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A Quantitative Review of Costs: Heart Failure Patients Before and After Implementation of an Integrated Practice Unit Model at University of Utah Health

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A QUANTITATIVE REVIEW OF COSTS: HEART FAILURE PATIENTS BEFORE AND AFTER IMPLEMENTATION OF AN INTEGRATED PRACTICE UNIT MODEL AT UNIVERSITY OF UTAH HEALTH

BY

Dayle E. Benson

A doctoral project submitted to the faculty of the Medical University of South Carolina in partial fulfillment of the requirements for the degree Doctor of Health Administration in the College of Health Professions

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Doctor of Health Administration

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Chairperson: Abby Swanson Kazley, Ph.D.
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Knowing the cost of delivering patient care is a mandatory first step as health care leaders are tasked with reducing the cost of US health care. The Integrated Practice Unit (IPU) model espoused by Michal Porter is a patient centered organizational framework whose tenets support value driven care. University of Utah Health has developed a proprietary costing model that gives them the ability to measure both costs and outcomes at the patient, provider, or in this research case, IPU program level.

An interrupted time series (ITS) study design methodology is used to evaluate whether there has been an immediate effect on HF patient costs and related indicators post implementation of the HF IPU. The ITS pre/post analyses show an overall declining trend in total HF costs, total HF technical costs, total HF professional costs, HF costs (total, surgical and non-surgical), admissions, ED visits, and mean LOS. While VAD costs dropped initially, they began to increase in the post intervention period. HF readmissions remained flat across the pre- and post periods. Statistically significant and declining trends were observed in HF surgical, and non-surgical cost trends. While not all trends were statistically significant, they may be deemed financially or clinically significant and worth further study.

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CHAPTER 1
INTRODUCTION

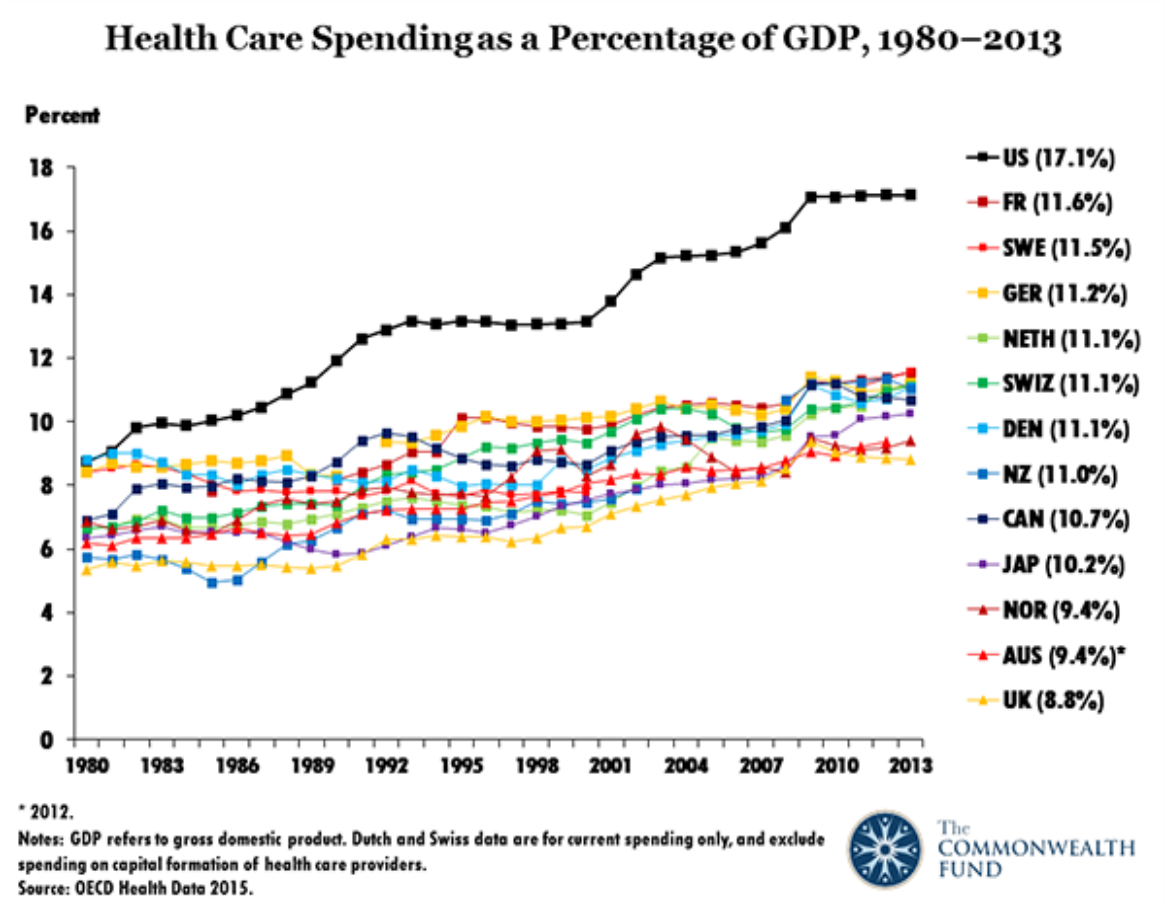
Novel models of health care delivery and partnerships, such as Accountable Care Organizations (ACOs), bundled payment programs, and other integrated practice models, have sprung up nationwide; however, we do not know their impact on health care costs or in improving the health of a population. As health system leaders and providers strive to deliver high-value care, we need to better understand, collect, and share patient cost and outcome data (Porter, 2009).

The University of Utah Health system is one of a handful in the nation with a data system that can track actual patient costs and quality outcomes, including both hospital and professional expenses (Lee et al., 2016). The University of Utah Health (U of U Health) team can quantify internal cost trends and evaluate the impact of interventions on the cost of patient care using a value-driven outcomes (VDO) costing model. Due to this unique ability, this research study includes a quantitative analysis of a program evaluation of the Heart Failure (HF) Integrated Practice Unit (IPU) delivery model at U of U Health, and compares differences in length of stay (LOS), hospital admissions, hospital re-admissions and average patient costs for heart failure patients admitted to the U of U Health before and after the implementation of the IPU. Specifically, the research will explore if sharing patient cost and related outcome data with clinicians has an impact on reducing those costs associated with the treatment of heart failure patients.

Background and Need for Study

Knowing the cost of delivering patient care is a mandatory first step as health care leaders are tasked with reducing the cost of US health care. Health spending in the US is projected to increase on average 5.8 percent annually for the period 2014 – 2024, and represents 19.6 percent of the gross domestic product (GDP) in 2014 (Keehan, Cuckler, Sisko, & Madison et al., 2015). US health care spending as a percent of GDP is significantly higher than other developed countries as shown in Figure 1 (The Commonwealth Fund, 2016).

Figure 1. US Health Care Spending Trends



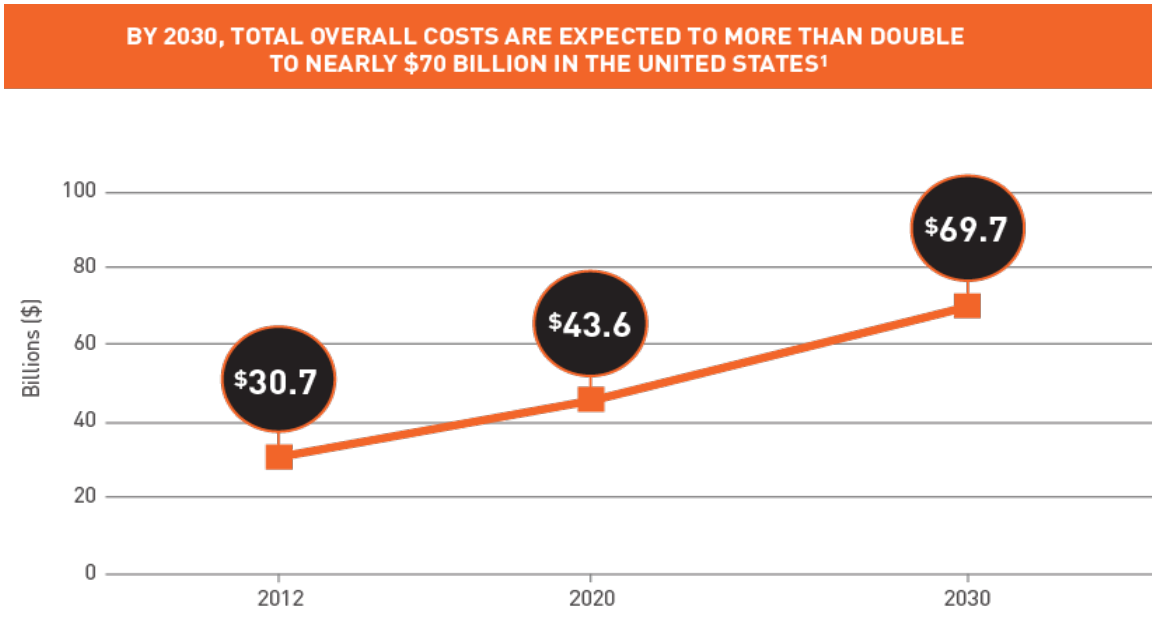
The Affordable Care Act (ACA) highlights the imperative to reduce the cost of health care in the US, and challenges health care leaders to experiment with new models

of health care delivery that improve the value of patient care. To evaluate these new models of care and payment methods, clinicians and hospital organizations must understand the actual costs and outcomes for individual patients with specific clinical conditions (Lee et al., 2016). The research outlined in this proposal will examine cost and cost related outcome trends in targeted heart failure patients.

Problem Statement

The Center for Medicare and Medicaid Services (CMS) has targeted heart failure patients and their related health care expenses as a potential opportunity to reduce national health care costs. In 2009, the estimated cost of treating heart failure patients in the US was greater than $30 billion, and costs are expected to more-than-double in 15 years, as illustrated in Figure 2 (Bogaev, 2010; Voigt et al., 2014; "What is the cost…", 2016).

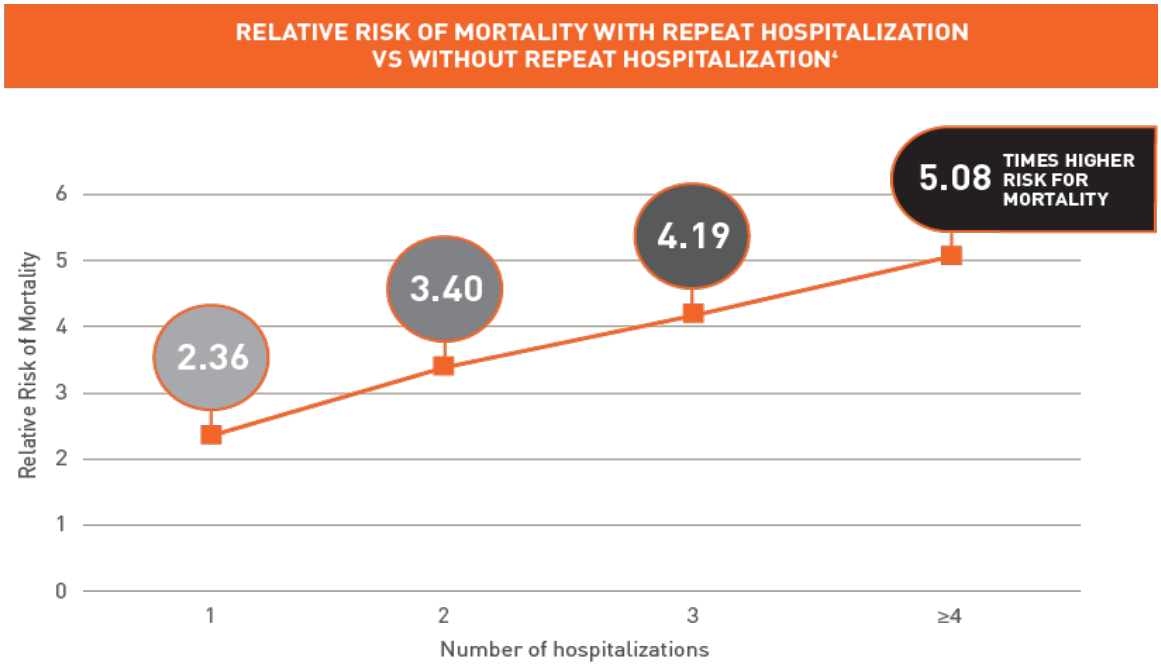
Figure 2. Projection of Total Overall Costs for HF Patients in the United States



(Source: www.heartfailure.com, 2016)

Acute heart failure (HF) is one of the most common reasons for overall hospital admissions in the United States (US), and the largest cause of readmissions for both medical and surgical patients (Sperry, B., Ruiz, G., & Najjar, S., 2014). One in four HF patients are readmitted within 30 days of discharge (Bogaev, 2010). With each hospitalization, the risk of HF mortality increases, as shown in Figure 3 ("What is the cost…", 2016). The high costs associated with the HF population make it ripe for experimenting with care delivery models that reduce cost and improve or maintain quality standards of care (Sperry, B., Ruiz, G., & Najjar, S., 2014).

Figure 3. Rising Risk of HF Mortality with Repeat Hospitalization



(Source: www.heartfailure.com, 2016)

This research study describes IPUs as a strategic redesign of how HF patients are managed within U of U Health, and quantifies the early impact on health care costs and other clinical outcomes. IPUs are defined using Michael Porter's definition as a

dedicated, multidisciplinary, team-based approach that focuses on comprehensive care for the patient's condition. The primary goal is to provide the highest value of care to the patient, with value being defined as quality and patient satisfaction over cost (Porter & Lee, 2013).

Objective of the Study

The University of Utah Health system is one of the few health care systems with a data system that tracks patient costs and quality outcomes for both hospital and professional expenses. That data is being shared with clinicians for further input on ways to streamline costs and improve care (Appleby, 2014). This research study uses archival data to compare U of U Health resource use and measure HF patient costs, observed to expected length of stay (LOS), hospital admissions, hospital readmissions within 30 days, and emergency department (ED) visits before and after IPU implementation. Heart failure patients will be categorized into the following population segments to improve comparability: Transplant, Ventricular Assisted Device (VAD), and Other Heart Failure patients. The study objective is to measure the association of the HF IPU implementation with HF patient costs and related hospital cost indicators. The findings will help clinical teams identify what processes need to be in place to measure the effectiveness of patient care for a targeted population.

Research Questions

This study compares resource use and measures cost for U of U Health HF patients before and after implementation of an IPU business model using archival data. The following questions have been addressed and will help inform administrators and

clinicians as to how to measure and compare patient cost data and related hospital cost indicators.

Research question number 1. Do HF patients post IPU implementation have improved quality outcomes, such as shorter length of stay, and fewer HF hospital readmissions than HF patients pre IPU?

Research question number 2. Do HF patients post IPU implementation have fewer ED visits than HF patients pre IPU?

Research question number 3. Do HF patients post IPU have lower average heart failure attributable cost-per-patient than patients pre IPU?

Hypotheses

The following research hypotheses will be examined. It is likely that the fidelity in which the IPU was implemented and the time frames being examined will influence early findings and conclusions.

Hypothesis H_1. HF patient costs at U of U Health will begin to decline post IPU implementation.

Hypothesis H_2. HF admissions, readmissions, observed/expected LOS, and ED visits will decline post IPU implementation.

Rationale for hypotheses. The above hypotheses are based off the following central tenets of an IPU:

1. An IPU is organized around a medical condition or a set of closely related conditions.
2. Care is delivered by a dedicated, multidisciplinary team of clinicians who devote a significant portion of their time to the medical condition.

3. Providers view themselves as part of a common organizational unit (IPU).
4. The team takes responsibility for the full cycle of care for the condition, encompassing outpatient, inpatient, rehabilitative care, and supporting services (such as social work, behavioral health, and nutrition).
5. Patient education, engagement, and follow-up are integrated into care.
6. The unit has a single administrative and scheduling structure.
7. A physician team captain or a clinical care manager (or both) oversees each patient's care process.
8. The team measures outcomes, costs, and processes for each patient using a common measurement platform.
9. The providers on the team meet formally and informally on a regular basis to discuss patients, processes, and results.
10. Joint accountability is accepted for outcomes and costs (Porter & Lee, 2013)

If these components of an IPU truly exist and incentives are aligned to improve outcomes and cost, then HF costs should decline as clinical teams strive to maximize patient value. Note that this study is a quantitative analysis of an IPU program evaluation specifically measuring the impact on actual patient costs at U of U Health. While other components of Porter and Lee's (2013) IPU model may be referenced and described, they will not be integral to the study.

The Integrated Practice Unit (IPU) Model at University of Utah Health

Beginning July 1, 2015, U of U Health implemented a HF IPU model similar in structure and purpose as Porter and Lee's IPU prototype referenced in their iconic article, "The Strategy that will Fix Health Care" (2013). The purpose was to improve the value

of care for this very large, costly HF population. This effort was considered a pilot, or experiment, with the intent to measure the impact of engaging clinical teams more directly in managing HF patient costs and outcomes by aligning care team governance, clinical goals, and financial incentives. One must understand the HF IPU model at the U of U Health to appreciate the context of this study's research question, and whether the implementation of an IPU model has led to a reduction of clinical costs. The following section contains a comparison of the U of U Health IPU framework to those tenets espoused by Porter and Lee, which serve as the rationale for the hypotheses. Porter and Lee's tenets are in bold.

It is important to note that the multidisciplinary team was comprised of stage C and D heart failure cardiologists and surgeons, and does not include other cardiology providers, primary care, rehabilitation or post discharge care. As such, the IPU team does not take complete responsibility for the full cycle of care for HF conditions as noted in number 4. This discrepancy in the model may have an influence on the study's outcomes.

1. **An IPU is organized around a medical condition or a set of closely related conditions.** The HF IPU at U of U Health has been defined to include specific eligibility criteria and includes a consistent methodology for identifying patients at the beginning of their care. It is organized around the patients' use of a multidisciplinary team focused on improving the care and health of HF patients in an expanded cycle of care.

2. **Care is delivered by a dedicated, multidisciplinary team of clinicians who devote a significant portion of their time to the medical condition.** Care delivery and management of the U of U Health HF population includes all patients who access a

dedicated, multidisciplinary care team for HF. There are existing care pathways, protocols, and care delivery processes in place.

3. **Providers view themselves as part of a common organizational unit (IPU).** The HF pilot is exclusive to a dedicated clinician team based on diagnosis and primary physician provider. A multidisciplinary governance team comprised of HF cardiologists, surgeons, nurses, midlevel, administration, and decision support staff meet regularly to discuss costs, clinical outcomes, and care processes. This team holds the decision rights for managerial decisions and is accountable for improving the value of patient care.

