  1.0847   4  0.897  1.2e+14    38.03   38.0982   38.5246  |
|  3 | -332.053  .43356   4  0.980  1.9e+14   38.4503   38.5458   39.1428  |
|  4 | -328.957  6.1908   4  0.185  2.3e+14   38.5508   38.6736   39.4412  |
|  5 | -325.249  7.4171   4  0.115  2.9e+14   38.5832   38.7333   39.6714  |
|  6 | -322.985  4.5271   4  0.339  5.1e+14   38.7761   38.9535   40.0622  |
|  7 |  -312.12  21.731   4  0.000  4.8e+14   38.0133   38.2179   39.4973  |
|  8 |  7.07426  638.39   4  0.000  1.91346*  2.99175   3.22365   4.67356  |
|  9 |  840.398  1666.6*  4  0.000       .  -89.3775   -89.132  -87.5968  |
| 10 |  844.341   7.886   4  0.096       .  -89.8156* -89.5701* -88.0349* |
+---------------------------------------------------------------------------+
 Endogenous:  expde opd
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 |   -321.9                      1.5e+13   35.9889   36.0025   36.0878  |
|  1 | -317.555  8.6899   4  0.069  1.4e+13   35.9505   35.9915   36.2473  |
|  2 | -316.703  1.7034   4  0.790  2.1e+13   36.3003   36.3685    36.795  |
|  3 | -316.075  1.2556   4  0.869  3.2e+13    36.675   36.7705   37.3675  |
|  4 | -313.221  5.7077   4  0.222  4.0e+13   36.8024   36.9252   37.6928  |
|  5 | -309.003  8.4373   4  0.077  4.8e+13   36.7781   36.9281   37.8663  |
|  6 | -304.619  8.7675   4  0.067  6.6e+13   36.7354   36.9128   38.0215  |
|  7 | -289.168  30.901*  4  0.000  3.7e+13   35.4632   35.6678   36.9471  |
|  8 |        .       .   4      .       0*        .         .         .  |
|  9 |   871.16       .   4      .       .  -92.7955*   -92.55* -91.0148* |
| 10 |   851.02 -40.279   4      .       .  -90.5578  -90.3122   -88.777  |
+---------------------------------------------------------------------------+
 Endogenous:  expde ch
  Exogenous:  _cons

. log close
----------------------------------------------------------------------------------------------------------
----------------------------------------------------------------------------------------------------------

. foreach var of varlist alos bur csr pde ipd ips opd ch{
  2. varsoc expde `var' if hospital==4,maxlag(10)
  3. }

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 | -180.318                      2.2e+06   20.2576   20.2712   20.3565  |
```

```
|  1 | -172.353  15.931   4  0.003  1.4e+06   19.817   19.8579   20.1137  |
|  2 | -171.653  1.3993   4  0.844  2.1e+06   20.1837   20.2519   20.6783  |
|  3 | -169.032  5.2419   4  0.263  2.5e+06   20.3369   20.4324   21.0294  |
|  4 | -150.235  37.594   4  0.000   548113   18.6928   18.8155   19.5831  |
|  5 |  -144.82  10.829   4  0.029   572734   18.5356   18.6857   19.6238  |
|  6 | -142.939  3.7625   4  0.439  1.0e+06   18.771   18.9484   20.0571  |
|  7 | -141.143  3.5932   4  0.464  2.7e+06   19.0158   19.2205   20.4998  |
|  8 |        .        .   4        .  -1.5e-10*        .        .        .  |
|  9 |  974.024        .   4        .        .  -104.225  -103.979  -102.444  |
| 10 |  999.685  51.322*  4  0.000        .  -107.076*  -106.831*  -105.295*  |
+---------------------------------------------------------------------------+
 Endogenous:  expde alos
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 |  -194.58                      1.0e+07   21.8422   21.8558   21.9411  |
|  1 | -191.646  5.8678   4  0.209  1.2e+07   21.9606   22.0016   22.2574  |
|  2 | -186.063  11.166   4  0.025  1.0e+07   21.7848    21.853   22.2794  |
|  3 | -184.543  3.0398   4  0.551  1.4e+07   22.0603   22.1558   22.7529  |
|  4 | -176.063  16.961   4  0.002  9.7e+06   21.5625   21.6853   22.4529  |
|  5 | -171.347  9.4326   4  0.051  1.1e+07   21.4829    21.633   22.5712  |
|  6 | -156.466   29.76   4  0.000  4.7e+06    20.274   20.4514   21.5601  |
|  7 | -140.023  32.886   4  0.000  2.4e+06   18.8915   19.0961   20.3754  |
|  8 |        .        .   4        .        0*        .        .        .  |
|  9 |  959.437        .   4        .        .  -102.604  -102.359  -100.823  |
| 10 |  969.819  20.764*  4  0.000        .  -103.758*  -103.512*  -101.977*  |
+---------------------------------------------------------------------------+
 Endogenous:  expde bur
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 | -185.193                      3.7e+06   20.7992   20.8128   20.8981  |
|  1 | -180.605  9.1751   4  0.057  3.5e+06   20.7339   20.7748   21.0307  |
|  2 |  -179.59  2.0292   4  0.730  5.0e+06   21.0656   21.1338   21.5603  |
|  3 | -174.761  9.6596   4  0.047  4.8e+06   20.9734   21.0689   21.6659  |
|  4 | -167.392  14.737   4  0.005  3.7e+06   20.5991   20.7219   21.4895  |
|  5 | -154.575  25.635   4  0.000  1.7e+06   19.6194   19.7695   20.7077  |
|  6 | -146.993  15.163   4  0.004  1.6e+06   19.2215   19.3988   20.5076  |
|  7 | -100.341  93.305   4  0.000  28826.1   14.4823    14.687   15.9663  |
|  8 |  236.228  673.14   4  0.000  1.7e-11*  -22.4698  -22.2379  -20.7879  |
|  9 |  977.774  1483.1   4  0.000        .  -104.642  -104.396  -102.861  |
| 10 |  996.901  38.255*  4  0.000        .  -106.767*  -106.521*  -104.986*  |
+---------------------------------------------------------------------------+
 Endogenous:  expde csr
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                        Number of obs      =       18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
```