4. **The team takes responsibility for the full cycle of care for the condition, encompassing outpatient, inpatient, rehabilitative care, and supporting services (such as, social work, behavioral health and nutrition).** To date, the HF IPU manages only patient care that occurs at U of U Health. This approach includes many of the patient's care needs, but has yet to incorporate those services, providers, or caregivers in other institutions outside of the U of U Health.

5. **Patient education, engagement, and follow-up are integrated into care.** This criterion is met for all patients who pursue follow up and education within the U of U Health.

6. **The unit has a single administrative and scheduling structure.** A dedicated team of administrators including physicians, nurses, management, schedulers, and decision support are focused on improving value for HF patients.

7. **A physician team captain or a clinical care manager (or both) oversees each patient's care process.** The division chiefs of cardiology and cardiovascular services in

conjunction with the administrative and care teams oversee the HF patient care processes, many of which are documented in the electronic medical record.

8. **The team measures outcomes, costs, and processes for each patient using a common measurement platform.** The team measures the following outcomes, costs and volume indicators for all HF patients admitted to the U of U Health:

- Observed/expected (O/E) morbidity and mortality
- New patient visits and scheduling lags
- Patient satisfaction
- Average total HF attributable costs (inpatient, outpatient, and professional)
- Admissions
- Emergency department (ED) HF visits
- Readmissions within 30 days of HF admission
- Inpatient HF market share
- HF IPU contribution margin
- Patient Reported Outcomes compliance
- HF Patient encounter total cost of care (hospital and professional using the VDO tool)

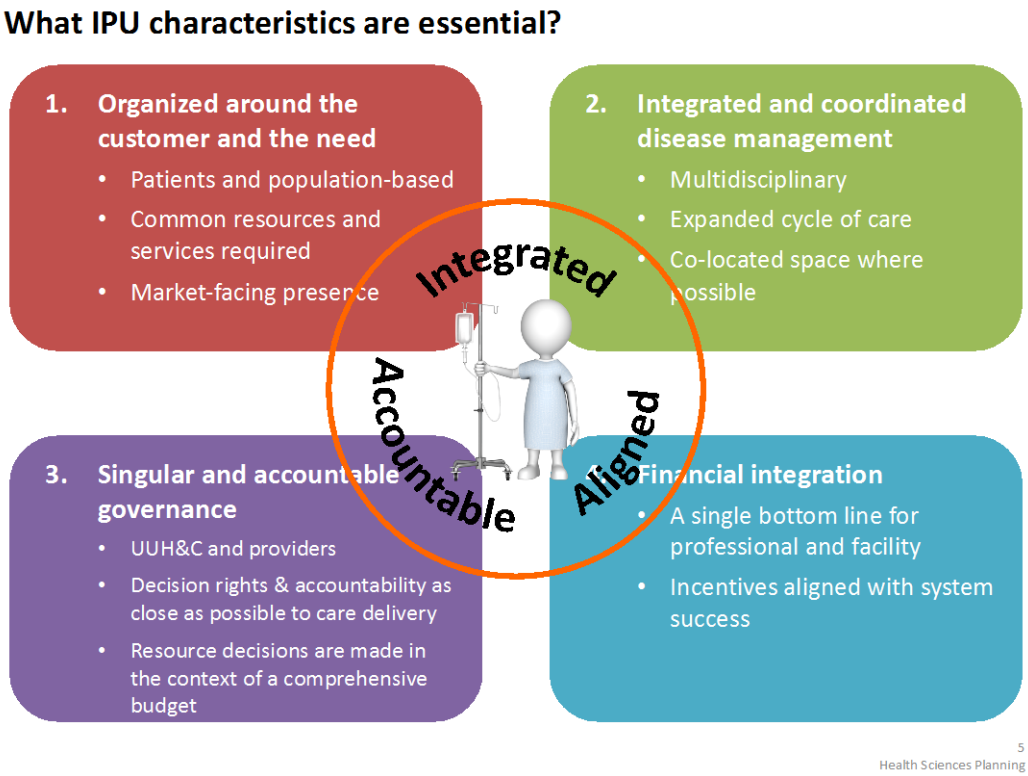
To date, systems are not in place to measure the longitudinal cost of care for patients, or those costs that occur outside of the U of U Health.

9. **The providers on the team meet formally and informally on a regular basis to discuss patients, processes, and results.** The HF IPU team meets twice a month to review metrics and discuss opportunities for care process improvement.

10. Joint accountability is accepted for outcomes and costs. A single bottom line has been established for professional and facility costs with incentives in place to align improved contribution margin performance (Porter & Lee, 2013).

Figure 4 illustrates the essential characteristics for IPUs at U of U Health.

Figure 4. Characteristics Essential for IPUs at U of U Health



(Source: U of U Health Strategic Planning, 2015)

Lastly, a financial framework has been established at U of U Health to include a minimum set of features required to align incentives around value. The economic model must provide sufficient financial incentives to the IPU when success is achieved, and be structured in a manner that allows for the evaluation and feasibility of the IPU financial framework for both the health system and the IPU (Stephen Petersen, personal interview, September 2015).

Population

The study population has been defined to meet the following criteria:

- Those patients whose initial HF encounter is organized around a patient's medical condition and includes an inpatient or outpatient HF diagnosis that is seen by one of the following HF physicians at U of U Health: five HF cardiologists, two cardiac surgeons, and supporting fellows and advanced practitioners. This team is highly functional and advanced at direct patient care and achieving goals.
- Once identified, any costs in subsequent HF encounters by this patient group will be contained in the costing analysis.

The above HF population sample results in approximately 3,288 unique patients and 53,000 visits over a three-year period (U of U Health Decision Support, 2016). The patient population data as defined will be segmented into three HF sub-populations and compared over a two-year period beginning July 1, 2014. The following codes were used to designate a transplant, VAD, or other HF type of visit and includes both professional and technical coding.

Transplant

CPT Codes

CPT Code	CPT Code Description
33935	Heart-lung transplant with recipient cardiectomy-pnumec
33945	Heart transplant with/without recipient cardiectomy

OR ICD Procedure Codes

ICD Procedure	ICD Procedure Description
02YA0Z0	Transplantation of Heart, Allogeneic, Open Approach
02YA0Z1	Transplantation of Heart, Syngeneic, Open Approach
37.51	HEART TRANSPLANTATION
02YA0Z2	Transplantation of Heart, Zooplastic, Open Approach

Ventricular Assisted Device (VAD)

ICD Procedure Codes

ICD Procedure	ICD Procedure Description
02HA0RS	Insert of Bivent Ext Heart Assist into Heart, Open Approach
02HA0RZ	Insertion of Ext Heart Assist into Heart, Open Approach
02HA3RS	Insert of Bivent Ext Heart Assist into Heart, Perc Approach
02HA3RZ	Insertion of Ext Heart Assist into Heart, Perc Approach
02HA4RZ	Insertion of Ext Heart Assist into Heart, Perc Endo Approach
02RK0JZ	Replacement of Right Ventricle with Synth Sub, Open Approach
02RL0JZ	Replacement of Left Ventricle with Synth Sub, Open Approach
02WA0JZ	Revision of Synthetic Substitute in Heart, Open Approach
02WA0QZ	Revision of Implant Heart Assist in Heart, Open Approach
02WA0RZ	Revision of Ext Heart Assist in Heart, Open Approach
02WA3QZ	Revision of Implant Heart Assist in Heart, Perc Approach
02WA3RZ	Revision of Ext Heart Assist in Heart, Perc Approach
02WA4QZ	Revise of Implant Heart Assist in Heart, Perc Endo Approach
02WA4RZ	Revision of Ext Heart Assist in Heart, Perc Endo Approach
37.52	IMPLNT TOTAL INT BIVENTRICULAR HEART REPLCMT SYS
37.53	REPL/REPAIR THORACIC UNIT TOTAL REPL HEART SYS
37.54	REPL/REPR OTH IMPL CMPNT TOT REPL HEART SYS
37.6	IMPLANTATON HEART & CIRCULATORY ASSIST SYSTEMS
37.6	IMPLANT/INSERT BIVENTRICULAR EXT HRT ASSIST SYS
37.62	INSERTION TEMP NON-IMPLANTABLE ECC ASSIST DEVICE
37.63	REPAIR OF HEART ASSIST SYSTEM
37.65	IMPLANT SINGLE VENT EC EXT HEART ASSIST SYS
37.66	INSERTION OF IMPLANTABLE HEART ASSIST SYSTEM
37.68	INSERTION PERQ EXTERNAL HEART ASSIST DEVICE
39.65	EXTRACORPOREAL MEMBRANE OXYGENATION
5A02116	Assist with Cardiac Output using Other Pump, Intermittent
5A02216	Assistance with Cardiac Output using Other Pump, Continuous
5A0221D	Assist with Cardiac Output using Impeller Pump, Continuous
5A15223	Extracorporeal Membrane Oxygenation, Continuous

OR CPT Codes

CPT CODE	CPT CODE DESC
0048T	IMPLTJ VENTR ASSIST DEV XTRCORP PRQ T-SEPTAL
33946	ECMO/ECLS INITIATION VENO-VENOUS
33947	ECMO/ECLS INITIATION VENO-ARTERIAL
33948	ECMO/ECLS DAILY MANAGEMENT EACH DAY VENO-VENOUS
33949	ECMO/ECLS DAILY MANAGEMENT EA DAY VENO-ARTERIAL
33952	ECMO/ECLS INSJ OF PRPH CANNULA 6 YRS&OLDER PERQ
33954	ECMO/ECLS INSJ OF PRPH CANNULA 6 YRS&OLDER OPEN
33956	ECMO/ECLS INSJ OF CENTRAL CANNULA 6 YRS & OLDER
33958	ECMO/ECLS REPOS PERPH CANNULA PRQ 6 YRS & OLDER
33962	ECMO/ECLS REPOS PERPH CANNULA OPEN 6 YRS & OLDER
33964	ECMO/ECLS ECLS REPOS CENTRAL CNULA 6YRS & OLDER
33975	INSJ VENTRIC ASSIST DEV XTRCORP SINGLE VENTRICLE
33976	INSJ VENTRIC ASSIST DEV XTRCORP BIVENTRICULAR
33979	INSJ VENTR ASSIST DEV IMPLTABLE ICORP 1 VNTRC
33981	RPLCMT XTRCORP VAD 1/BIVENTR PUMP 1/EA PUMP
33982	PLCMT VAD PMP IMPLTBL ICORP 1 VENTR W/O BYPASS
33983	RPLCMT VAD PMP IMPLTBL ICORP 1 VNTR W/BYPASS
33988	INSERT LEFT HEART VENT BY THORACIC INC ECMO/ECLS
33990	INSJ PERQ VAD W/IMAGING ARTERY ACCESS ONLY
33991	INSJ PERQ VAD TRNSPTAL W/IMAGE ART&VENOUS ACCESS

Other Heart Failure

Includes all visits and associated codes when there were no codes for either transplants or VADs as defined and the visit fit the population sample definition. Lastly,

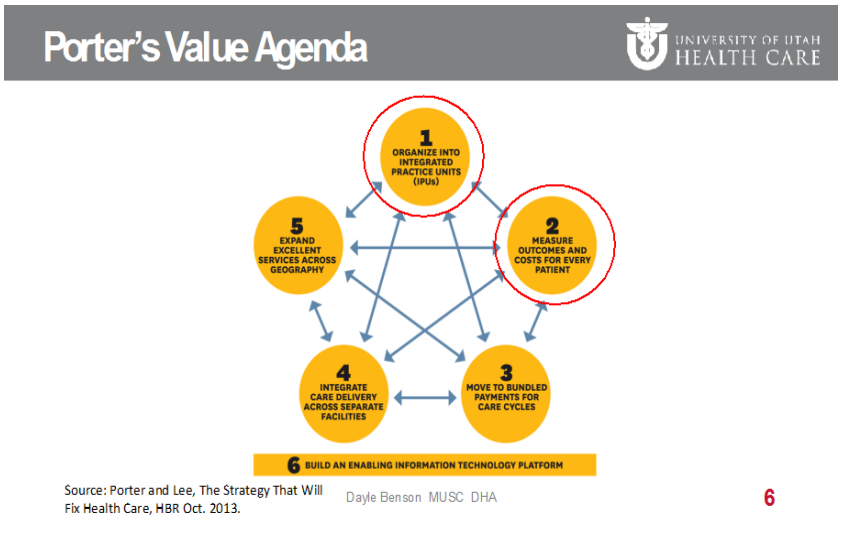
cost indicators are segmented and trended for both HF surgical and HF non-surgical in order to more closely align patient type with outcomes.

Summary

Conditions have never been more favorable for structural redesign and examination of innovative care delivery models focused on improving the value of health care. The results of this program evaluation will add to the body of research knowledge on the design of IPUs and their subsequent impact on costs, as well as inform health care leaders of the challenges and lessons learned in managing a specific population, aligning incentives and costs, identifying and measuring outcomes, and developing analytical tools that support a more integrated, longitudinal treatment approach to improving patients' health.

CHAPTER II
REVIEW OF THE LITERATURE

There is very little scientific research specific to studying the outcomes of Porter and Lee's IPU model; however, there is much to be learned about its fundamental components, one of which is measuring outcomes and costs for every patient (Porter & Lee, 2013). This study focuses primarily on a quantitative analysis of HF costs and related hospital cost indicators post implementation of a similar IPU business model. As such, the literature review concentrates on the following bodies of research: US health care costs, transformative care models, integrated care delivery, integrated practice units, common hospital costing methodologies, and interrupted time series studies in a post study.



Literature Search Method

The literature search began with an exploration of the more recent works in the PubMed database through the Eccles Health Sciences Library at the University of Utah. The search focused primarily on years 1996 to current, since IPUs and value based health care are relatively recent topics. The search site is integrated so that information in other databases can be identified; thereby, incorporating literature from EBSCO Business Source Premier, Scopus and other more business related search sites. Since much of

economist Michael Porter's value driven care and IPU work has been published in the Harvard Business Review, Google Scholar's search engine was used to collect those relevant articles. Key search words included health care costs, integrated care, heart failure, integrated practice units, heart failure costs, hospital costing models, value driven outcomes, cost to charge ratios, time driven activity-based costing, Michael Porter, interrupted time series, and segmented regression analysis in various combinations.

Electronically accessible documents were downloaded when available, and abstracts were obtained. The literature collected also included key peer reviewed reference articles, which were often added to the body of literature. All searches were completed in August through November 2016 resulting in the discovery of approximately 80 articles and references relevant to this study. In addition, other opportune information was obtained from various expert websites, such as CMS.gov, and through expert content received during personal interviews. The remainder of this section summarizes the significant findings and subsequent learnings from this comprehensive literature search.

Value Based Health Care

There is overwhelming evidence that an opportunity exists to improve the value of health care in the US (DiSesa & Kaiser, 2015; IOM, 2001; James, 2007; Kohn, Corrigan, & Donaldson, 1999; Wennberg, 1999). To facilitate improved cost control, quality and access, US health care delivery is moving from a primarily fee-for-service payment delivery into various integrated, risk based models, such as accountable care organizations (ACOs), patient centered medical homes (PCMHs), bundled payments for a defined service, and integrated practice units (IPUs) (Herzingler, Schleicher, & Mullangi, 2016). The Department of Health and Human Services (HHS) is focusing its energies on

using incentives to motivate higher value care, tying reimbursement through alternative payment models that reward value, and paying greater attention to population health and coordination of care across settings (Burwell, 2015).

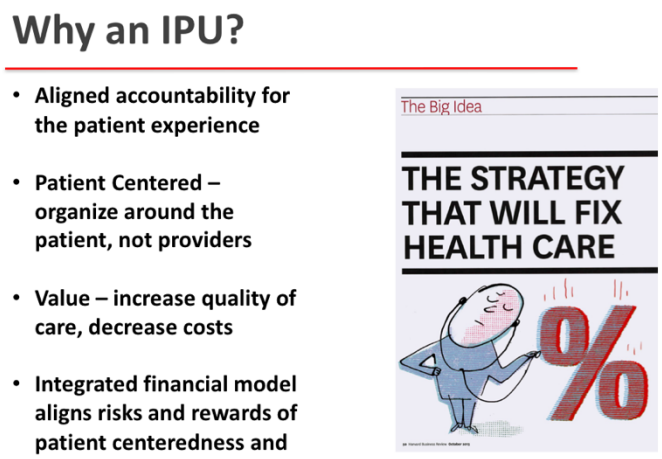
In the transition from volume to value focus, health system leaders and providers will need to develop different care team models focused on the patients' continuum of care and service needs. This is a significant change in the medical culture and the traditional one on one relationship between the provider and patient. Physician leadership is essential to be effective at reorganizing and executing under this new order. (Porter and Teisberg, 2007; Herzlinger, Schleicher, & Mullangi, 2016; Weisenberg, 2016).

In addition to the cost, quality, and patient experience tenets of value based care and the "Triple Aim" routinely referenced in the literature, the Institute for Health Care Improvement in a seven-year study of the "Triple Aim" identified three main elements for successful population management: identifying the relevant population, creating a governance structure, and articulating a clear purpose for the work. These foundational beliefs are consistent with Porter & Lee's central tenets of an IPU in achieving high value for the patient (Whittington, Nolan, Lewis & Torres, 2015; Porter, 2010).

Another important aspect of successful value based care is aligning incentives and funds flow mechanisms to support effective patient care coordination. Health care funds flow and financial partnership arrangements are complex, and beyond the scope of this study; however, it remains essential that organizations understand their true patient costs to distribute revenues or share in savings associated with high value patient care (Bird, Reney, & Ross, 2015).

All the above has led to an unprecedented interest in innovative, integrated delivery models focused on improving patient value and lowering US health care costs.

Integrated Care Delivery and Other Transformative Practice Models



At the core of this proposed value transformation is changing the way clinicians are organized to deliver care and the importance of physicians engaging with their patients in this effort (Porter & Lee, 2013).

Several health care systems have experimented with IPU models including MD Anderson, Cleveland Clinic and others. MD Anderson in Texas organizes patient care around the type of cancer being treated, with all the applicable specialties collocated in a dedicated practice facility. The Cleveland Clinic has organized IPUs in cardiac and eye care (Porter & Teisberg, 2006).

To understand the impact of these models, it is essential to be able to measure both risk adjusted, clinical outcomes and actual care delivery costs over a defined period. A fundamental conceptual framework espoused by Porter is that improving clinical outcomes results in reduced costs. However, most health care systems and physicians do not have a good understanding of their actual health care delivery costs for a patient population, nor do they have incentives to improve value (Algorithms for Innovation, 2013; Kaplan & Porter, 2011; Porter & Teisberg, 2007). A common theme in the

literature is the temptation to look at only the quality or outcomes side of the value equation (Pollock, 2008).

In a recent systematic review on integrated models of health care delivery, the authors (Mitchell et al., 2015) note an urgent need for future research and quantitative study of complex, chronic disease delivery models, and their impact on outcomes, quality of life and resource effectiveness. Most of the literature and study to date highlight advances in care delivery processes, such as communications and interdisciplinary team work, and focuses on improvement in clinical outcomes (Bogaev, 2010; Mitchell, et al., 2015). Researchers reinforce the importance of coordination between health professionals and better integration of treatment with preventative, rehabilitation and disease management, which is believed will lead to improved clinical outcomes and cost (McKay and Wieck, 2014; Porter & Teisberg, 2007). However, there continues to be a strong need for research studies that measure both clinical outcomes and their associated costs; the current state of available cost information is abysmal (Porter & Teisberg, 2007).

Considering reimbursement changes and readmission penalties emphasizing care across the continuum, several systems have developed multidisciplinary, care coordination models that they hope will help manage costs and improve patient health. As example, Parkview Heart Institute developed a three-phased approach to reduce readmissions that included 1) improving inpatient care and transitioning the patient post discharge, optimizing the use of tele-management services, and working with primary care physicians to promote early interventions and avoid admissions. Their efforts

showed significant reductions in readmission, length of stay, and HF mortality (Advisory Board, 2012).

MD Anderson has also experimented with value based care and implementing an IPU model for the treatment of cancer disease specific clusters or multidisciplinary care centers. In their experience, researchers note that much better measurements of outcomes and true costs are critically needed (Porter & Teisberg, 2006).

Others are also developing innovative approaches around managing the increasing burden of chronic diseases, such as diabetes, cancer, and cardiovascular disease. These programs are very much in their infancy and face significant barriers around patient data sharing, payment mechanisms that are not aligned with the delivery of value based care, and a cultural mindset based on a history of professional autonomy in clinical practice (Dunbar-Rees, Panch, & Dancy, 2013).

Significance of Heart Failure Costs

HF has a major effect on patients' health status, whether it be symptom burden, functional status, or quality of life. Not only is it expensive, but it remains the leading cause of disability, hospitalization and death in the US (Bekelman, et al., 2015). There have been numerous studies experimenting with heart failure care delivery models focused on the HF population. The National Health Service (NHS) in 2013 published its Cardiovascular Disease Outcomes Strategy with the primary recommendation to clinically manage cardiovascular disease as a single grouping of conditions to improve patient outcomes, coordination of care, and reduce costs (Dunbar-Rees, Panch, & Dancy, 2014). The Texas Heart Institute in 2010 sponsored a white paper highlighting measures, such as communicating, evaluating from a business perspective, aligning physicians and

hospitals, and enhancing support services, to ensure VAD therapy was affordable and accessible (Bogaev, 2010). Parkview Heart Institute in 2011 developed a multidisciplinary project to coordinate heart failure care and reduce associated readmission by improving inpatient care and the post discharge process, optimizing tele-management in continuum of care and working with primary care physicians to prevent care (Advisory Board, 2012). These are just a few examples of recent studies that hoped to contribute knowledge towards improving the value of care for heart failure patients. However, there is still not clear consensus as to what interventions demonstrate improved health status or lead to sustainable reductions in cost.

In a large collaborative, researchers explored the effectiveness of a patient centered disease management (PCDM) intervention to improve the health of HF patients. Unfortunately, this multisite randomize trial did not demonstrate improved patient health status and patient costs were not analyzed (Bekelman, et al., 2015).

Episode based payments or bundled payments are at the forefront of national discussion on combating rising health care costs. In August 2016, CMS announced the addition of Acute Myocardial Infarction (AMI) and Coronary Artery Bypass Graft (CABG) to Medicare's bundled payment programs (CMS, 2016). While this bundle is not directly related to HF patients, cardiovascular care is an arena in which bundled payments may become increasingly visible and be most impactful. An interesting debate is emerging as to whether bundled payment approaches are just another form of silo care around a disease condition, such as Geisinger's focused factory delivery model, versus an integrated approach that leads to real improvement in patient value. Early evidence on the impact of bundled payments on health care costs remains inconclusive. In addition,

there is very little evidence based research in the literature to support these alternative payment models (Shih, Chen & Nallamothu, 2015).

Understanding the Cost Side of the Value Equation

Determining value in health care as defined as outcomes over unit costs is dependent upon accurately capturing and measuring those unit costs (Kaplan et al., 2014). Accurately assigning costs is challenging and approaches vary depending on stakeholder perspectives, such as the health care system, payer, patient or society (Lee et al, 2016). To access profitability under existing payment systems, most organizations use one of three costing methodologies: ratio of cost to charges (RCC), relative value unit (RVU) or the activity based costing (ABC). Some of these costing methods have proven to be more reliable than others; however, their external reliability is limited due to each organizations' unique cost structure (West, Balas, & West, 1996).

Management accounting in health care has experienced somewhat of an evolution from estimated cost determination models to those that are focused on creation of value (Esmalifalak, Albin, & Behzadpoor, 2014). For these reasons, understanding the costing methodologies, and their strengths and weaknesses becomes an integral component of this research analysis. Any research model's usefulness is largely predicated upon the reliability of its output (Esmalifalak, Albin, & Behzadpoor, 2014).

Accurate cost measurement in health care is challenging because a patient's treatment involves so many different types of resources. To measure true costs, these shared resource costs need to be attributed to each patient based on their actual resource use (Kaplan & Porter, 2011; Porter, 2010). This literature search seeks to understand and compare popular and proven hospital costing models, including the Value Driven

Outcomes (VDO) costing model used at U of U Health, the Cost to Charge ratio method (RCC), and Time Driven Activity – Based costing method (TDABC).

Value Driven Outcomes. A pragmatic, modular and extensible software framework is used to capture and allocate clinical care costs to individual patient encounters. This Value Driven Outcomes (VDO) software was developed by U of U Health, and has been shown to accurately reflect organizational cost accounting, as well as support the measurement of quality, outcome and value (Kawamoto, et al., 2015). The software is built on existing organizational cost measurement and analytical capabilities to establish robust analytics for improving outcomes relative to costs. A key component of the methodology is creating a timely process for reporting and analysis of patient centered cost and outcomes data (Kip Williams, personal interview, 2014). The ability to quantify costs at the individual patient level is necessary in transforming health care from episodic, volume oriented care to patient centered, value based care (Lee et al., 2016).

The scope of VDO costs include actual inpatient and outpatient costs for both the facility and the professional expenses; therefore, it is crucial that physician leadership understand the data methodology. The facility costing is derived from clinical data sources and billing data, which is based off acquisition and utilization costs whenever available. The costing models applied include actual, time based, and equal distribution costing methodologies depending on the output being measured. In summary, it is a fully absorbed costing process that is reconciled to the organization's general ledger. The VDO approach to assigning direct costs is contained in Table 1. (Lee et al., 2016).

Table 1. VDO Approach to Assigning Costs

Table 1. Value-Driven Outcomes Approach to Assigning Direct Cost for a Given Area

Area of Cost	Sources of Cost Data	Method of Cost Assignment
Facility utilization[1]	All facility-paid general ledger expenses for operating a clinical unit where patients can be located (e.g., emergency department, cardiology inpatient ward, family medicine clinic), including nursing, space, and equipment costs	For inpatient units, time the patient spent on the unit; for outpatient clinics, average facility expenses for a visit to that clinic
Imaging[2]	All facility-paid general ledger expenses for operating an imaging unit (e.g., magnetic resonance imaging unit, computed tomography unit), including equipment, space, and technician costs	Time-based for patient use
Laboratory testing[3]	Existing contracts	Actual patient use
Therapy services	All facility-paid general ledger expenses associated with operating a therapy service (e.g., respiratory therapy, physical therapy), including personnel and equipment costs	Patient use of services as identified from billing charges
Medications administered[3]	Acquisition costs	Actual patient use
Supplies	Acquisition costs	Actual patient use
Professional services	Physician human resource costs for clinical care, as well as other general ledger clinical expenses paid by physicians and their representatives (e.g., medical assistant costs paid by medical group), grouped by unit (e.g., cardiology)	wRVU billing by physician

Abbreviation: wRVU, work relative value unit.

[1]Costs related to maintenance, renovation, and new construction are considered indirect costs and are not included in the direct costs.

[2]General ledger expenses for clinical units refer to all expenses recorded in the organization's complete record of financial transactions.

[3]Outpatient laboratory, pharmacy (medications administered), and imaging costs include only that care delivered at the University of Utah.

A detailed description of the VDO methodology, including sample reports, can be found in the *Journal of American Medical Informatics* as referenced (Kawamoto, 2013).

The strength of the VDO methodology is that it allows for comprehensive study of both sides of the value equation – cost and quality outcomes – and includes facility and professional costs at the patient, episode of care, and even provider levels. The tool can be used in quality improvement, clinical outcome, and cost effectiveness studies to help understand practice variability and clinical cost effectiveness. The primary limitation is that it is proprietary to University of Utah Health and has not yet been replicated elsewhere (Kawamoto, 2013).

Cost to Charge Ratio. Historically, many health care leaders and managerial decision makers have estimated hospital costs by using RCCs applied to a unit of service. While this methodology may work well when examining average costs across a diagnosis related group (DRG) or other broad units of service, it has not proven to be a good methodology for determining costs associated with a particular patient. This is because there is too much variability in costs within departments, and patients consume resources across many different departments, which then exacerbates the error of the averages used in RCCs. Hence, the level of granularity for cost analysis is precisely affected by how an organization captures utilization (Cary Martin, U of U Health, personal interview).

Shwartz, Young and Siegrist collected and studied cost data on seven hospitals comparing Relative Value Unit (RVU) based costing with RCCs. There was a high correlation between the two methodologies in comparing individual patient costs. However, their study showed that 30% of the DRGs had an error greater than 10% using RCC estimated costs compared to RVU estimated costs (1995). In another study of a

Midwest renal clinic, researchers found RCCs to be the least accurate measure of cost when compared to RVU and ABC models (West, Balas, & West, 1996). These small inquiries exemplify the need for further study and exploration of accurate costing models in health systems. While RCC may not be the most accurate costing method, it could be helpful when comparing to external information where other common cost collection metrics are not available.

Time Driven Activity – Based Costing (TDABC). Health care economists at Harvard Business School developed this novel costing strategy in order to more accurately estimate true cost. TDABC relies on managerial cost estimates of resources utilized in each encounter, product or patient using multiple time drivers that can be applied more precisely than traditional activity based costing. The TDABC model was developed to help health care leaders and managers understand clinical costs and identify ways to improve value in an era of shared risk for costs (Kaplan, 2015) (West & Balas, 1995).

As example, Cleveland Clinic partnered with the Harvard Business School to determine whether the TDABC methodology would improve the accuracy of costs, enhance value opportunities, and help drive improvements in practice for heart valve procedures. They compared the TDABC design to their current RVU cost allocation methodology in evaluating the strengths and weaknesses of each. The researchers found that the TDABC enabled them to gain additional insights into their costing technique, and improve clinical processes (Donovan, Hopkins, Kimmel, Koberna & Montie, 2014). TDABC has been shown to be a useful tool to measure costs and value in clinical care.

Knowing and understanding actual health care costs for an episode of care is becoming increasingly important for health care leaders, as the financial risk for health care shifts more to the providers (Kaplan, 2015). Contrasting VDO costs with those found in other costing methodologies may provide useful insights and perhaps improve the external reliability of this study.

Summary

In conclusion, conditions have never been more favorable for structural redesign and examination of innovative care delivery models focused on improving the value of health care. Integral to improving value is measuring and understanding actual costs at the individual, patient level. The IPU is a patient centered organizational framework whose tenets support population health for specific conditions, and value driven care. One of the central precepts of the IPU is that the team measures outcomes, costs and processes using a common measurement platform. To date, there are very few health systems that can measure actual patient care delivery costs that include both hospital and professional expenses for inpatient and outpatient care.

U of U Health has developed a proprietary costing model that gives them the ability to measure both costs and outcomes at the patient, provider, program, or in this research case, IPU level. Hence, the results of this quantitative analysis of a HF IPU program evaluation will add to the body of research knowledge on the design of IPUs and their subsequent impact on costs, as well as inform health care leaders of the challenges and lessons learned in managing a specific population, aligning incentives and costs, and developing analytical tools that support a more integrated, longitudinal treatment approach to improving patients' health.

CHAPTER III
METHODOLOGY

Study Design

The design of the study is a quantitative analysis of a program evaluation using archival data from University of Utah Health. An interrupted time series (ITS) study design methodology is used to evaluate whether there has been an immediate effect on HF patient costs post implementation of the HF IPU. The ITS is one of the strongest, quasi – experimental approaches for evaluating the effects of population level health interventions that are implemented at a point in time. One of the most common quasi – experimental design approaches is the Comparison Group Pretest/Posttest design. The ITS pre/posttest design is often used to test statistical change in an outcome rate in the time periods before and after implementation of a program designed to change the outcome (Wagner, Soumerai, Zhang, & Ross – Degan, 2002; Bernal, Cummins, & Gasparrini, 2016).

Statistical modeling using regression analysis assures that post study HF patients have similar severity and match. Multivariable statistical modeling controls for differences in patient characteristics. Segmented regression analyses are then used to evaluate whether the observed changes reflect random variation or a true change (Shi, 2008; Penfold & Zhang, 2013; Fretheim & Tomic, 2015).

The strengths of the ITS design include its wide applicability in evaluating the effectiveness of interventions absent a randomized control study, the ability to study outcomes data using population level data, clear graphical or visual representation of the data and results, and use of statistical control processes to correct for changes that might

have occurred without the intervention (Penfold & Zhang, 2013; Fretheim & Tomic, 2015).

The ITS study design limitations include the short-term view of outcomes, which may not reflect the full potential or impact of the program, and an assumption of linearity when longer term changes may not be linear. The segmented regression analysis approach aggregates individual level data, and does not necessarily reflect individual level characteristics or covariates (Wagner, Soumerai, Zhang, & Ross – Degan, 2002; Jaewhan Kim, personal interview, 2016). To minimize these limitations, the research design enforces statistical regression models, consistency in methods, and employs other controls to improve external validity.

Hypotheses

A retrospective, quantitative analysis of an IPU program evaluation using archival data from U of U Health will be conducted to analyze its impact on HF costs. An uncontrolled, pre and post, longitudinal, and observational study design was implemented to measure costs from 2014-2016. An interrupted time series (ITS) regression with a design methodology was used with aggregated outcome variables to evaluate whether there was an immediate effect on HF patient costs/utilization post implementation of the HF IPU.

$$Y_t = \alpha + \beta_1 T + \beta_2 X_t + \beta_3 (T * X_t)$$

, where Y is the outcome at time t, α is the baseline level in the outcome at T=0, β_1 represents a coefficient related to changes in the outcome over time, T is the time variable indicating time since the study starts, X_t is an indicator variable (0 before intervention and 1 after intervention), β_2 is a coefficient indicating the level change after

intervention, $T * X_t$ is an interaction variable, and β_3 indicates the slope change after intervention (Bernal, Cummins & Gasparrini, 2016).

This research study compared U of U Health resource use and measured HF patient inpatient costs, observed to expected length of stay (LOS), hospital admissions, hospital readmissions within 30 days, and Emergency Department (ED) visits before and after IPU implementation using archival data. Heart failure patients were categorized into the following population segments to improve comparability: Transplant, Ventricular Assisted Device (VAD), and Other Heart Failure patients. Analyzing HF patients as a single group blends episode of care and population health data for those patients who received care at U of U Health (James Fang, personal interview, February 14, 2017).

The primary aim of this study was to address the following research questions in order to inform administrators and clinicians as to how to measure and compare patient cost data and related hospital cost indicators.

Research question number 1. Do HF patients post IPU implementation have improved quality outcomes, such as shorter length of stay, and fewer hospital admissions and readmissions than patients pre IPU?

Research question number 2. Do HF patients post IPU implementation have fewer ED visits than HF patients pre IPU?

Research question number 3. Do HF patients post IPU have lower average heart failure attributable cost-per-patient than patients pre IPU?

These questions helped to inform the following hypotheses:

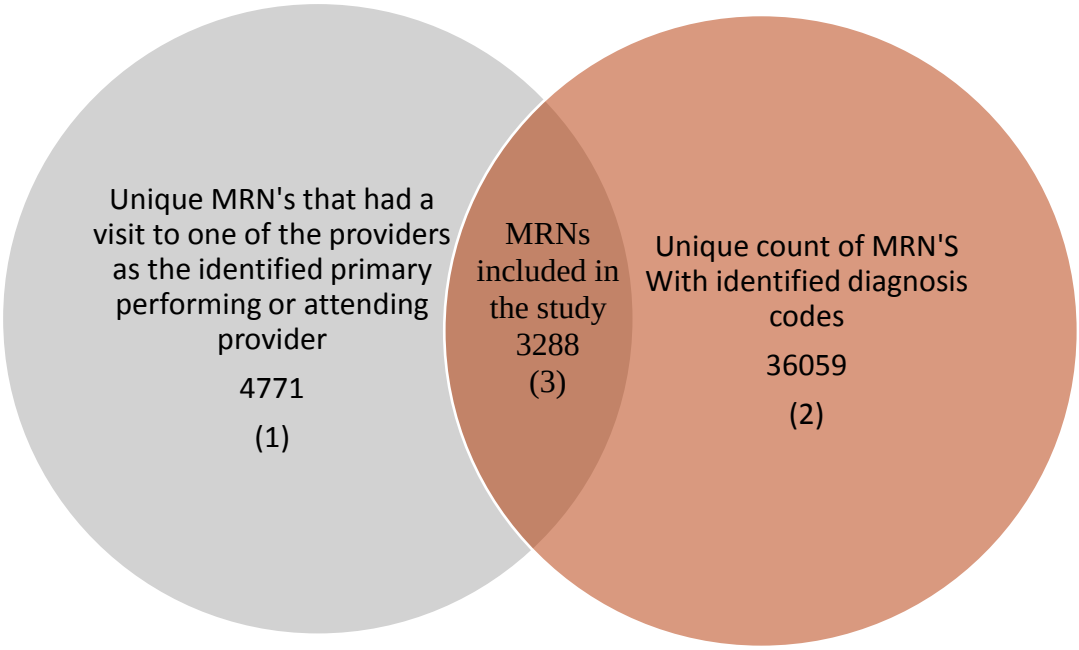
Hypothesis H_1. HF patient costs at U of U Health will decline post IPU implementation.