```
|  0 | -350.145                3.4e+14   39.1272   39.1408   39.2261  |
|  1 | -341.154  17.981    4  0.001  1.9e+14   38.5727   38.6136   38.8695  |
|  2 | -339.519  3.2712    4  0.514  2.6e+14   38.8354   38.9036   39.3301  |
|  3 | -338.716  1.6057    4  0.808  3.9e+14   39.1907   39.2861   39.8832  |
|  4 | -327.577  22.278    4  0.000  2.0e+14   38.3974   38.5202   39.2878  |
|  5 | -324.738  5.6769    4  0.225  2.8e+14   38.5265   38.6765   39.6147  |
|  6 | -321.459  6.5596    4  0.161  4.3e+14   38.6065   38.7838   39.8926  |
|  7 | -319.763  3.3914    4  0.495  1.1e+15   38.8625   39.0672   40.3465  |
|  8 |   .38758   640.3    4  0.000   4.0224*  3.73471   3.96661   5.41653  |
|  9 |  824.996  1649.2*   4  0.000        .  -87.6663* -87.4207* -85.8855* |
| 10 |   817.91 -14.173    4      .        .  -86.8789  -86.6333  -85.0981  |
+---------------------------------------------------------------------------+
 Endogenous:  expde pde
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                          Number of obs      =        18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 | -328.794                3.1e+13   36.7549   36.7685   36.8538  |
|  1 | -323.398  10.792    4  0.029  2.7e+13   36.5998   36.6407   36.8966  |
|  2 | -323.116  .56303    4  0.967  4.2e+13   37.0129   37.0811   37.5076  |
|  3 | -320.758  4.7159    4  0.318  5.3e+13   37.1954   37.2909   37.8879  |
|  4 | -313.727  14.064    4  0.007  4.2e+13   36.8585   36.9813   37.7489  |
|  5 |  -306.65  14.153    4  0.007  3.7e+13   36.5167   36.6667   37.6049  |
|  6 |  -297.62  18.061    4  0.001  3.0e+13   35.9577   36.1351   37.2438  |
|  7 | -278.772  37.695    4  0.000  1.2e+13    34.308   34.5126   35.7919  |
|  8 |        .       .    4      . -.003855*        .         .         .  |
|  9 |  797.278       .    4      .        .  -84.5864  -84.3409  -82.8057  |
| 10 |  860.749  126.94*   4  0.000        .  -91.6388* -91.3933* -89.8581* |
+---------------------------------------------------------------------------+
 Endogenous:  expde ipd
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                          Number of obs      =        18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 | -327.348                2.7e+13   36.5942   36.6078   36.6931  |
|  1 | -318.544  17.607    4  0.001  1.6e+13   36.0605   36.1014   36.3573  |
|  2 | -318.134  .82074    4  0.936  2.4e+13   36.4593   36.5275    36.954  |
|  3 | -315.589  5.0901    4  0.278  3.0e+13    36.621   36.7165   37.3135  |
|  4 | -296.138  38.901    4  0.000  6.0e+12   34.9042    35.027   35.7946  |
|  5 | -293.266  5.7452    4  0.219  8.3e+12   35.0295   35.1796   36.1177  |
|  6 | -291.405  3.7213    4  0.445  1.5e+13   35.2672   35.4446   36.5533  |
|  7 | -283.758  15.294    4  0.004  2.0e+13    34.862   35.0666   36.3459  |
|  8 |  124.241     816    4  0.000  4.2e-06* -10.0268  -9.79492    -8.345  |
|  9 |  869.416  1490.3    4  0.000        .  -92.6017  -92.3562   -90.821  |
| 10 |  879.351  19.871*   4  0.001        .  -93.7057* -93.4601* -91.9249* |
+---------------------------------------------------------------------------+
 Endogenous:  expde ips
  Exogenous:  _cons

 Selection-order criteria
 Sample:  11 - 28                          Number of obs      =        18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
```