Hypothesis H_2. HF admissions, readmissions, observed/expected LOS, and ED visits will decline post IPU implementation.

Population and Sample

All Advanced HF patients meeting the following criteria were included in both the post study samples: A patient who 1) identified with an initial HF diagnosis encounter either as an inpatient or outpatient in the U of U Health system and was treated by specific cardiology and cardiovascular providers, and 2) any subsequent HF encounters incurred by this patient group for the fiscal years 2014 – 2016. The U of U Health fiscal year is July 1 – June 30th. The diagnostic codes for inclusion are outlined in Appendix A. In addition, the patient population count is illustrated in Figure 5 (U of U Health Enterprise Data Warehouse, 2016.

Figure 5. U of U Health HF Population Sample Counts



1 – Contains a list of all distinct Medical Record numbers (MRNs) where patient was seen by a designated provider. The designation was applied to 8 different providers and the discharge date needed to have occurred after or equal to July 1, 2012.
2 – Contains a list of distinct MRNs where patient received a specifically defined diagnosis code either from technical or professional billing, and the discharge date needed to have occurred after or equal to July 1, 2012.
3 – Contains a list of distinct MRNs where patient belonged to the list of defined diagnosis codes and was seen by one of the designated providers to include in the dataset.

De-identified patient data was used. The Medical University of South Carolina (MUSC) and University of Utah Institutional Review Boards (IRBs) classified the study as non-human subjects research.

Definition of Variables

A definition of cost outcome variables is contained in Table 2. These variables were collected for all subgroups of the HF population: Transplants, VADs and Other HF patients, excluding Veteran Administration patients, using the U of U Health VDO

costing model. HF readmission inclusion criteria are illustrated in the 2 x 2 box in Table 3.

Table 2. U of U Health Cost Outcome Variables

Cost Indicators	Definition VDO Model
Cost Per Procedure: Transplants and VADs	Sum of total direct costs divided by the total count of transplants or VADs
Inpatient Average Discharge Costs: Other HF	Sum of total direct cost divided by the total count of inpatient visits for HF patients only
Observed to expected (O/E) Length of Stay (LOS): Transplants, VADs and Other HF	Sum of observed LOS divided by expected LOS for all inpatient visits; expected LOS determined by Vizient* clinical database
HF Volume: Transplant, VAD, and Other HF	Counts of total number of discharged transplants, VAD procedures, and HF new patient visits (NPVS)
ED Visit Counts: Transplants, VADs, and Other HF	Count of number of ED visits, regardless of last discharge date
HF 30 Day Readmission Rates: Transplants, VADS, and Other HF	Sum of the number of Vizient* 30 day readmits divided by the number of inpatient discharges

*Vizient is the clinical benchmarking database used by most academic medical centers and defines 30-day all cause readmission rates for adult, non-OB patients as the percentage of patients within certain service lines who return to the hospital for any reason within 30 days of discharge from the prior (index) admission (U of U Health Decision Support, 2016)

Table 3. HF Readmission Inclusion 2 x 2 Box

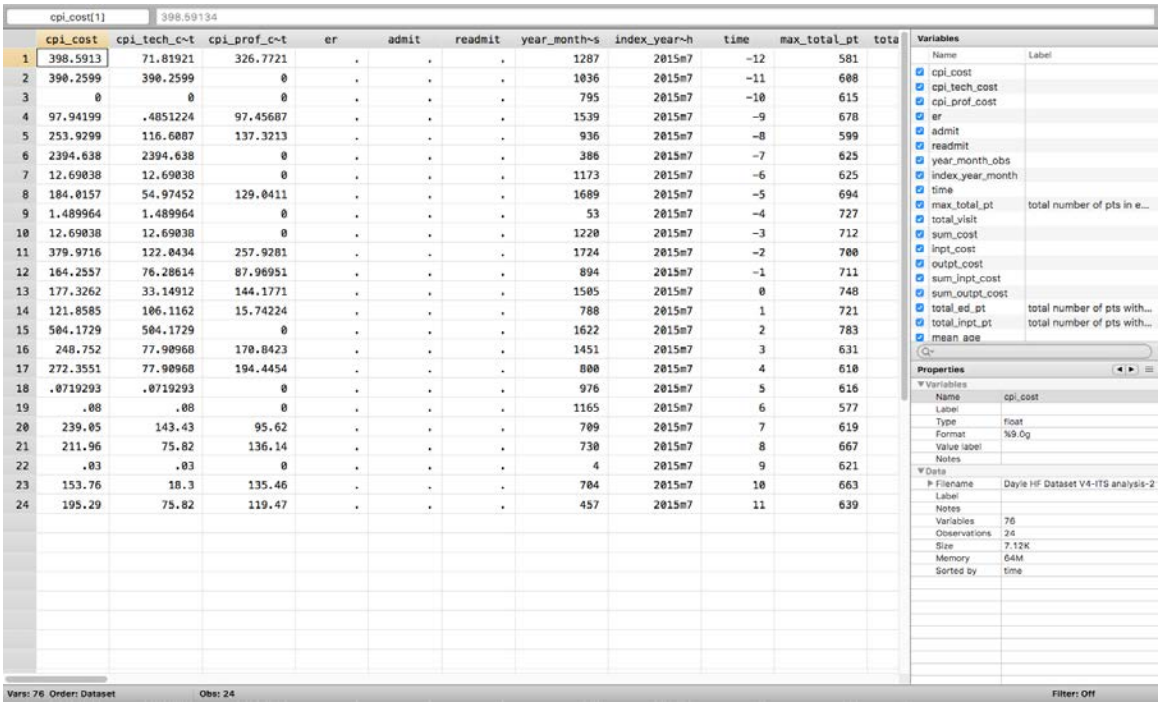
	HF Readmits	**Non – HF Readmits**
HF Admits		
Non – HF Admits		

The predictor variable was the implementation of the IPU business model as previously defined beginning July 1, 2015. Other independent variables collected and included in the descriptive statistics and regression analyses include age at admission, de-identified medical record number, gender, race and ethnicity, zip code, block group, ICD-10, CPT, ICD Procedure Codes, DRG, date of service, severity index (CMI) and Hierarchical Clinical Categorization (HCCs). A complete list of variables, codes and corresponding queries are contained in Appendix B.

Data Set Description and Structure

A finer data structure in long format was used to model the ITS regression analysis. A data set sample with corresponding variables and properties is illustrated in Figure 6.

Figure 6. HF Population Data Structure Example (Screenshot)



	cpi_cost	cpi_tech_c~t	cpi_prof_c~t	er	admit	readmit	year_month~s	index_year~h	time	max_total_pt	tota
1	398.5913	71.81921	326.7721	.	.	.	1287	2015m7	-12	581	
2	390.2599	390.2599	0	.	.	.	1036	2015m7	-11	608	
3	0	0	0	.	.	.	795	2015m7	-10	615	
4	97.94199	.4851224	97.45687	.	.	.	1539	2015m7	-9	678	
5	253.9299	116.6087	137.3213	.	.	.	936	2015m7	-8	599	
6	2394.638	2394.638	0	.	.	.	386	2015m7	-7	625	
7	12.69038	12.69038	0	.	.	.	1173	2015m7	-6	625	
8	184.0157	54.97452	129.0411	.	.	.	1689	2015m7	-5	694	
9	1.489964	1.489964	0	.	.	.	53	2015m7	-4	727	
10	12.69038	12.69038	0	.	.	.	1220	2015m7	-3	712	
11	379.9716	122.0434	257.9281	.	.	.	1724	2015m7	-2	700	
12	164.2557	76.28614	87.96951	.	.	.	894	2015m7	-1	711	
13	177.3262	33.14912	144.1771	.	.	.	1505	2015m7	0	748	
14	121.8585	106.1162	15.74224	.	.	.	788	2015m7	1	721	
15	504.1729	504.1729	0	.	.	.	1622	2015m7	2	783	
16	248.752	77.90968	170.8423	.	.	.	1451	2015m7	3	631	
17	272.3551	77.90968	194.4454	.	.	.	800	2015m7	4	610	
18	.0719293	.0719293	0	.	.	.	976	2015m7	5	616	
19	.08	.08	0	.	.	.	1165	2015m7	6	577	
20	239.05	143.43	95.62	.	.	.	709	2015m7	7	619	
21	211.96	75.82	136.14	.	.	.	730	2015m7	8	667	
22	.03	.03	0	.	.	.	4	2015m7	9	621	
23	153.76	18.3	135.46	.	.	.	704	2015m7	10	663	
24	195.29	75.82	119.47	.	.	.	457	2015m7	11	639	

The data comes from multiple health care information systems and was obtained from the U of U Health enterprise data warehouse (EDW). All patient data was de-identified using surrogate identification numbers. Cost data was adjusted annually for inflation using the medical consumer price index (CPI) and will be presented in 2016 dollars (Bureau of Labor Statistics, 2016). A finer data structure in long format was used in preparing the data for regression analysis using Stata version 14.0 (StataCorp).

Data Analysis

The ITS regression analysis identifies and compares cost and outcome data one year prior implementation of the HF IPU, and one-year post implementation using data collected from July 1, 2014 through June 30, 2015 as the timeframe before implementation, and July 1, 2015 through June 30, 2016 as the data collection period post implementation of the HF IPU. The data was set up in a long file format where each row is one time point per subject, or in this case per visit (Grace-Martin, 2016). Both professional and technical costs were aggregated based on primary visit. Missing values were excluded where there were either invalid visit numbers or duplicate visits.

In addition, outliers were adjusted to remove those representing the top .10 percent of all HF patient costs including VADs and Transplants. Stata version 14.0 (StataCorp) was used for the analysis whereby results are interpreted as follows:

_t = the slope of the cost variable before intervention

_x0 = the change in cost immediately after the intervention

_x _ t0 = the difference in slope of the cost between the pre and post intervention

A p-value ≤ 0.05 will be interpreted as statistically significant not correcting for multiple comparisons. Cumby – Huizinga actest for autocorrelation was completed on all

pre/post data comparisons and was not statistically significant in all cases (Baum & Schaffer, 2013).

All cost data trends are normalized and adjusted for mean age, percent male, percent white, and the mean CCI in the regression analysis. Cost data was normalized or indexed based on the following equation and scaled to a range of (0,1) (Grus, 2015):

Normalized cost = (cost – minimum cost)/ (maximum cost – minimum cost)

A detailed description of the data set and statistical queries can be found in Appendices D and E.

Limitations

Key limitations of the study include the relatively short term view of outcomes, whereby the IPU model and related systems may not have reached its full power to show the true impact on cost or cost trends. Also, there is very little external reliability since the study includes archival data from just one hospital and compares average costs using a proprietary costing model (Shi, 2008; Rachel Hess, U of U Health, personal interview, 2016). However, in a quasi-experimental design such as this, an interrupted time series (ITS) with segmented regression analysis is one of the strongest research designs used to examine the impact on a population from programmatic interventions implemented at a point in time (Wagner, Soumerai, Zhang, & Ross – Degan, 2002; Bernal, Cummins, & Gasparrini, 2016).

In addition, there are inherent limitations in the ITS methodologies, including but not limited to, over-dispersion of time series data, autocorrelation, seasonal trends, and time varying confounders (Bernal, Cummins, & Gasparrini, 2016). Much of this will be controlled through statistical analysis. Lastly, results could be due to confounding factors

or spurious events; and therefore, are not causal but correlated effects. There is also possible instrumentation and researcher bias that may influence the results and conclusions (Shi, 2008).

CHAPTER IV
RESULTS

The ITS pre/post analyses show overall declining trends in total HF costs, total HF technical costs, total HF professional costs, HF costs (total, surgical and non-surgical), admissions, ED visits, and mean LOS. While VAD costs dropped initially, they began to increase in the post intervention period. HF readmissions remained flat across the pre and post periods. HF surgical and non-surgical costs have seen statistically significant declines post implementation of the HF IPU. While most of the other trends are not statistically significant, they are trending in the right direction and might become statistically significant over time.

Population Characteristics

As previously defined in the methodology chapter, the population includes all advanced HF patients meeting the following criteria: a patient who 1) identified with an initial HF diagnosis encounter either as an inpatient or outpatient in the U of U Health system and was treated by select cardiology and cardiovascular providers, and 2) any subsequent HF encounters incurred by this patient group for the fiscal years 2015 – 2016. Fiscal year 2014 data was eliminated due to inconsistencies in the data collection methodology with the other years, resulting in fewer number of patients studied. Other population characteristics obtained included age, gender, race, and the Charleston Co-morbidity index. A complete list of the data set and associated variables is contained in Appendix D.

Based on their coefficient of variations, there was less than a five percent variance across aggregated monthly patient characteristics in mean age, percent male, percent white, and mean CCI; therefore, the study did not test for statistical significance. On

average, there were approximately 656 patients and 1,521 visits each month. The average aggregate monthly patient age was 63 years old, 66 percent of the patients were male (44 percent female), 86 percent of the patients were white (14 percent other), and the average clinical severity index was 5.13. A summary of the data set aggregated by month is listed in Table 4.

Table 4. Summary of Population Characteristics Aggregated by Month Tables 1-2

Summary Table 1

Months	Total Patients	Visits	Age	Percent Male	Percent White	Avg CCI
-12	580	1340	63.00	67.24	86.72	5.10
-11	608	1390	63.00	66.61	86.02	5.14
-10	612	1382	63.00	65.20	86.27	4.95
-9	676	1652	64.00	63.46	87.43	4.99
-8	597	1317	63.00	64.99	85.59	5.28
-7	624	1510	64.00	63.94	87.02	5.03
-6	624	1506	64.00	64.74	86.70	5.21
-5	694	1616	63.00	67.15	87.03	4.98
-4	724	1822	63.00	64.09	84.94	5.15
-3	711	1649	63.00	64.56	86.08	5.10
-2	699	1679	64.00	64.66	86.98	5.17
-1	711	1751	64.00	66.81	87.48	5.17
0	748	1820	64.00	64.30	86.23	5.17
1	721	1706	64.00	65.05	85.71	5.17
2	782	1887	63.00	66.75	86.57	4.98
3	630	1408	63.00	64.76	85.40	5.15
4	610	1326	62.00	67.54	83.61	5.10
5	614	1409	62.00	68.57	83.88	5.38
6	576	1219	61.00	67.01	83.51	5.21
7	618	1341	62.00	66.83	84.63	5.17
8	666	1585	62.00	67.57	84.83	5.14
9	620	1409	61.00	69.03	85.81	5.10
10	663	1391	61.00	67.12	83.56	5.12
11	639	1386	62.00	70.74	83.41	5.15
Average	**656**	**1521**	**62.83**	**66.20**	**85.64**	**5.13**

Summary Table 2

Months	Norm Total Cost	Norm Tech Cost	Norm Prof Cost	Avg LOS	ED Visits 1000	Admits 1000	Readmits 1000
-12	0.68	0.64	0.90	8.29	17.24	162.07	0.16
-11	0.63	0.59	0.91	8.65	18.09	171.05	0.18
-10	0.47	0.44	0.67	9.07	21.24	130.72	0.15
-9	0.54	0.53	0.59	7.72	13.31	159.76	0.31
-8	0.62	0.61	0.63	8.06	21.78	139.03	0.16
-7	0.93	0.93	0.88	9.08	22.44	169.87	0.26
-6	0.85	0.82	1.00	9.29	28.85	171.47	0.21
-5	0.55	0.51	0.78	8.22	28.82	162.82	0.22
-4	0.69	0.68	0.74	10.04	27.62	132.60	0.11
-3	0.46	0.47	0.36	7.69	30.94	126.58	0.19
-2	1.00	1.00	0.96	9.33	21.46	171.67	0.21
-1	0.43	0.42	0.46	8.09	15.47	143.46	0.19
0	0.67	0.67	0.62	8.64	12.03	140.37	0.19
1	0.63	0.64	0.56	9.21	22.19	141.47	0.21
2	0.67	0.66	0.73	9.48	34.53	154.73	0.18
3	0.93	0.92	0.98	8.93	12.70	160.32	0.16
4	0.50	0.50	0.50	6.59	11.48	165.57	0.21
5	0.98	0.99	0.84	10.10	16.29	154.72	0.19
6	0.50	0.50	0.50	7.05	17.36	161.46	0.22
7	0.67	0.67	0.63	8.71	14.56	155.34	0.17
8	0.81	0.80	0.80	6.75	10.51	168.17	0.16
9	0.67	0.68	0.60	8.14	20.97	143.55	0.24
10	0.71	0.72	0.62	8.79	16.59	131.22	0.22
11	0.00	0.00	0.00	5.72	21.91	118.94	0.18
Average	**0.65**	**0.64**	**0.68**	**8.40**	**19.93**	**151.54**	**0.19**

Data Analysis

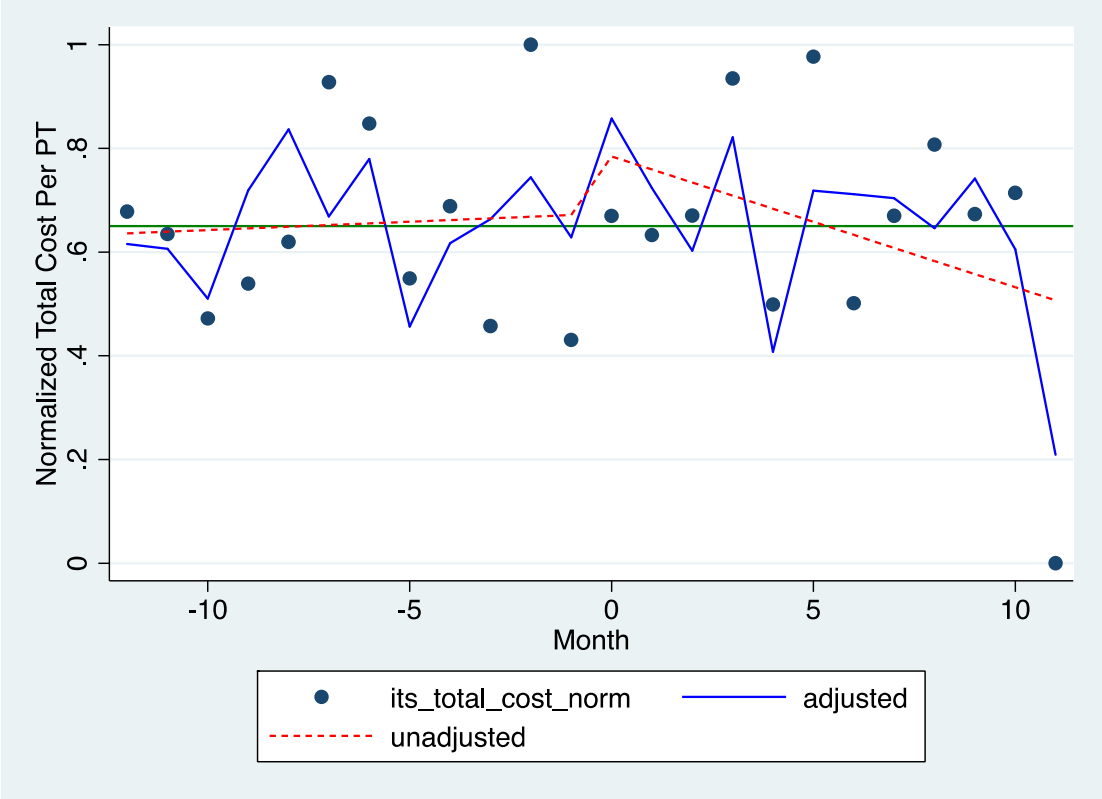
The remainder of this section illustrates trends for each of the cost and outcome variables studied. Study results and related detail are organized within the context of the hypotheses. All ITS regression tables with autocorrelation analysis are contained in Appendix E.