```
|----+---------------------------------------------------------------------|
|  0 | -368.484                  2.6e+15   41.1649   41.1786   41.2639  |
|  1 | -360.514  15.941   4  0.003  1.7e+15   40.7238   40.7647   41.0206  |
|  2 | -358.069  4.8895   4  0.299  2.0e+15   40.8966   40.9648   41.3912  |
|  3 | -356.988  2.1629   4  0.706  3.0e+15   41.2209   41.3164   41.9134  |
|  4 | -347.194  19.587   4  0.001  1.8e+15   40.5771   40.6999   41.4675  |
|  5 |  -345.39  3.6096   4  0.461  2.7e+15   40.8211   40.9711   41.9093  |
|  6 | -343.311  4.1577   4  0.385  4.9e+15   41.0345   41.2119   42.3206  |
|  7 | -342.334   1.954   4  0.744  1.4e+16   41.3704    41.575   42.8544  |
|  8 |  18.9314  722.53   4  0.000  .512456*  1.67429   1.90619   3.35611  |
|  9 |  712.556  1387.2   4  0.000        .  -75.1729  -74.9273  -73.3921  |
| 10 |  816.461  207.81*  4  0.000        .  -86.7179* -86.4724* -84.9371* |
+---------------------------------------------------------------------------+
  Endogenous:  expde opd
   Exogenous:  _cons

  Selection-order criteria
  Sample:  11 - 28                          Number of obs      =        18
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+---------------------------------------------------------------------|
|  0 | -319.006                  1.1e+13   35.6673   35.6809   35.7662  |
|  1 |  -309.54   18.93   4  0.001  5.8e+12     35.06    35.101   35.3568  |
|  2 | -309.369  .34292   4  0.987  9.1e+12   35.4854   35.5536   35.9801  |
|  3 | -308.828  1.0812   4  0.897  1.4e+13   35.8698   35.9653   36.5623  |
|  4 |  -302.41  12.837   4  0.012  1.2e+13   35.6011   35.7239   36.4915  |
|  5 | -301.352  2.1161   4  0.714  2.0e+13    35.928    36.078   37.0162  |
|  6 | -301.021  .66271   4  0.956  4.4e+13   36.3356    36.513   37.6217  |
|  7 | -287.681  26.678   4  0.000  3.2e+13   35.2979   35.5025   36.7819  |
|  8 |  47.6629  670.69   4  0.000  .021048*  -1.5181   -1.2862   .163714  |
|  9 |  867.931  1640.5   4  0.000        .  -92.4368  -92.1913  -90.6561  |
| 10 |   878.26  20.658*  4  0.000        .  -93.5845* -93.3389* -91.8037* |
+---------------------------------------------------------------------------+
  Endogenous:  expde ch
   Exogenous:  _cons

. log close
```

AUTOCORRELATION

```
. ***Hospital One***
. corrgram expde if hospital==1, lag(10)

                                          -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1        0.4938   0.5062   7.5854  0.0059          |---               |----
2        0.5001   0.3953   15.665  0.0004          |----              |---
3        0.4518   0.3397   22.523  0.0001          |---               |--
4        0.3523   0.2558   26.868  0.0000          |--                |--
5        0.2116   0.0358   28.503  0.0000          |-                 |
6        0.2295   0.2089   30.514  0.0000          |-                 |-
7        0.2170   0.5884   32.398  0.0000          |-                 |----
8        0.0651   0.0737   32.576  0.0001          |                  |
9        0.1699   0.4656   33.853  0.0001          |-                 |---
10       0.0534   0.6047   33.986  0.0002          |                  |----

. corrgram alos if hospital==1, lag(10)
```

```
                              -1       0       1 -1       0       1
 LAG      AC       PAC     Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.7581   0.9760    17.88  0.0000         |------           |-------
2       0.5611  -0.0204   28.052  0.0000         |----             |
3       0.3709   0.3290   32.673  0.0000         |--               |--
4       0.2003   0.0802   34.078  0.0000         |-                |
5       0.1314   0.2153   34.708  0.0000         |-                |-
6       0.0660  -0.1300   34.874  0.0000         |                -|
7       0.0058   0.3733   34.875  0.0000         |                 |--
8      -0.0793   0.0509    35.14  0.0000         |                 |
9      -0.0632   0.3125   35.316  0.0001         |                 |--
10      -0.0104  -0.1123   35.321  0.0001         |                 |

. corrgram bur if hospital==1, lag(10)

                              -1       0       1 -1       0       1
 LAG      AC       PAC     Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      -0.0404  -0.0403   .05078  0.8217         |                 |
2      -0.3441  -0.3553    3.876  0.1440       --|               --|
3      -0.0521  -0.1397   3.9672  0.2650         |                -|
4       0.1495   0.1088   4.7497  0.3140         |-                |
5       0.0358   0.0190   4.7966  0.4412         |                 |
6      -0.1221  -0.0885   5.3656  0.4978         |                 |
7       0.0060   0.0814   5.3671  0.6153         |                 |
8       0.1441   0.0429   6.2398  0.6204         |-                |
9       0.0413   0.0899    6.315  0.7080         |                 |
10      -0.1516  -0.0673   7.3874  0.6884        -|                 |

. corrgram csr if hospital==1, lag(10)

                              -1       0       1 -1       0       1
 LAG      AC       PAC     Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.0114   0.0114   .00405  0.9493         |                 |
2      -0.1934  -0.1941   1.2128  0.5453        -|                -|
3       0.0234   0.0291   1.2312  0.7455         |                 |
4      -0.1390  -0.1902   1.9079  0.7527        -|                -|
5      -0.1610  -0.1771   2.8545  0.7224        -|                -|
6       0.0290  -0.0292   2.8866  0.8229         |                 |
7      -0.0648  -0.1441   3.0546  0.8799         |                -|
8      -0.0405  -0.1193   3.1235  0.9264         |                 |
9       0.0615  -0.0447   3.2905  0.9517         |                 |
10       0.0453   0.0380   3.3863  0.9708         |                 |

. corrgram pde if hospital==1, lag(10)

                              -1       0       1 -1       0       1
 LAG      AC       PAC     Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      -0.0385  -0.0386   .04613  0.8299         |                 |
2      -0.0223  -0.0242   .06218  0.9694         |                 |
3      -0.0191  -0.0216   .07441  0.9947         |                 |
4      -0.0556  -0.0599   .18257  0.9961         |                 |
5      -0.0266  -0.0359   .20836  0.9990         |                 |
6      -0.0079  -0.0191   .21076  0.9998         |                 |
7      -0.0315  -0.0445   .25046  0.9999         |                 |
8      -0.0136   0.0034   .25828  1.0000         |                 |
9      -0.0002   0.0195   .25828  1.0000         |                 |
10      -0.0249  -0.0141   .28725  1.0000         |                 |

. corrgram ipd if hospital==1, lag(10)

                              -1       0       1 -1       0       1
 LAG      AC       PAC     Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.0525   0.0525    .0857  0.7697         |                 |
```

```
2     -0.2388  -0.2451   1.9277  0.3814      -|           -|
3     -0.0648  -0.0517   2.0689  0.5582       |            |
4      0.0561   0.0410   2.1792  0.7028       |            |
5     -0.0645  -0.0854    2.331  0.8017       |            |
6     -0.2038  -0.1650   3.9167  0.6879      -|           -|
7     -0.0202   0.0394    3.933  0.7875       |            |
8      0.1204   0.0332    4.542  0.8052       |            |
9     -0.0049  -0.0184    4.543  0.8722       |            |
10    -0.2042  -0.1942   6.4897  0.7726      -|           -|

. corrgram ips if hospital==1, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.4726   0.5492   6.9491  0.0084       |---         |----
2      0.2812   0.1577   9.5038  0.0086       |--          |-
3      0.1833   0.1461   10.633  0.0139       |-           |-
4      0.1765   0.1493   11.724  0.0195       |-           |-
5      0.1426   0.1323   12.467  0.0289       |-           |-
6      0.0568  -0.0219    12.59  0.0500       |            |
7     -0.0091   0.0531   12.594  0.0826       |            |
8     -0.0138   0.1895   12.602  0.1263       |            |-
9      0.0566   0.2668   12.743  0.1746       |            |--
10     0.0104  -0.0738   12.748  0.2381       |            |

. corrgram opd if hospital==1, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.5397   0.5550   9.0616  0.0026       |----        |----
2      0.2609   0.0074   11.261  0.0036       |--          |
3      0.2589   0.2261   13.514  0.0036       |--          |-
4      0.2482   0.0929   15.669  0.0035       |-           |
5      0.2313   0.1739   17.623  0.0035       |-           |-
6      0.0824  -0.0898   17.882  0.0065       |            |
7     -0.0645  -0.0321   18.048  0.0118       |            |
8     -0.1528  -0.1596   19.028  0.0147      -|           -|
9      0.1332   0.5315   19.813  0.0191       |-           |----
10     0.1092  -0.0533    20.37  0.0259       |            |

. corrgram ch if hospital==1, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.6193   0.6361   11.931  0.0006       |----        |-----
2      0.5104   0.2109   20.347  0.0000       |----        |-
3      0.3774   0.0334   25.133  0.0000       |---         |
4      0.1403  -0.2934   25.822  0.0000       |-         --|
5      0.0974   0.1256   26.169  0.0001       |            |-
6     -0.0347  -0.1944   26.215  0.0002       |           -|
7     -0.2662  -0.3825    29.05  0.0001     --|         ---|
8     -0.2723   0.2837   32.163  0.0001     --|            |--
9     -0.3931  -0.2388   38.993  0.0000    ---|           -|
10    -0.4422  -0.1872   48.117  0.0000    ---|           -|
```