Hypothesis H_1. HF patient costs at U of U Health will begin to decline post IPU implementation.

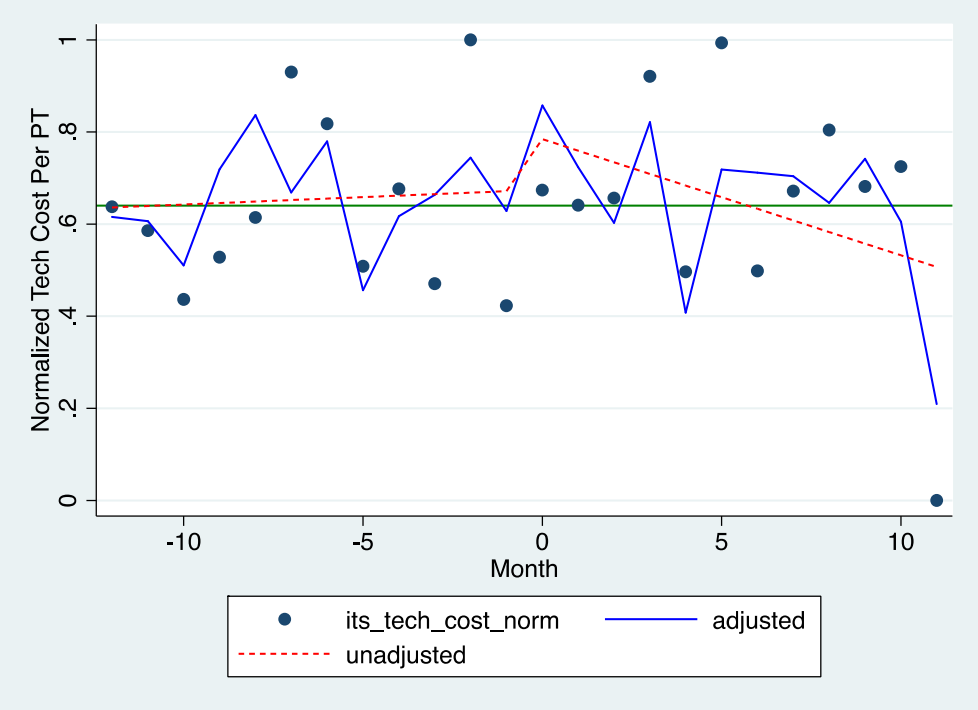
Total Heart Failure Cost Per Patient (All HF, VAD, and Transplant)

There was a 21% initial increase in costs post IPU implementation followed by a 1% increase in cost slope between the pre and post intervention time periods, which is not statistically significant with a p-value of .712. This similar pattern in cost trend occurred in both technical and professional fees with p-values of .706 and .759 respectively, as illustrated in Graphs 1 – 3.

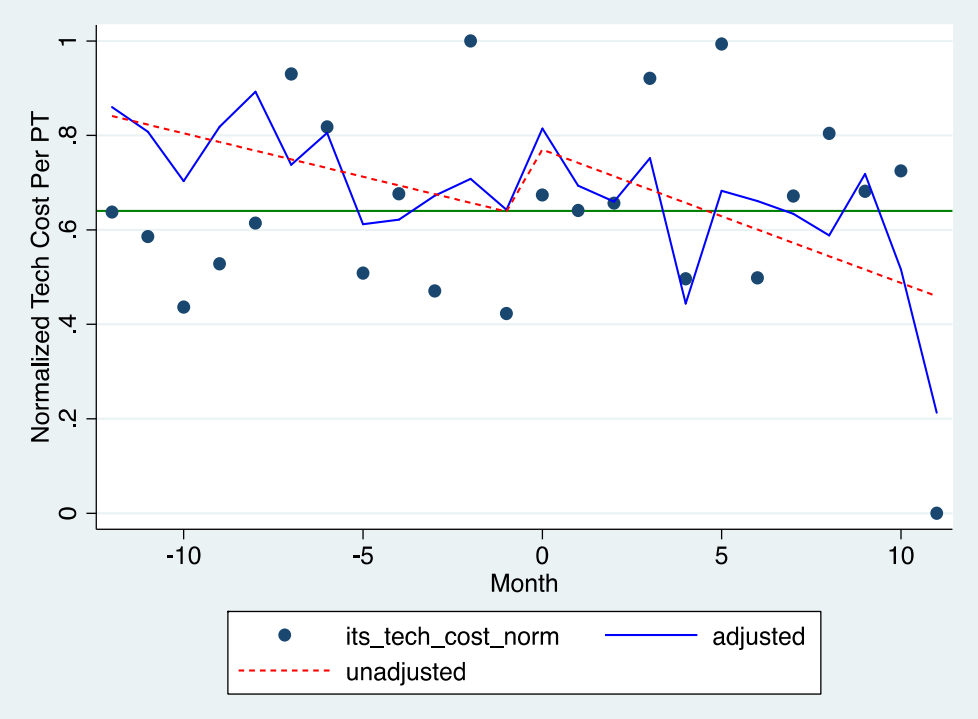
Graph 1. HF Cost Per Patient (All) Normalized and Adjusted Trends



Graph 2. HF Technical Cost Per Patient (All) Normalized and Adjusted Trends



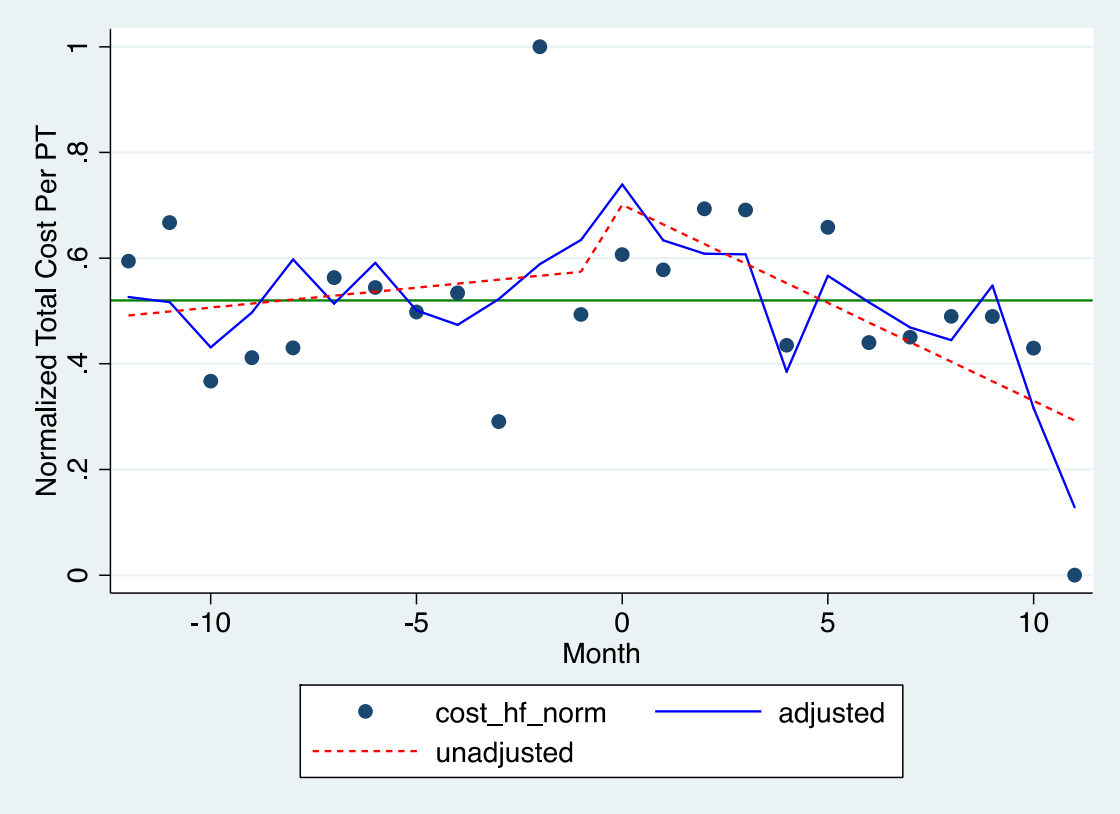
Graph 3. HF Professional Cost Per Patient (All) Normalized and Adjusted Trends



Heart Failure Costs – HF Patients Only

Costs for HF patients only, excluding VADs and Transplants, increased 23% post implementation of the IPU and declined in slope by 3% between the post time periods. The change in slope is not statistically significant for these HF patients with a p-value of .096 (Graph 4).

Graph 4. HF Cost Normalized and Adjusted Trends

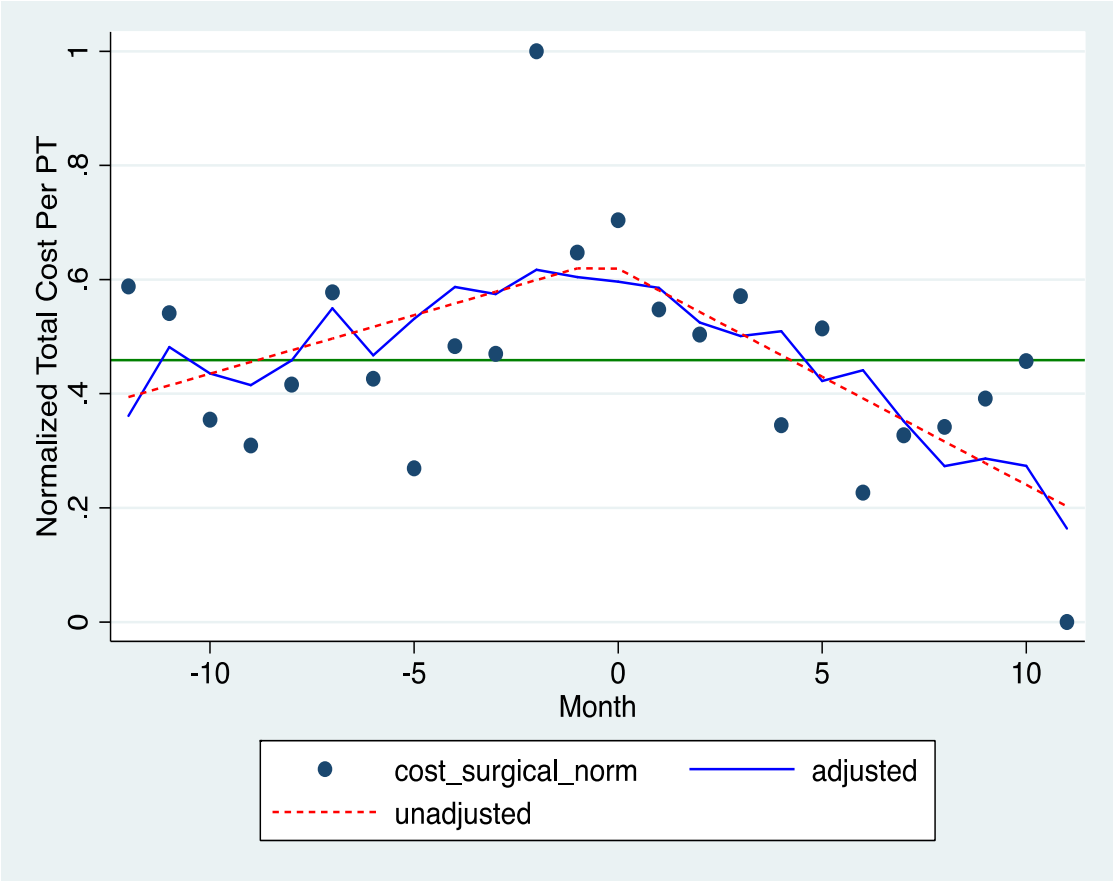


Heart Failure Cost – Surgical and Nonsurgical

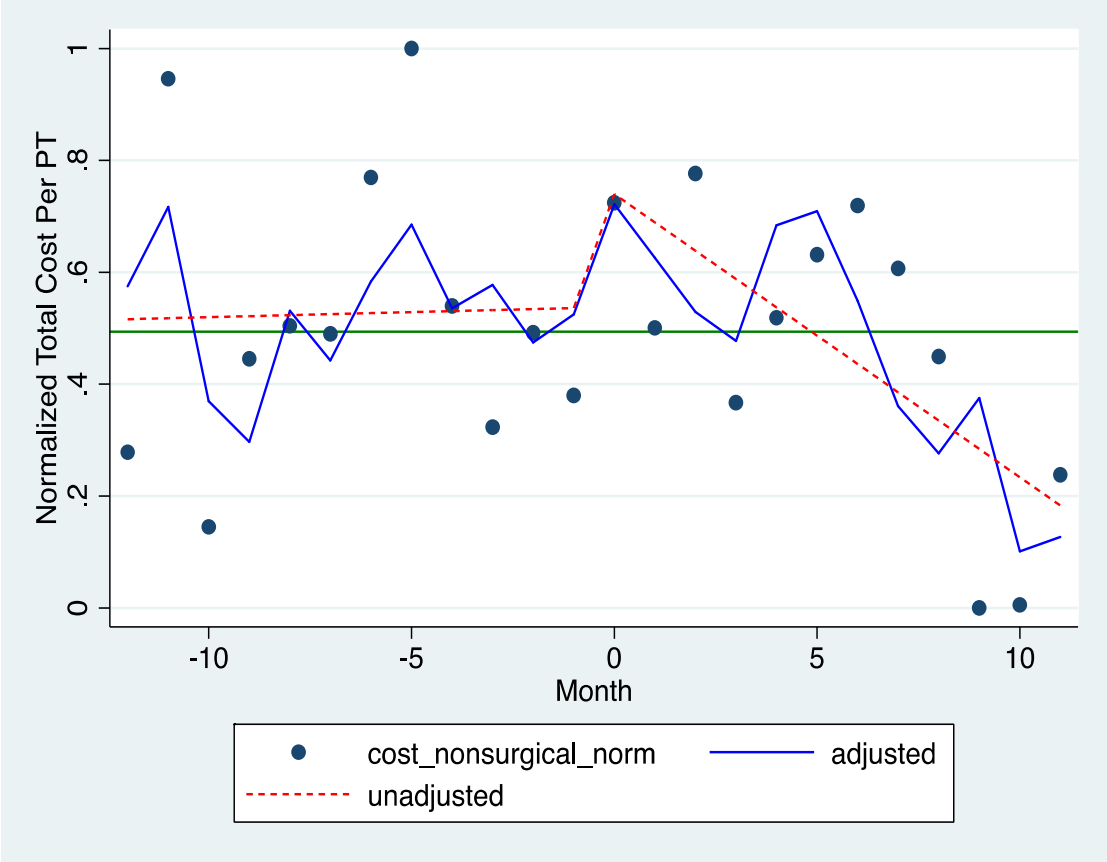
There are statistically significant changes when the population cost data is segmented by surgical and non-surgical patients. Heart failure cost for surgical patients show an initial decline (3%) in costs post implementation of the IPU followed by a statistically significant downward trend (p-value .041) of 6% in slope between the pre and post intervention periods. This trend is especially strong in the post intervention time

period with a p-value of .005. Nonsurgical HF costs are also on the decline with a statistically significant reduction in the post intervention time period (p-value .025) as illustrated in Graphs 5 and 6.

Graph 5. HF Cost – Surgical Normalized and Adjusted Trends



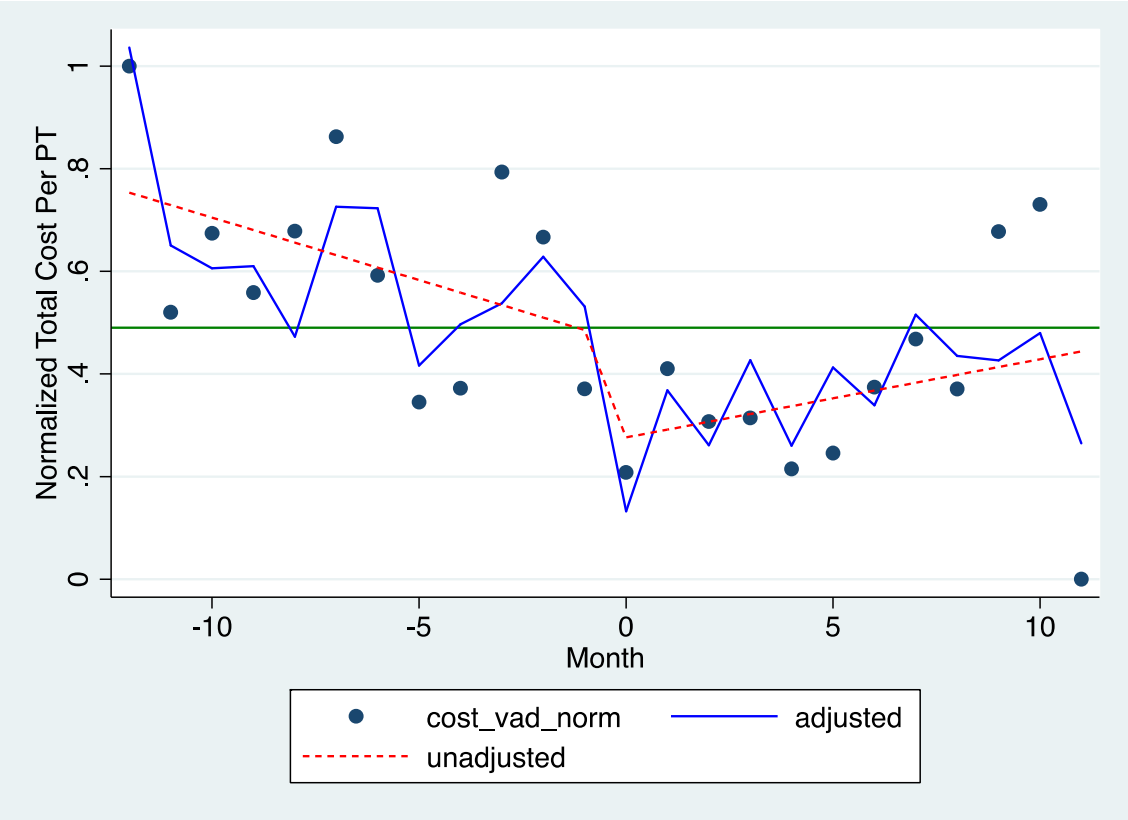
Graph 6. HF Cost – Nonsurgical Normalized and Adjusted Trends



HF Ventricular Assisted Device (VAD) Cost

HF VAD costs experienced an initial drop of 23% post implementation of the HF IPU, and a slight increase of 4% in slope between the pre and post intervention period. The slope change was not statistically significant with a p-value of .097 (Graph 7).