```
. ***Hospital Two***
. corrgram expde if hospital==2, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.3621   0.3911   4.0785  0.0434       |--          |---
2      0.4225   0.4165   9.8456  0.0073       |---         |---
3      0.3572   0.3486   14.132  0.0027       |--          |--
4      0.2624   0.2692   16.543  0.0024       |--          |--
5      0.1769   0.1433   17.686  0.0034       |-           |-
6     -0.0431  -0.2764   17.757  0.0069       |          --|
7      0.0259   0.0258   17.784  0.0130       |            |
8      0.0640   0.4422   17.956  0.0216       |            |---
```

```
9      0.0477   1.2468   18.056  0.0345         |               |--------
10     -0.0992  -0.0465   18.516  0.0469         |               |

. corrgram alos if hospital==2, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.4063   0.4219   5.1355  0.0234         |---           |---
2      0.2096   0.0578   6.5545  0.0377         |-             |
3      0.0214  -0.0214   6.5698  0.0869         |              |
4      0.0667   0.1658   6.7257  0.1511         |              |-
5      0.1510   0.2096   7.5579  0.1823         |-             |-
6      0.0474  -0.0383   7.6437  0.2654         |              |
7      0.2242   0.4605   9.6552  0.2090         |-             |---
8      0.1440   0.3631   10.526  0.2300         |-             |--
9      0.0461   0.0920    10.62  0.3027         |              |
10     -0.0823   0.1903   10.936  0.3625         |              |-

. corrgram bur if hospital==2, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.5681   0.5932   10.039  0.0015         |----          |----
2      0.2648  -0.0801   12.304  0.0021         |--            |
3      0.2547   0.3228   14.484  0.0023         |--            |--
4      0.2358   0.1912   16.429  0.0025         |-             |-
5      0.2025   0.1629   17.927  0.0030         |-             |-
6      0.2474   0.3160   20.264  0.0025         |-             |--
7      0.1906   0.2043   21.718  0.0028         |-             |-
8      0.0983   0.2947   22.123  0.0047         |              |--
9      0.0664   0.2159   22.318  0.0079         |              |-
10     -0.0041   0.0803   22.319  0.0136         |              |

. corrgram csr if hospital==2, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.6878   0.7089   14.716  0.0001         |-----         |-----
2      0.5145   0.1381   23.269  0.0000         |----          |-
3      0.2376  -0.0750   25.165  0.0000         |-             |
4      0.1017  -0.0020   25.527  0.0000         |              |
5      0.0197   0.1321   25.541  0.0001         |              |-
6     -0.0249   0.1293   25.565  0.0003         |              |-
7      0.0135   0.1514   25.572  0.0006         |              |-
8      0.0166  -0.0260   25.583  0.0012         |              |
9     -0.0425  -0.1279   25.663  0.0023         |             -|
10     -0.0643   0.3775   25.856  0.0039         |              |---

. corrgram pde if hospital==2, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.6649   0.6989   13.753  0.0002         |-----         |-----
2      0.4223  -0.0278   19.516  0.0001         |---           |
3      0.4055   0.4045    25.04  0.0000         |---           |---
4      0.3465   0.1774   29.241  0.0000         |--            |-
5      0.2876   0.1784   32.261  0.0000         |--            |-
6      0.3065   0.3280   35.848  0.0000         |--            |--
7      0.1978   0.0559   37.413  0.0000         |-             |
8      0.0877   0.2397   37.736  0.0000         |              |-
9      0.0704  -0.0030   37.955  0.0000         |              |
10      0.0007  -0.0340   37.955  0.0000         |              |

. corrgram ipd if hospital==2, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.5719   0.5965   10.175  0.0014         |----          |----
```

```
2       0.2727  -0.0746   12.578  0.0019        |--             |
3       0.2483   0.2937   14.648  0.0021        |-              |--
4       0.2347   0.2028   16.577  0.0023        |-              |-
5       0.1957   0.1369   17.975  0.0030        |-              |-
6       0.2525   0.3393   20.409  0.0023        |--             |--
7       0.1853   0.1758   21.782  0.0028        |-              |-
8       0.1029   0.3189   22.226  0.0045        |               |--
9       0.0586   0.2012   22.378  0.0078        |               |-
10     -0.0031   0.1125   22.378  0.0133        |               |

. corrgram ips if hospital==2, lag(10)

                              -1      0      1 -1      0      1
 LAG      AC      PAC     Q    Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.2694   0.2713   2.2571  0.1330        |--             |--
2      -0.1836  -0.2807    3.346  0.1877       -|             --|
3      -0.2141  -0.1006    4.886  0.1803       -|               |
4       0.0166   0.0713   4.8957  0.2982        |               |
5       0.1175   0.0601   5.3995  0.3691        |               |
6       0.1759   0.1846   6.5808  0.3614        |-              |-
7      -0.0741  -0.1557   6.8006  0.4499        |              -|
8      -0.0532   0.2019   6.9194  0.5454        |               |-
9       0.1019   0.1206   7.3786  0.5978        |               |
10      0.1392   0.1316   8.2828  0.6012        |-              |-

. corrgram opd if hospital==2, lag(10)