Graph 7. HF VAD Cost Normalized and Adjusted Trends



HF Transplant Cost

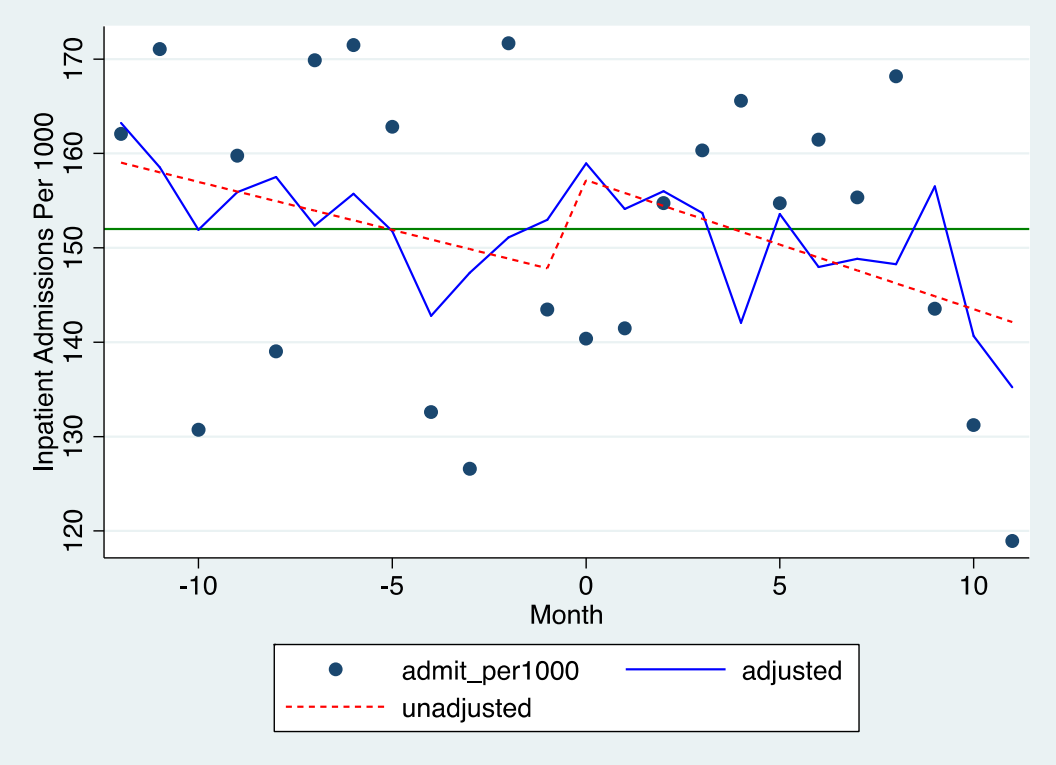
After normalizing and adjusting for outliers, there were not enough HF Transplant patients to measure statistical significance.

Hypothesis H_2. HF admissions, ED visits, readmissions, and observed/expected LOS will decline post IPU implementation.

HF Admissions

Admissions per 1000 patients increased in the post period by 15.7 with a slope increase of .29 between the pre and post periods, reflecting little change in admission patterns. Change in admissions were not statistically significant with a p-value of .930 (Graph 8).

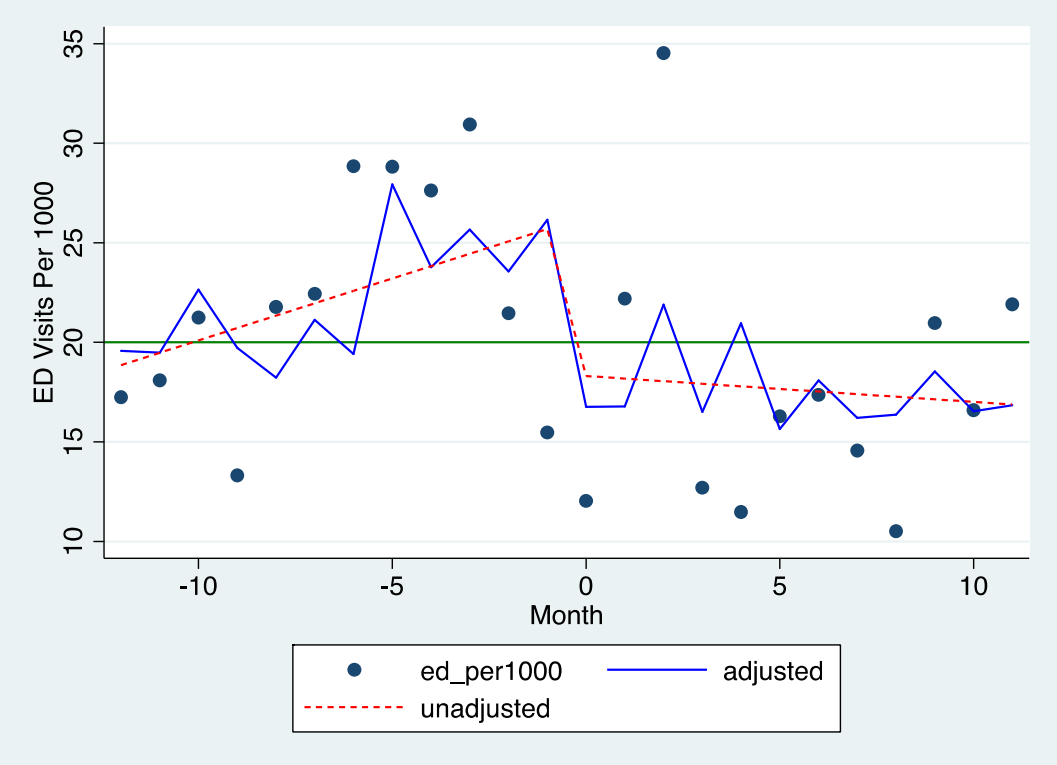
Graph 8. HF Admissions Per 1000 Patients Adjusted Trends



HF Emergency Department Visits

Emergency Department (ED) visits per 1000 patients have declined post implementation of the IPU by -8.61 with a slope decline of -.1.75 between the pre and post periods. This trend is not statistically significant with a p-value of .259 (Graph 9). However, the decline in visits is remarkable and appears to have been sustainable over the post period.

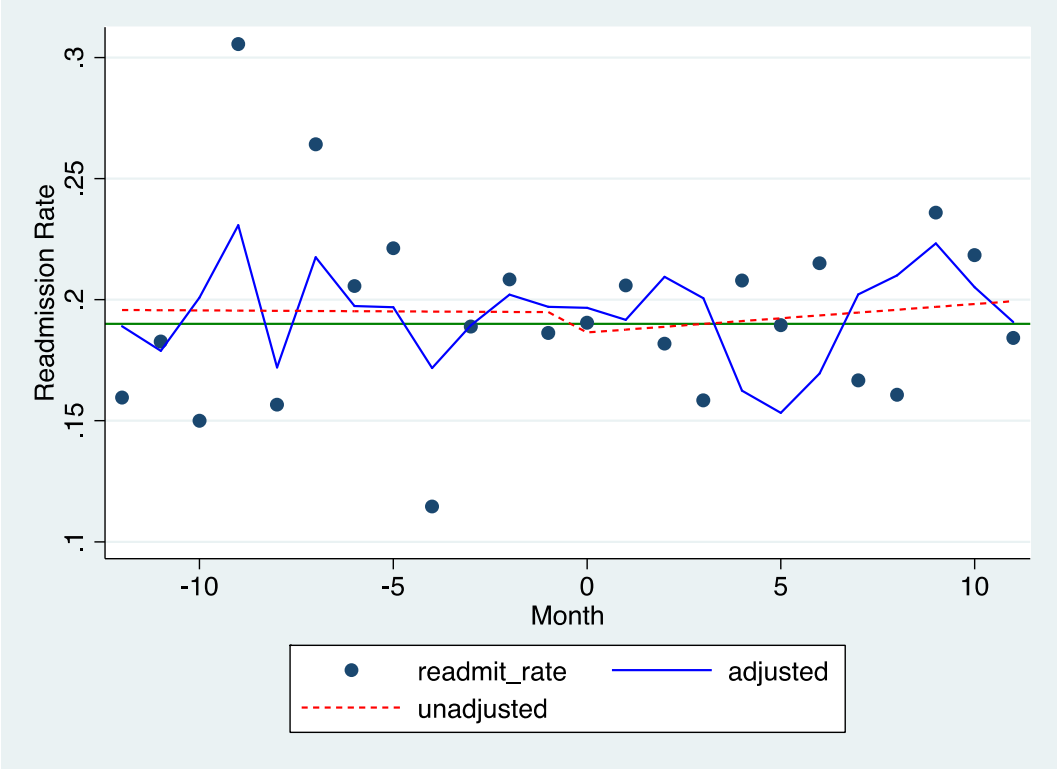
Graph 9. HF ED Visits Per 1000 Patients Adjusted Trends



HF Readmissions

Heart failure all cause readmission rates dropped .005 post IPU implementation with a slope change of .008 between the pre and post periods. Trends are not statistically significant with a p-value of .383. In addition, there appears to be less variability in readmission patterns post implementation of the IPU model (Graph 10).

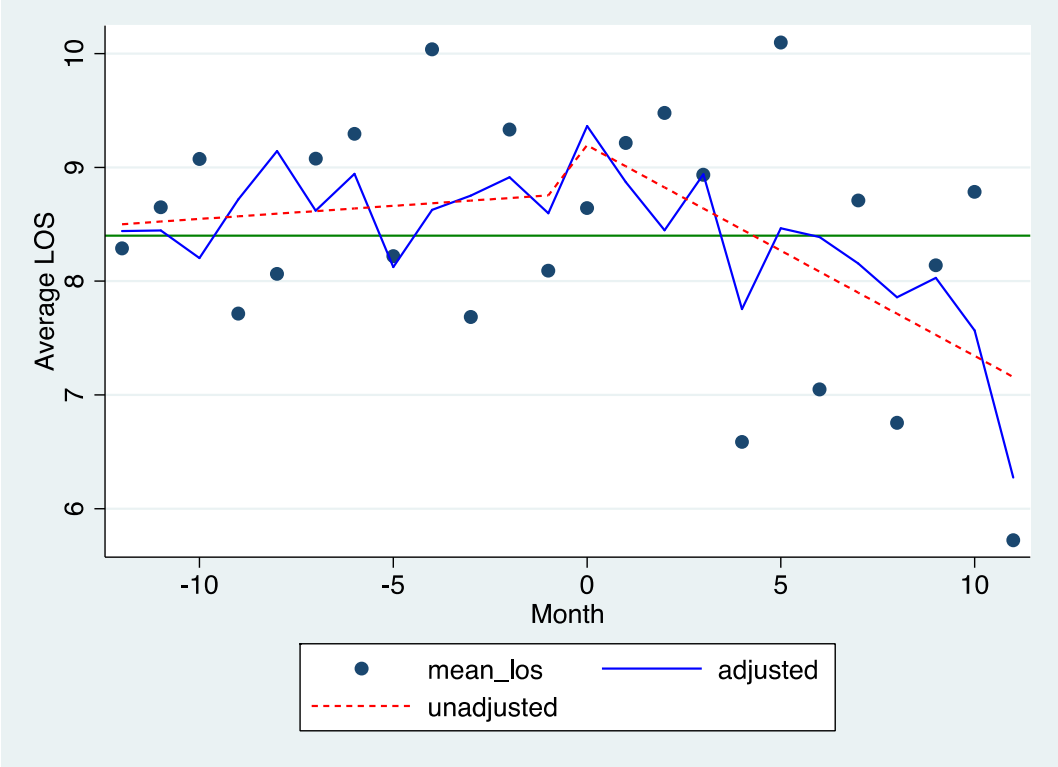
Graph 10. HF Readmission Rate Adjusted Trends



HF Mean Length of Stay

HF mean length of stay increased post implementation .69 with a slope decline of -.12 between pre and post periods. This decline is not statistically significant with a p-value of .515 (Graph 11).

Graph 11. HF Mean Length of Stay



CHAPTER V

DISCUSSION

Discussion of Results

Implementation of the HF IPU model in and of itself did not have a statistically significant impact on total HF costs; however, when costs were broken down into HF Surgical and Non-surgical patients, there were statistically significant declines in costs. Other cost indicators such as mean LOS, ED visits, technical, and professional cost trends were also on the decline, yet not statistically significant.

In some cases, however, the declining trends may be financially or clinically significant. It is important to note the difference between statistical significance and clinical significance. The p-values represent the probability that the results were due to some level of chance. It does not measure the treatment effect or significance of the change. One measure may be more statistically significant than another; however, the magnitude of change may be greater or less. ITS graphs allow the researchers to observe the level of change while also testing for statistical significance in trying to determine if the results are robust enough to be clinically significant (P values, 2016).

This research had similar outcomes to another study published in JAMA measuring the association of this same value driven outcomes tool with cost reduction and improvement in health outcomes. The researchers concluded that identifying variability in costs and quality outcomes and sharing this data with physicians may help in improving care (Lee, et al., 2016). While both studies are unique to University of Utah Health, other costing methodologies that incorporate patient level cost data could be used to track change over time. The ability to identify and monitor actual health care delivery

costs is a critical component of improving the value of health care (Lee et al., 2016; Porter & Lee, 2013).

The Integrated Time Series (ITS) regression analysis and design approach is perhaps the most generalizable aspect of this research. This methodology can be extended to incorporate other interventions; and more importantly, be applied to other quality improvement initiatives in measuring the impact of an intervention on cost and/or quality outcomes. ITS is a simple, persuasive tool used to evaluate the impact of a change or intervention on an outcome for a specific population of individuals. It is especially useful when a randomized control study is not possible, or perhaps even unethical (Penfold & Zhang, 2013).

If we do see a change in cost, what is driving it? Do you need an IPU model to improve patient costs and outcomes? The study does not answer these questions directly; however, in order to study a population, practice patterns, or cost and quality data, there needs to be a physician-led team that is motivated to improve patient value, and accountable for performance defined by measurable outcomes. Identifying variability in care often requires external review by value engineers or process improvement experts. The tenets of Porter and Lee's IPU model as well as the other integrated care approaches reinforce these principles (Mitchell, et al., 2015; McKay and Wieck, 2014; Bogaev, 2010; Porter & Teisberg, 2007).

In subsequent dialogue with the HF IPU leadership, participants noted challenges such as the ability to obtain reliable data, variability in patient mix, identification of meaningful process improvements, clinical team coordination, episode of care verses longitudinal care coordination, budgetary and other more cultural issues. As one leader

stated, “Committee driven implementation is slow. There is much work to be done translating ideas from the board room to the bedside.” Also important were discussions about how best to build the academic and research components into the IPU model. (James Fang, personal interview, 2017).

Some of the advantages cited by the HF IPU leadership team included improved organizational alignment and service integration, creation of more formal goals, focus on patient-centered care and clinical care pathways, and development of a framework for patient reported outcomes measures to support future research. Future IPU opportunities were noted, such as extending the IPU to the entire service line, creating more actionable data, developing and monitoring “perfect care” indices for patient procedures, implementing heart failure discharge interventions to further reduce readmissions, and improving the heart failure care pathway from primary care through more home-based care. Lastly, suggestions for change within the IPU model encompassed the need for a dedicated budget and support staff, broader operational representation with a population health approach, and more efficient decision making power (U of U Health HF IPU Leadership, personal interviews, 2017).

Conclusions

There were several lessons learned or additional conclusions drawn from this study, including the following:

- Segmenting the analysis by patient type is important in understanding true cost variation. By aggregating all HF patient costs, statistically significant differences are masked by the data.

- Extending the time period of both the post periods, will increase the power of the study results (Bernal, Cummins, & Gasparrini, 2016). The initial research plan was to use two years one year post; however, the integrity of the FY14 costing data was questionable.
- Moving the post period out six months or more may impact results, since with any new program implementation there is often a learning curve or ramp up in the beginning before real change can occur.
- Focusing on changes in practice that reduce technical costs, such as supplies, operating room time and diagnostic tests will have the greatest impact on costs. Total HF cost and total HF technical cost trends and slope change are almost identical. Total HF professional costs did not appear to have a significant impact on total cost as illustrated in the differences observed in the pre intervention period.
- Understanding the Hawthorne effect whereby providers are changing their behavior based on new knowledge, different incentives, or just the fact that they are being studied is important given that there were no significant changes in practice or providers noted over the post periods (Shuttleworth, 2016).
- Rewarding the same fee for service driven care even in an IPU model does not necessarily incentivize population health approaches to care; rather it supports continuous improvement in both volumes and quality.
- Measuring episode of care costs and even other related costs within the same health care delivery system is a start; however, we need access to patient data sources from other facilities and over different time periods to understand true

population health costs. Currently, this level of reliable data sharing is nonexistent. Therefore, most cost studies are from the perspective of established payer databases and not based on actual patient care delivery costs.

Future Study

There are plenty of opportunities for future cost studies both within University of Utah Health and beyond. Internally, researchers may choose to extend the study time period to test whether the change is truly linear and sustainable. Layering in other interventions that might further impact cost and patient outcomes would strengthen the power of the study. Comparing this population of HF patients in the IPU to another similar cohort outside of the IPU would also enhance the study's validity.

Combining quality outcomes research, such as patient mortality and other HF related patient outcome indicators, with this type of cost analysis would add to the understanding of value-based outcomes research and potential study methodologies.

Incorporating patient reported outcomes and examining the correlation between these reported outcomes and cost would lend to the body of comparative effectiveness research, and bring a unique cost perspective to traditionally more clinically oriented outcomes studies.

In addition, the costing methodology using ITS regression analysis can be refined and applied to other services to track interventions across disease types, and serve as a model for standardizing the impact of costs across the organization. Studying the financial integration and alignment of incentives within the IPU model and its operational structure may also shed additional light on motivations behind changes in cost.

Externally, the research could be expanded to include a broader HF population through collaborations with other cardiologists and primary care physicians. Careful attention would need to be given to defining the population, and obtaining a consistent data set for comparison.

Analyzing payer costs for those HF patients treated at University of Utah Health versus other health systems utilizing data from an all payer data base or Medicare may be another useful comparison. It would be interesting to see if payer costs correlate with actual patient care delivery costs.

Summary

Knowing the cost of delivering patient care is a mandatory first step as health care leaders are tasked with reducing the cost of US health care. The Center for Medicare and Medicaid Services (CMS) has targeted heart failure patients and their related health care expenses as a potential opportunity to reduce national health care costs. In 2009, the estimated cost of treating heart failure patients in the US was greater than $30 billion, and costs are expected to more-than-double in 15 years.

Conditions have never been more favorable for structural redesign and examination of innovative care delivery models focused on improving the value of health care. Integral to improving value is measuring and understanding actual costs at the individual patient level. The IPU is a patient-centered organizational framework whose principles support population health for specific conditions and value-driven care. To date, there are very few health systems that can measure actual patient care delivery costs that include both hospital and professional expenses for inpatient and outpatient care. U of U Health has developed a proprietary costing model that gives them the ability to

measure both costs and outcomes at the patient, provider, program, or in this research case, IPU level.

The design of the study is a quantitative analysis of a program evaluation using archival data from U of U Health. An interrupted time series (ITS) study design methodology is used to evaluate whether there has been an immediate effect on HF patient costs post implementation of the HF IPU. The ITS is one of the strongest, quasi-experimental approaches for evaluating the effects of population level health interventions that are implemented at a point in time. The ITS pre/posttest design is often used to test statistical change in an outcome rate in the time periods before and after implementation of a program designed to change the outcome (Wagner, Soumerai, Zhang, & Ross-Degan, 2002; Bernal, Cummins, & Gasparrini, 2016).

The ITS pre/post analyses show an overall declining trend in total HF costs, total HF technical costs, total HF professional costs, HF costs (total, surgical and non-surgical), admissions, ED visits, and mean LOS. While VAD costs dropped initially, it began to increase in the post intervention period. HF readmissions remained flat across the pre and post periods. Statistically significant and declining trends were observed in HF surgical, and non-surgical cost trends. While some trends were not statistically significant, they may be deemed financially or clinically significant and worth further study.

There are plenty of opportunities for additional research. The results of this quantitative analysis of a HF IPU program adds to the body of research knowledge on the design of IPUs and their subsequent impact on costs, as well as informs health care leaders of the challenges and lessons learned in managing a specific population, aligning

incentives and costs, and developing analytical tools that support a more integrated, longitudinal treatment approach to improving patients' health.

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APPENDIX A

Diagnosis Codes Used to Define HF Patient Population

Diagnosis Code	Diagnosis Code Description
428.9	UNSPECIFIED HEART FAILURE
745.2	TETRALOGY OF FALLOT
V43.21	ORGAN/TISSUE REPL OTH MEANS HRT ASSIST DEVICE
428.22	CHRONIC SYSTOLIC HEART FAILURE
402.91	HYPERTENSIVE HEART DISEASE UNSPEC W/HEART FAIL
398.91	RHEUMATIC HEART FAILURE
428.41	ACUTE COMBINED SYSTOLIC&DIASTOLIC HEART FAILURE
I50.31	ACUTE DIASTOLIC CONGESTIVE HEART FAILURE
Z95.3	PRESENCE OF XENOGENIC HEART VALVE
O90.3	PERIPARTUM CARDIOMYOPATHY
I40.0	INFECTIVE MYOCARDITIS
Z48.22	ENCOUNTER AFTERCARE FOLLOWING KIDNEY TRANSPLANT
Z48.23	ENCOUNTER AFTERCARE FOLLOWING LIVER TRANSPLANT
D86.84	SARCOID PYELONEPHRITIS
Z48.290	ENCOUNTER AFTERCARE FLW BONE MARROW TRANSPLANT
I50.40	UNSPECIFIED COMBINED SYSTOLIC & DIASTOLIC CHF
T81.11XA	POSTPROCEDURAL CARDIOGENIC SHOCK INITIAL ENC
I25.750	ATHEROSCLER NATV COR ART TPLNT HRT W/UNSTABLE AP
276.69	OTHER FLUID OVERLOAD
428.42	CHRONIC COMB SYSTOLIC&DIASTOLIC HEART FAILURE
746.7	HYPOPLASTIC LEFT HEART SYNDROME
277.39	OTHER AMYLOIDOSIS
422.91	IDIOPATHIC MYOCARDITIS
404.13	HTN HEART & CKD BEN W/HF & CKD STAGE V/ESRD
E87.70	FLUID OVERLOAD UNSPECIFIED
I51.81	TAKOTSUBO SYNDROME
I11.0	HYPERTENSIVE HEART DISEASE WITH HEART FAILURE
Z95.4	PRESENCE OF OTHER HEART-VALVE REPLACEMENT
E85.4	ORGAN-LIMITED AMYLOIDOSIS
Z48.21	ENCOUNTER AFTERCARE FOLLOWING HEART TRANSPLANT
B25.9	CYTOMEGALOVIRAL DISEASE UNSPECIFIED
B25.0	CYTOMEGALOVIRAL PNEUMONITIS
T86.22	HEART TRANSPLANT FAILURE
E85.2	HEREDOFAMILIAL AMYLOIDOSIS UNSPECIFIED
I40.1	ISOLATED MYOCARDITIS
J18.2	HYPOSTATIC PNEUMONIA UNSPECIFIED ORGANISM

Z48.280	ENCOUNTER AFTERCARE FOLLOW HEART-LUNG TRANSPLANT
T86.31	HEART-LUNG TRANSPLANT REJECTION
423.2	CONSTRICTIVE PERICARDITIS
V42.1	CAR PSGR INJ COLL 2/3-WHL MOTOR VEH NONTRAF ACC
V42.1	HEART REPLACED BY TRANSPLANT
425.11	HYPERTROPHIC OBSTRUCTIVE CARDIOMYOPATHY
428.32	CHRONIC DIASTOLIC HEART FAILURE
996.83	COMPLICATIONS OF TRANSPLANTED HEART
428.1	LEFT HEART FAILURE
404.11	HTN HRT & CKD BEN W/HF & W/CKD STAGE I-IV/UNS
R57.0	CARDIOGENIC SHOCK
Q23.4	HYPOPLASTIC LEFT HEART SYNDROME
I42.1	OBSTRUCTIVE HYPERTROPHIC CARDIOMYOPATHY
I50.30	UNSPECIFIED DIASTOLIC CONGESTIVE HEART FAILURE
D86.81	SARCOID MENINGITIS
I40.9	ACUTE MYOCARDITIS UNSPECIFIED
B25.1	CYTOMEGALOVIRAL HEPATITS
V58.44	AFTERCARE FOLLOWING ORGAN TRANSPLANT
514	PULMONARY CONGESTION AND HYPOSTASIS
425.5	ALCOHOLIC CARDIOMYOPATHY
428.21	ACUTE SYSTOLIC HEART FAILURE
429.83	TAKOTSUBO SYNDROME
428.43	ACUTE CHRONIC COMB SYSTOLIC&DIASTOLIC HEART FAIL
B25.8	OTHER CYTOMEGALOVIRAL DISEASES
I50.22	CHRONIC SYSTOLIC CONGESTIVE HEART FAILURE
J81.1	CHRONIC PULMONARY EDEMA
I13.0	HTN HEART & CKD W/HF & CKD STAGE 1-4 OR UNS CKD
I51.7	CARDIOMEGALY
I42.0	DILATED CARDIOMYOPATHY
I09.81	RHEUMATIC HEART FAILURE
Z95.811	PRESENCE OF HEART ASSIST DEVICE
I42.8	OTHER CARDIOMYOPATHIES
Z48.288	ENCOUNTER AFTERCARE FLW MULTI ORGAN TRANSPLANT
I42.7	CARDIOMYOPATHY DUE TO DRUG AND EXTERNAL AGENT
T86.20	UNSPECIFIED COMPLICATION OF HEART TRANSPLANT
I42.4	ENDOCARDIAL FIBROELASTOSIS
B25.2	CYTOMEGALOVIRAL PANCREATITIS
D86.3	SARCOIDOSIS OF SKIN
E85.1	NEUROPATHIC HEREDOFAMILIAL AMYLOIDOSIS
425.4	OTHER PRIMARY CARDIOMYOPATHIES

V42.2	HEART VALVE REPLACED BY TRANSPLANT
789.59	OTHER ASCITES
V43.21	PERSON OUTSIDE CAR INJURED COLL SUV NONTRAF ACC
428.31	ACUTE DIASTOLIC HEART FAILURE
I50.20	UNSPECIFIED SYSTOLIC CONGESTIVE HEART FAILURE
I50.33	ACUTE ON CHRON DIASTOLIC CONGESTIV HEART FAILURE
D86.0	SARCOIDOSIS OF LUNG
I13.2	HTN HEART & CKD W/HF W/STAGE 5 CKD OR ESRD
I50.43	ACUTE ON CHRONIC COMB SYSTOLIC & DIASTOLIC CHF
D86.89	SARCOIDOSIS OF OTHER SITES
I42.2	OTHER HYPERTROPHIC CARDIOMYOPATHY
D86.85	SARCOID MYOCARDITIS
I31.1	CHRONIC CONSTRICTIVE PERICARDITIS
T86.23	HEART TRANSPLANT INFECTION
T86.39	OTHER COMPLICATIONS OF HEART-LUNG TRANSPLANT
429.3	CARDIOMEGALY
425.3	ENDOCARDIAL FIBROELASTOSIS
414.06	COR ATHEROSLERO COR ART TRANSPLANTED HEART
R18.8	OTHER ASCITES
I50.9	HEART FAILURE UNSPECIFIED
D86.9	SARCOIDOSIS UNSPECIFIED
I50.1	LEFT VENTRICULAR FAILURE
I50.23	ACUTE CHRON SYSTOLIC HEART FAILURE
I50.32	CHRONIC DIASTOLIC CONGESTIVE HEART FAILURE
Q20.3	DISCORDANT VENTRICULOARTERIAL CONNECTION
T86.290	CARDIAC ALLOGRAFT VASCULOPATHY
Z48.298	ENCOUNTER AFTERCARE FOLLOW OTH ORGAN TRANSPLANT
D86.1	SARCOIDOSIS OF LYMPH NODES
425.18	OTHER HYPERTROPHIC CARDIOMYOPATHY
V87.46	PERSONAL HISTORY OF IMMUNOSUPPRESSION THERAPY
428.23	ACUTE ON CHRONIC SYSTOLIC HEART FAILURE
785.51	CARDIOGENIC SHOCK
674.54	PERIPARTUM CARDIOMYOPATHY POSTPARTUM COND/COMP
428	HEART FAILURE
I50.21	ACUTE SYSTOLIC CONGESTIVE HEART FAILURE
E87.79	OTHER FLUID OVERLOAD
I50.41	ACUTE COMBINED SYSTOLIC AND DIASTOLIC CHF
Q21.3	TETRALOGY OF FALLOT
Z94.1	HEART TRANSPLANT STATUS
E85.3	SECONDARY SYSTEMIC AMYLOIDOSIS
D86.83	SARCOID IRIDOCYCLITIS

T86.21	HEART TRANSPLANT REJECTION
T86.298	OTHER COMPLICATIONS OF HEART TRANSPLANT
Z94.3	HEART AND LUNGS TRANSPLANT STATUS
D86.87	SARCOID MYOSITIS
I25.759	ATHEROSCLEROSIS NATV COR ART TPLNT HRT W/UNS AP
425.9	UNSPECIFIED SECONDARY CARDIOMYOPATHY
135	SARCOIDOSIS
V42.2	PERS OUTSIDE CAR INJ COLL 2/3-WHL MV NONTRAF ACC
428.33	ACUTE ON CHRONIC DIASTOLIC HEART FAILURE
998.01	POSTOPERATIVE SHOCK CARDIOGENIC
I42.9	CARDIOMYOPATHY UNSPECIFIED
I50.42	CHRONIC COMBINED SYSTOLIC AND DIASTOLIC CHF
I42.6	ALCOHOLIC CARDIOMYOPATHY
I51.4	MYOCARDITIS UNSPECIFIED
I25.811	ATHEROSCLEROSIS NATIVE COR ART TPLNT HRT W/O AP
Z92.25	PERSONAL HISTORY OF IMMUNOSUPRESSION THERAPY
E85.9	AMYLOIDOSIS UNSPECIFIED
E85.8	OTHER AMYLOIDOSIS
I42.5	OTHER RESTRICTIVE CARDIOMYOPATHY
D86.86	SARCOID ARTHROPATHY
Z48.24	ENCOUNTER AFTERCARE FOLLOWING LUNG TRANSPLANT
D86.2	SARCOIDOSIS OF LUNG W/SARCOIDOSIS OF LYMPH NODES

(Source: U of U Health, EDW, October 2016)

APPENDIX B

HF Patient Population Independent Data Codes and Queries (July 1, 2013 – June 30, 2016)

Visit Codes:

```
,V. VISIT_NO
,PRM.VISIT_NO AS PRIMARY_VISIT_NO
,REPROV.PERFORMING_CONTACT_DWID
,P.PAT_ID AS PATIENT_MRN
,P. BIRTH_DATE
,LOC.UNIT_TYPE_CODE
,PMATTD.PROV_EXTERNAL_NAME
,PMATTD.DIVISION
,GNDR.CODE AS GENDER
,GNDR.D_GENDER_DESC AS GENDER_DESC
,RCE.CODE AS RACE
,RCE.D_RACE_DESC AS RACE_DESC
,ETHNC.CODE AS ETHNICITY
,ETHNC.D_ETHNICITY_DESC AS ETHNICITY_DESC
,PC.CODE AS PAT_CLASS
,PC.D_PAT_CLASS_DESC AS PAT_CLASS_DESC
,P.ZIP
,V.ADM_DATE
,V.DSCH_DATE
,DBP.MIN_ADM_DATE
,VDC.CCI_SCORE AS CHARLSON_COMORBIDITY_INDEX
```

Diagnosis Codes:

```
,DX1.CODE AS DX1_CODE
,DX1.D_ICD_DX_DESC AS DX1_CODE_DESC
,DX2.CODE AS DX2_CODE
,DX2.D_ICD_DX_DESC AS DX2_CODE_DESC
,DX3.CODE AS DX3_CODE
,DX3.D_ICD_DX_DESC AS DX3_CODE_DESC
,DX4.CODE AS DX4_CODE
,DX4.D_ICD_DX_DESC AS DX4_CODE_DESC
,DX5.CODE AS DX5_CODE
,DX5.D_ICD_DX_DESC AS DX5_CODE_DESC
,DX6.CODE AS DX6_CODE
,DX6.D_ICD_DX_DESC AS DX6_CODE_DESC
,DX7.CODE AS DX7_CODE
,DX7.D_ICD_DX_DESC AS DX7_CODE_DESC
,DX8.CODE AS DX8_CODE
,DX8.D_ICD_DX_DESC AS DX8_CODE_DESC
```

```
,DX9.CODE AS DX9_CODE
,DX9.D_ICD_DX_DESC AS DX9_CODE_DESC
,DX10.CODE AS DX10_CODE
,DX10.D_ICD_DX_DESC AS DX10_CODE_DESC
```

ICD Procedure Codes:

```
,PX1.CODE AS PX1_CODE
,PX1.D_ICD_PX_DESC AS PX1_CODE_DESC
,PM1.PROV_EXTERNAL_NAME AS PX1_PROVIDER
,PX2.CODE AS PX2_CODE
,PX2.D_ICD_PX_DESC AS PX2_CODE_DESC
,PM2.PROV_EXTERNAL_NAME AS PX2_PROVIDER
,PX3.CODE AS PX3_CODE
,PX3.D_ICD_PX_DESC AS PX3_CODE_DESC
,PM3.PROV_EXTERNAL_NAME AS PX3_PROVIDER
,PX4.CODE AS PX4_CODE
,PX4.D_ICD_PX_DESC AS PX4_CODE_DESC
,PM4.PROV_EXTERNAL_NAME AS PX4_PROVIDER
,PX5.CODE AS PX5_CODE
,PX5.D_ICD_PX_DESC AS PX5_CODE_DESC
,PM5.PROV_EXTERNAL_NAME AS PX5_PROVIDER
,PX6.CODE AS PX6_CODE
,PX6.D_ICD_PX_DESC AS PX6_CODE_DESC
,PM6.PROV_EXTERNAL_NAME AS PX6_PROVIDER
,PX7.CODE AS PX7_CODE
,PX7.D_ICD_PX_DESC AS PX7_CODE_DESC
,PM7.PROV_EXTERNAL_NAME AS PX7_PROVIDER
,PX8.CODE AS PX8_CODE
,PX8.D_ICD_PX_DESC AS PX8_CODE_DESC
,PM8.PROV_EXTERNAL_NAME AS PX8_PROVIDER
,PX9.CODE AS PX9_CODE
,PX9.D_ICD_PX_DESC AS PX9_CODE_DESC
,PM9.PROV_EXTERNAL_NAME AS PX9_PROVIDER
,PX10.CODE AS PX10_CODE
,PX10.D_ICD_PX_DESC AS PX10_CODE_DESC
,PM10.PROV_EXTERNAL_NAME AS PX10_PROVIDER
```

CPT Codes:

```
,CPT1.CODE AS CPT1_CODE
,CPT1.D_CPT_HCPC_DESC AS CPT1_CODE_DESC
,CPT2.CODE AS CPT2_CODE
,CPT2.D_CPT_HCPC_DESC AS
,CPT3.CODE AS CPT3_CODE
,CPT3.D_CPT_HCPC_DESC AS CPT3_CODE_DESC
,CPT04.CODE AS CPT4_CODE
,CPT04.D_CPT_HCPC_DESC AS CPT4_CODE_DESC
```

```
,CPT5.CODE AS CPT5_CODE
,CPT5.D_CPT_HCPC_DESC AS CPT5_CODE_DESC
,CPT6.CODE AS CPT6_CODE
,CPT6.D_CPT_HCPC_DESC AS CPT6_CODE_DESC
,CPT7.CODE AS CPT7_CODE
,CPT7.D_CPT_HCPC_DESC AS CPT7_CODE_DESC
,CPT8.CODE AS CPT8_CODE
,CPT8.D_CPT_HCPC_DESC AS CPT8_CODE_DESC
,CPT9.CODE AS CPT9_CODE
,CPT9.D_CPT_HCPC_DESC AS CPT9_CODE_DESC
,CPT10.CODE AS CPT10_CODE
,CPT10.D_CPT_HCPC_DESC AS CPT10_CODE_DESC
```