                              -1      0      1 -1      0      1
 LAG      AC      PAC     Q    Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.7915   0.8303   19.493  0.0000        |------         |------
2       0.7196   0.2874   36.224  0.0000        |-----          |--
3       0.6555   0.2026   50.659  0.0000        |-----          |-
4       0.5601   0.1631    61.64  0.0000        |----           |-
5       0.4072  -0.1442   67.696  0.0000        |---           -|
6       0.3587   0.1032    72.61  0.0000        |--             |
7       0.1670  -0.4227   73.726  0.0000        |-           ---|
8       0.0758  -0.0027   73.967  0.0000        |               |
9       0.0181   0.2893   73.981  0.0000        |               |--
10     -0.0598  -0.0551   74.148  0.0000        |               |

. corrgram ch if hospital==2, lag(10)

                              -1      0      1 -1      0      1
 LAG      AC      PAC     Q    Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.5749   0.6175   10.283  0.0013        |----           |----
2       0.3251   0.0192   13.697  0.0011        |--             |
3       0.3753   0.4146   18.429  0.0004        |---            |---
4       0.3614   0.2440   23.001  0.0001        |--             |-
5       0.1493  -0.1170   23.815  0.0002        |-              |
6       0.0474   0.1900   23.901  0.0005        |               |-
7      -0.0396  -0.1324   23.964  0.0012        |              -|
8      -0.1314  -0.4079    24.69  0.0018       -|             ---|
9      -0.1135   0.1060   25.259  0.0027        |               |
10     -0.0388   0.2271   25.329  0.0048        |               |-
```

```
. ***Hospital Three***
. corrgram expde if hospital==3, lag(10)

                              -1      0      1 -1      0      1
 LAG      AC      PAC     Q    Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.3314   0.3402   3.4159  0.0646        |--             |--
2       0.2265   0.1731   5.0733  0.0791        |-              |-
3       0.0992   0.0368   5.4041  0.1445        |               |
4      -0.1938  -0.2782   6.7184  0.1515       -|             --|
5      -0.0868   0.0428   6.9935  0.2211        |               |
6      -0.1614  -0.1600   7.9885  0.2389       -|              -|
7       0.0087   0.5984   7.9915  0.3333        |               |----
```

```
8       0.0037   0.0957   7.9921  0.4342          |               |
9      -0.0219  -0.2084   8.0132  0.5328          |              -|
10     -0.0659  -0.4199   8.2161  0.6077          |             ---|

. corrgram alos if hospital==3, lag(10)

                                  -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.8124   0.8897   20.534  0.0000          |------          |-------
2       0.6976   0.1734   36.258  0.0000          |-----           |-
3       0.5465   0.0326   46.292  0.0000          |----            |
4       0.3625  -0.1750   50.892  0.0000          |--             -|
5       0.2939   0.4669   54.046  0.0000          |--              |---
6       0.2273   0.1550   56.018  0.0000          |-               |-
7       0.1853   0.7721   57.391  0.0000          |-               |------
8       0.1453   0.4842   58.278  0.0000          |-               |---
9       0.0815  -0.2080   58.572  0.0000          |               -|
10      0.0339   0.0689   58.625  0.0000          |                |

. corrgram bur if hospital==3, lag(10)

                                  -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.0419   0.0419   .05471  0.8151          |                |
2       0.1031   0.1067   .39824  0.8195          |                |
3      -0.0896  -0.1051   .66796  0.8807          |                |
4      -0.0188  -0.0219   .68032  0.9537          |                |
5      -0.1932  -0.1853   2.0431  0.8431         -|               -|
6      -0.0752  -0.0591   2.2588  0.8944          |                |
7      -0.0703   0.0247   2.4568  0.9303          |                |
8      -0.2328  -0.2897   4.7333  0.7857         -|              --|
9      -0.0167  -0.1021   4.7457  0.8559          |                |
10     -0.0293   0.1139   4.7858  0.9050          |                |

. corrgram csr if hospital==3, lag(10)

                                  -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.3004   0.3097    2.807  0.0939          |--              |--
2       0.0157  -0.0622    2.815  0.2447          |                |
3       0.2170   0.3990   4.3977  0.2216          |-               |---
4       0.0139  -0.2147   4.4045  0.3540          |               -|
5       0.1021   0.2851   4.7854  0.4426          |                |--
6       0.0915  -0.0363    5.105  0.5304          |                |
7      -0.0265   0.2368   5.1331  0.6437          |                |-
8       0.0354   0.0927   5.1859  0.7375          |                |
9      -0.1596  -1.0998   6.3123  0.7083         -|        --------|
10     -0.2071  -1.6675   8.3142  0.5982         -|        --------|

. corrgram pde if hospital==3, lag(10)

                                  -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.0188   0.0188   .01098  0.9165          |                |
2      -0.0070  -0.0075   .01257  0.9937          |                |
3       0.0238   0.0236   .03165  0.9985          |                |
4      -0.0662  -0.0616     .185  0.9960          |                |
5      -0.2293  -0.2075   2.1049  0.8344         -|               -|
6      -0.0598   0.0019   2.2416  0.8962          |                |
7      -0.1020   0.0066   2.6579  0.9147          |                |
8      -0.1727  -0.1670   3.9105  0.8651         -|               -|
9       0.0829   0.0877   4.2147  0.8967          |                |
10     -0.0323   0.0350   4.2632  0.9347          |                |

. corrgram ipd if hospital==3, lag(10)

                                  -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
```

```
1     -0.0588  -0.0588   .10773  0.7427        |              |
2     -0.0086  -0.0134   .11013  0.9464        |              |
3     -0.1613  -0.1714   .98438  0.8050       -|             -|
4     -0.0084  -0.0011   .98686  0.9118        |              |
5     -0.1591  -0.1651   1.9117  0.8612       -|             -|
6      0.0106  -0.0046    1.916  0.9273        |              |
7     -0.0209   0.0211   1.9334  0.9634        |              |
8     -0.1598  -0.2242   3.0063  0.9340       -|             -|
9      0.0577  -0.0069   3.1534  0.9579        |              |
10    -0.0458  -0.0181   3.2513  0.9749        |              |
```

```
. corrgram ips if hospital==3, lag(10)

                             -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.7439   0.7931   17.219  0.0000        |-----           |------
2      0.5967   0.2111   28.723  0.0000        |----            |-
3      0.4462   0.0403   35.411  0.0000        |---             |
4      0.3486  -0.0755   39.665  0.0000        |--              |
5      0.2547   0.1650   42.034  0.0000        |--              |-
6      0.2247   0.3102   43.962  0.0000        |-               |--
7      0.1525   0.1214   44.891  0.0000        |-               |
8      0.1275   0.1741   45.574  0.0000        |-               |-
9      0.1393   0.3769   46.432  0.0000        |-               |---
10     0.0704   0.0464   46.663  0.0000        |                |
```

```
. corrgram opd if hospital==3, lag(10)

                             -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.4550   0.4654   6.4415  0.0111        |---             |---
2      0.3092   0.1212   9.5305  0.0085        |--              |
3      0.4429   0.4519   16.121  0.0011        |---             |---
4      0.0723  -0.2310   16.303  0.0026        |               -|
5     -0.0285   0.0095   16.333  0.0060        |                |
6      0.1121   0.1829   16.813  0.0100        |                |-
7      0.0094  -0.0319   16.817  0.0186        |                |
8      0.1112   0.3116   17.337  0.0268        |                |--
9      0.2264   0.3317   19.603  0.0205        |-               |--
10     0.1082  -0.0118   20.149  0.0279        |                |
```

```
. corrgram ch if hospital==3, lag(10)

                             -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.7645   0.7734   18.182  0.0000        |------          |------
2      0.5685   0.0250   28.622  0.0000        |----            |
3      0.4300   0.0716   34.836  0.0000        |---             |
4      0.3918   0.1043   40.208  0.0000        |---             |
5      0.2679  -0.1094    42.83  0.0000        |--              |
6      0.1254  -0.0692    43.43  0.0000        |-               |
7      0.0157   0.0035    43.44  0.0000        |                |
8     -0.0746  -0.0557   43.673  0.0000        |                |
9     -0.0237   0.3543   43.698  0.0000        |                |--
10    -0.0951  -0.2674   44.121  0.0000        |              --|
```

```
. ***Hospital Four***
. corrgram expde if hospital==4, lag(10)

                             -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.4441   0.4966   6.1358  0.0132        |---             |---
2      0.2153   0.0263    7.634  0.0220        |-               |
3     -0.0136  -0.1410   7.6402  0.0541        |               -|
4     -0.4028  -0.5789   13.319  0.0098     ---|            ----|
5     -0.2962   0.2927   16.523  0.0055      --|                |--
6     -0.1918   0.2712   17.928  0.0064       -|                |--
7     -0.1402  -0.2438   18.714  0.0091       -|               -|
```

```
8      0.0260   0.4530   18.743  0.0163        |              |---
9      0.1080   0.7868   19.259  0.0231        |              |------
10      0.0211  -0.2708   19.279  0.0369        |            --|

. corrgram alos if hospital==4, lag(10)

                                 -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.6275   0.6330   12.251  0.0005        |-----          |-----
2      0.3052  -0.1449    15.26  0.0005       |--            -|
3      0.0215  -0.1761   15.276  0.0016        |             -|
4     -0.3536  -0.4579   19.653  0.0006      --|           ---|
5     -0.3260   0.2846   23.535  0.0003      --|             |--
6     -0.3018  -0.2080   27.013  0.0001      --|             -|
7     -0.2722  -0.0895   29.977  0.0001      --|              |
8     -0.2160  -0.5301   31.937  0.0001       -|          ----|
9     -0.1457   1.6478   32.875  0.0001       -|             |--------
10     -0.0710  -0.3576   33.111  0.0003        |            --|

. corrgram bur if hospital==4, lag(10)

                                 -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.1171   0.1178   .42635  0.5138        |              |
2     -0.0007  -0.0146   .42637  0.8080        |              |
3      0.1410   0.1544   1.0944  0.7784        |-             |-
4      0.1419   0.1565   1.7987  0.7727        |-             |-
5     -0.0651  -0.0766   1.9533  0.8556        |              |
6      0.0846   0.1787   2.2265  0.8977        |              |-
7      0.0405   0.0700   2.2919  0.9419        |              |
8      0.1404   0.3078   3.1201  0.9266        |-             |--
9     -0.0525   0.0859   3.2422  0.9539        |              |
10     -0.1434   0.0538   4.2014  0.9378       -|              |

. corrgram csr if hospital==4, lag(10)

                                 -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.7979   0.7995   19.804  0.0000        |------         |------
2      0.6654   0.1605   34.108  0.0000        |-----          |-
3      0.6096   0.3686   46.594  0.0000        |----           |--
4      0.4764  -0.2155   54.539  0.0000        |---           -|
5      0.2876  -0.0825    57.56  0.0000       |--             |
6      0.1812  -0.0780   58.814  0.0000        |-             |
7      0.0783  -0.1936   59.059  0.0000        |             -|
8     -0.0155  -0.1969    59.07  0.0000        |             -|
9     -0.0818   0.0564   59.365  0.0000        |              |
10     -0.2136  -0.2179   61.494  0.0000       -|             -|

. corrgram pde if hospital==4, lag(10)

                                 -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1      0.8192   0.8193    20.88  0.0000       |------         |------
2      0.6871   0.0647   36.134  0.0000        |-----          |
3      0.5809   0.0600   47.473  0.0000        |----           |
4      0.4531   0.0663   54.657  0.0000        |---            |
5      0.3524  -0.0862   59.192  0.0000        |--             |
6      0.2668   0.0096    61.91  0.0000       |--             |
7      0.1262  -0.2429   62.547  0.0000        |-            -|
8     -0.0402  -0.3285   62.615  0.0000        |            --|
9     -0.1305   0.1469   63.368  0.0000       -|             |-
10     -0.2426  -0.2362   66.115  0.0000       -|             -|

. corrgram ipd if hospital==4, lag(10)

                                 -1       0       1 -1       0       1
 LAG      AC      PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
```

```
1       0.2619   0.2823   2.1347  0.1440        |--           |--
2       0.0784   0.0283   2.3335  0.3114        |             |
3       0.2335   0.2540    4.166  0.2441        |-            |--
4       0.1410   0.0896   4.8616  0.3018        |-            |
5      -0.0701  -0.2086   5.0411  0.4109        |            -|
6       0.0270   0.0855   5.0689  0.5350        |             |
7       0.0186  -0.1190   5.0828  0.6499        |             |
8       0.0247   0.0091   5.1085  0.7459        |             |
9      -0.1189  -0.2578   5.7334  0.7663        |           --|
10     -0.2228  -0.3504   8.0496  0.6240       -|           --|

. corrgram ips if hospital==4, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.6613   0.6749   13.604  0.0002        |-----        |-----
2       0.4147  -0.0348   19.159  0.0001        |---          |
3       0.1888  -0.1308   20.357  0.0001        |-           -|
4      -0.1097  -0.3065   20.778  0.0004        |           --|
5      -0.1360   0.2041   21.453  0.0007       -|             |-
6      -0.1436  -0.0177   22.241  0.0011       -|             |
7      -0.2187  -0.2528   24.155  0.0011       -|           --|
8      -0.2405  -0.2082   26.584  0.0008       -|            -|
9      -0.1961   0.2542   28.284  0.0009       -|             |--
10     -0.1906  -0.1209   29.979  0.0009       -|             |

. corrgram opd if hospital==4, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.8401   0.8449   21.957  0.0000        |------       |------
2       0.6996   0.0035   37.769  0.0000        |-----        |
3       0.5719  -0.0285   48.758  0.0000        |----         |
4       0.4829   0.1566   56.918  0.0000        |---          |-
5       0.3782  -0.0540   62.143  0.0000        |---          |
6       0.2653  -0.1267    64.83  0.0000        |--          -|
7       0.1096  -0.2215    65.31  0.0000        |            -|
8      -0.0249  -0.1231   65.336  0.0000        |             |
9      -0.1220   0.0804   65.994  0.0000        |             |
10     -0.2301  -0.1624   68.464  0.0000       -|            -|

. corrgram ch if hospital==4, lag(10)

                              -1       0       1 -1       0       1
 LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]
-------------------------------------------------------------------------------
1       0.8168   0.8391   20.756  0.0000        |------       |------
2       0.6686   0.0885   35.198  0.0000        |-----        |
3       0.5791   0.1862   46.466  0.0000        |----         |-
4       0.4697  -0.1849   54.187  0.0000        |---         -|
5       0.3588   0.0831   58.889  0.0000        |--           |
6       0.2640   0.0429    61.55  0.0000        |--           |
7       0.1207  -0.1250   62.133  0.0000        |            -|
8       0.0162   0.0839   62.144  0.0000        |             |
9       0.0228   0.4105   62.167  0.0000        |             |---
10     -0.0879  -0.2159   62.528  0.0000        |            -|
```