Imaging, Supplies, Pharmacy, Facility, and Professional Cost Queries:

```
,ROUND(CLC.IMAGING_DIR_COST_AMT + SUPPLY_DIR_COST_AMT +
PHARMACY_DIR_COST_AMT +
        LAB_DIR_COST_AMT + OTHER_SRVC_DIR_COST_AMT
+  FACILITY_UTIL_DIR_AMT +
        PROF_DEPT_STAFF_COST_AMT + PROF_PROVIDER_COST_AMT +
PROF_NON_PERSONNEL_COST_AMT +
        IMPLANT_DIR_COST_AMT + LAB_MNGMNT_DIR_COST_AMT +
INSTITUTIONAL_DIR_COST_AMT, 2) AS TOTAL_DIR_COST
```

(Source: U of U Health EDW, October 2016)

APPENDIX C

All Syntax Data Definitions and Queries using Stata 14.0

```
***All patients

*total cost

tsset time

itsa its_total_cost_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)

figure posttrend

actest, lag(5)

ge adjusted=_s_its_total_cost_norm_pred

drop _t _x0 _x_t0 _s_its_total_cost_norm_pred


itsa its_total_cost_norm , single trperiod(0) lag(1)  figure posttrend

actest, lag(5)

ge unadjusted=_s_its_total_cost_norm_pred

drop _t _x0 _x_t0 _s_its_total_cost_norm_pred


twoway (scatter its_total_cost_norm time) (line adjusted time, lcolor(blue)) (line

unadjusted time, lcolor(red) lpattern(shortdash) ), yline(0.65, lcolor(green))  ///

ytitle(Normalized Total Cost Per PT)   xtitle(Month)

drop adjusted unadjusted


*total tech cost

tsset time
```

```
itsa its_tech_cost_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)
figure posttrend
actest, lag(5)
ge adjusted=_s_its_tech_cost_norm_pred
drop _t _x0 _x_t0 _s_its_tech_cost_norm_pred

itsa its_tech_cost_norm , single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted=_s_its_tech_cost_norm_pred
drop _t _x0 _x_t0 _s_its_tech_cost_norm_pred

twoway (scatter its_tech_cost_norm time) (line adjusted time, lcolor(blue)) (line
unadjusted time, lcolor(red) lpattern(shortdash) ), yline(0.64, lcolor(green))  ///
ytitle(Normalized Tech Cost Per PT)   xtitle(Month)
drop adjusted unadjusted

*total prof cost
tsset time
itsa its_prof_cost_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)
figure posttrend
actest, lag(5)
ge adjusted=_s_its_prof_cost_norm_pred
drop _t _x0 _x_t0 _s_its_prof_cost_norm_pred
```

```
itsa its_prof_cost_norm , single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted=_s_its_prof_cost_norm_pred
drop _t _x0 _x_t0 _s_its_prof_cost_norm_pred

twoway (scatter its_prof_cost_norm time) (line adjusted time, lcolor(blue)) (line
unadjusted time, lcolor(red) lpattern(shortdash) ), yline(0.68, lcolor(green))  ///
ytitle(Normalized professional Cost Per PT)   xtitle(Month)
drop adjusted unadjusted

*ED per 1000
tsset time
itsa ed_per1000 pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)  figure
posttrend
actest, lag(5)
ge adjusted= _s_ed_per1000_pred
drop _t _x0 _x_t0 _s_ed_per1000_pred

itsa ed_per1000, single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted= _s_ed_per1000_pred
drop _t _x0 _x_t0 _s_ed_per1000_pred
```

```
twoway (scatter ed_per1000 time) (line adjusted time, lcolor(blue)) (line unadjusted time,
lcolor(red) lpattern(shortdash) ), yline(20, lcolor(green))  ///
ytitle(ED Visits Per 1000)   xtitle(Month)
drop adjusted unadjusted

*admit per 1000
tsset time
itsa admit_per1000 pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)
figure posttrend
actest, lag(5)
ge adjusted=_s_admit_per1000_pred
drop _t _x0 _x_t0 _s_admit_per1000_pred

itsa admit_per1000, single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted=_s_admit_per1000_pred
drop _t _x0 _x_t0 _s_admit_per1000_pred

twoway (scatter admit_per1000 time) (line adjusted time, lcolor(blue)) (line unadjusted
time, lcolor(red) lpattern(shortdash) ), yline(152, lcolor(green))  ///
ytitle(Inpatient Admissions Per 1000)   xtitle(Month)
drop adjusted unadjusted
```

```
*readmit per 1000
tsset time
itsa readmit_rate pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)  figure
posttrend
actest, lag(5)
ge adjusted=_s_readmit_rate_pred
drop _t _x0 _x_t0 _s_readmit_rate_pred

itsa readmit_rate, single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted=_s_readmit_rate_pred
drop _t _x0 _x_t0 _s_readmit_rate_pred

twoway (scatter readmit_rate time) (line adjusted time, lcolor(blue)) (line unadjusted
time, lcolor(red) lpattern(shortdash) ), yline(0.19, lcolor(green))  ///
ytitle(Readmission Rate)   xtitle(Month)
drop adjusted unadjusted

*average LOS
tsset time
itsa mean_los pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)  figure
posttrend
actest, lag(5)
```

```
ge adjusted=_s_mean_los_pred
drop _t _x0 _x_t0 _s_mean_los_pred

itsa mean_los, single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted=_s_mean_los_pred
drop _t _x0 _x_t0 _s_mean_los_pred

twoway (scatter mean_los time) (line adjusted time, lcolor(blue)) (line unadjusted time,
lcolor(red) lpattern(shortdash) ), yline(8.4, lcolor(green))  ///
ytitle(Average LOS)   xtitle(Month)
drop adjusted unadjusted

***subsets*****
*VAD
tsset time
itsa cost_vad_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)
figure posttrend
actest, lag(5)
ge adjusted=_s_cost_vad_norm_pred
drop _t _x0 _x_t0 _s_cost_vad_norm_pred

itsa cost_vad_norm, single trperiod(0) lag(1)  figure posttrend
```

```
actest, lag(5)
ge unadjusted=_s_cost_vad_norm_pred
drop _t _x0 _x_t0 _s_cost_vad_norm_pred

twoway (scatter cost_vad_norm time) (line adjusted time, lcolor(blue)) (line unadjusted
time, lcolor(red) lpattern(shortdash) ), yline(0.49, lcolor(green))  ///
ytitle(Normalized Total Cost Per PT)   xtitle(Month)
drop adjusted unadjusted

*HF
tsset time
itsa cost_hf_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)
figure posttrend
actest, lag(5)
ge adjusted=_s_cost_hf_norm_pred
drop _t _x0 _x_t0 _s_cost_hf_norm_pred

itsa cost_hf_norm, single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted=_s_cost_hf_norm_pred
drop _t _x0 _x_t0 _s_cost_hf_norm_pred
```

```
twoway (scatter cost_hf_norm time) (line adjusted time, lcolor(blue)) (line unadjusted
time, lcolor(red) lpattern(shortdash) ), yline(0.52, lcolor(green))  ///
ytitle(Normalized Total Cost Per PT)   xtitle(Month)
drop adjusted unadjusted

*HF-surgical
tsset time
itsa cost_surgical_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)
figure posttrend
actest, lag(5)
ge adjusted=_s_cost_surgical_norm_pred
drop _t _x0 _x_t0 _s_cost_surgical_norm_pred

itsa cost_surgical_norm, single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted=_s_cost_surgical_norm_pred
drop _t _x0 _x_t0 _s_cost_surgical_norm_pred

twoway (scatter cost_surgical_norm time) (line adjusted time, lcolor(blue)) (line
unadjusted time, lcolor(red) lpattern(shortdash) ), yline(0.459, lcolor(green))  ///
ytitle(Normalized Total Cost Per PT)   xtitle(Month)
drop adjusted unadjusted
```

```
 *HF-nonsurgical
tsset time
itsa cost_nonsurgical_norm pc_male pc_white mean_cci mean_age, single trperiod(0)
lag(1)  figure posttrend
actest, lag(5)
ge adjusted=_s_cost_nonsurgical_norm_pred
drop _t _x0 _x_t0 _s_cost_nonsurgical_norm_pred

itsa cost_nonsurgical_norm, single trperiod(0) lag(1)  figure posttrend
actest, lag(5)
ge unadjusted=_s_cost_nonsurgical_norm_pred
drop _t _x0 _x_t0 _s_cost_nonsurgical_norm_pred

twoway (scatter cost_nonsurgical_norm time) (line adjusted time, lcolor(blue)) (line
unadjusted time, lcolor(red) lpattern(shortdash) ), yline(0.4937, lcolor(green))  ///
ytitle(Normalized Total Cost Per PT)   xtitle(Month)
drop adjusted unadjusted
```

APPENDIX D

ITS Regression Analysis Data Set

Summary Table 1

Time in Months	Number of Total Patients	Total Visits	Average Age	% Male	% White	Average CCI
-12	580	1340	63.00	67.24	86.72	5.10
-11	608	1390	63.00	66.61	86.02	5.14
-10	612	1382	63.00	65.20	86.27	4.95
-9	676	1652	64.00	63.46	87.43	4.99
-8	597	1317	63.00	64.99	85.59	5.28
-7	624	1510	64.00	63.94	87.02	5.03
-6	624	1506	64.00	64.74	86.70	5.21
-5	694	1616	63.00	67.15	87.03	4.98
-4	724	1822	63.00	64.09	84.94	5.15
-3	711	1649	63.00	64.56	86.08	5.10
-2	699	1679	64.00	64.66	86.98	5.17
-1	711	1751	64.00	66.81	87.48	5.17
0	748	1820	64.00	64.30	86.23	5.17
1	721	1706	64.00	65.05	85.71	5.17
2	782	1887	63.00	66.75	86.57	4.98
3	630	1408	63.00	64.76	85.40	5.15
4	610	1326	62.00	67.54	83.61	5.10
5	614	1409	62.00	68.57	83.88	5.38
6	576	1219	61.00	67.01	83.51	5.21
7	618	1341	62.00	66.83	84.63	5.17
8	666	1585	62.00	67.57	84.83	5.14
9	620	1409	61.00	69.03	85.81	5.10
10	663	1391	61.00	67.12	83.56	5.12
11	639	1386	62.00	70.74	83.41	5.15
	15747	**36501**	**62.83**	**66.20**	**85.64**	**5.13**

ITS Regression Analysis Data Set

Summary Table 2

Time in Months	Normalized Total Cost	Normalized Tech Cost	Normalized Prof Cost	Avg LOS	ED Visits Per 1000	Admits Per 1000	Readmits Per 1000
-12	0.68	0.64	0.90	8.29	17.24	162.07	0.16
-11	0.63	0.59	0.91	8.65	18.09	171.05	0.18
-10	0.47	0.44	0.67	9.07	21.24	130.72	0.15
-9	0.54	0.53	0.59	7.72	13.31	159.76	0.31
-8	0.62	0.61	0.63	8.06	21.78	139.03	0.16
-7	0.93	0.93	0.88	9.08	22.44	169.87	0.26
-6	0.85	0.82	1.00	9.29	28.85	171.47	0.21
-5	0.55	0.51	0.78	8.22	28.82	162.82	0.22
-4	0.69	0.68	0.74	10.04	27.62	132.60	0.11
-3	0.46	0.47	0.36	7.69	30.94	126.58	0.19
-2	1.00	1.00	0.96	9.33	21.46	171.67	0.21
-1	0.43	0.42	0.46	8.09	15.47	143.46	0.19
0	0.67	0.67	0.62	8.64	12.03	140.37	0.19
1	0.63	0.64	0.56	9.21	22.19	141.47	0.21
2	0.67	0.66	0.73	9.48	34.53	154.73	0.18
3	0.93	0.92	0.98	8.93	12.70	160.32	0.16
4	0.50	0.50	0.50	6.59	11.48	165.57	0.21
5	0.98	0.99	0.84	10.10	16.29	154.72	0.19
6	0.50	0.50	0.50	7.05	17.36	161.46	0.22
7	0.67	0.67	0.63	8.71	14.56	155.34	0.17
8	0.81	0.80	0.80	6.75	10.51	168.17	0.16
9	0.67	0.68	0.60	8.14	20.97	143.55	0.24
10	0.71	0.72	0.62	8.79	16.59	131.22	0.22
11	0.00	0.00	0.00	5.72	21.91	118.94	0.18
	0.65	**0.64**	**0.68**	**8.40**	**19.93**	**151.54**	**0.19**

APPENDIX E

ITS Regression Analysis Detail

Normalized and Adjusted Total HF Cost

```
. itsa its_total_cost_norm pc_male pc_white mean_cci mean_age, single trperiod(0) l
> ag(1)  figure posttrend
       time variable:  time, -12 to 11
             delta:  1 unit
Regression with Newey-West standard errors      Number of obs     =         24
maximum lag: 1                                  F(  7,       16) =       2.62
                                                Prob > F          =     0.0522
------------------------------------------------------------------------------
             |             Newey-West
its_total_~m |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    pc_male |  -.0813916   .0389965    -2.09   0.053    -.1640604    .0012773
   pc_white |   .1411029   .0472786     2.98   0.009     .0408767    .2413291
   mean_cci |   1.288993   .4859287     2.65   0.017     .2588704    2.319116
   mean_age |  -.1268248   .1059795    -1.20   0.249    -.3514914    .0978418
         _t |  -.0080645   .0121131    -0.67   0.515     -.033743     .017614
        _x0 |   .2105958   .1148896     1.83   0.085    -.0329593     .454151
      _x_t0 |    .012119   .0322314     0.38   0.712    -.0562085    .0804464
      _cons |    -4.7369   7.283367    -0.65   0.525    -20.17695    10.70315
------------------------------------------------------------------------------
```

Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

Linear Trend | Coeff Std. Err. t P>|t| [95% Conf. Interval]

Treated | 0.0041 0.0253 0.1600 0.8749 -0.0497 0.0578

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

H0: variable is MA process up to order q

HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) | H0: q=specified lag-1

HA: s.c. present at range specified | HA: s.c. present at lag specified

---

lags | chi2 df p-val | lag | chi2 df p-val

---

1 - 1 | 1.180 1 0.2773 | 1 | 1.180 1 0.2773

1 - 2 | 1.884 2 0.3899 | 2 | 0.123 1 0.7257

1 - 3 | 3.476 3 0.3239 | 3 | 0.505 1 0.4772

1 - 4 | 8.360 4 0.0792 | 4 | 3.391 1 0.0655

1 - 5 | 8.360 5 0.1375 | 5 | 2.065 1* 0.1507

Normalized and Adjusted HF Technical Costs

```
itsa its_tech_cost_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1
> )  figure posttrend
       time variable:  time, -12 to 11
             delta:  1 unit
Regression with Newey-West standard errors      Number of obs     =         24
maximum lag: 1                                  F(  7,        16) =       3.39
                                                Prob > F          =     0.0206
------------------------------------------------------------------------------
             |               Newey-West
its_tech_c~m |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    pc_male |  -.0862635   .0391301    -2.20   0.042    -.1692155   -.0033115
   pc_white |   .1416851   .0465157     3.05   0.008     .0430762    .2402939
   mean_cci |   1.331886   .4902058     2.72   0.015      .292696    2.371076
   mean_age |  -.1261176   .1049957    -1.20   0.247    -.3486986    .0964634
         _t |  -.0052261   .0116497    -0.45   0.660    -.0299224    .0194702
        _x0 |   .2041695   .1101865     1.85   0.082    -.0294154    .4377543
      _x_t0 |   .0121568   .0316548     0.38   0.706    -.0549485    .0792621
      _cons |  -4.766756   7.262495    -0.66   0.521    -20.16256    10.62905
------------------------------------------------------------------------------
                  Postintervention Linear Trend: 0
Treated: _b[_t]+_b[_x_t0]
```

Linear Trend | Coeff Std. Err. t P>|t| [95% Conf. Interval]

---+---

Treated | 0.0069 0.0253 0.2738 0.7877 -0.0467 0.0606

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

H0: variable is MA process up to order q

HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) | H0: q=specified lag-1

HA: s.c. present at range specified | HA: s.c. present at lag specified

---+---

lags | chi2 df p-val | lag | chi2 df p-val

---+---+---

1 - 1 | 1.402 1 0.2364 | 1 | 1.402 1 0.2364

1 - 2 | 2.324 2 0.3129 | 2 | 0.166 1 0.6841

1 - 3 | 3.622 3 0.3053 | 3 | 0.267 1 0.6051

1 - 4 | 8.617 4 0.0714 | 4 | 3.306 1 0.0690

1 - 5 | 8.624 5 0.1250 | 5 | 2.057 1* 0.1515

Normalized and Adjusted HF Professional Costs

itsa its_prof_cost_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1

>) figure posttrend

time variable: time, -12 to 11

delta: 1 unit

Regression with Newey-West standard errors Number of obs = 24

maximum lag: 1 F(7, 16) = 1.66

Prob > F = 0.1905

| Newey-West

its_prof_c~m | Coef. Std. Err. t P>|t| [95% Conf. Interval]

---+---

pc_male | -.0483567 .0392867 -1.23 0.236 -.1316409 .0349275

pc_white | .1321997 .0535278 2.47 0.025 .0187259 .2456735

mean_cci | .9765595 .4812447 2.03 0.059 -.0436338 1.996753

mean_age | -.1263904 .1111147 -1.14 0.272 -.3619429 .1091622

_t | -.0252181 .0155628 -1.62 0.125 -.0582096 .0077735

_x0 | .2421771 .1495381 1.62 0.125 -.0748296 .5591838

_x_t0 | .0114289 .0366845 0.31 0.759 -.0663386 .0891965

_cons | -4.374606 7.537823 -0.58 0.570 -20.35408 11.60486

Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

Linear Trend | Coeff Std. Err. t P>|t| [95% Conf. Interval]

```
-------------+------------------------------------------------------------------
   Treated   |    -0.0138   0.0259   -0.5320    0.6020    -0.0687    0.0412
-------------------------------------------------------------------------------
```

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

H0: variable is MA process up to order q

HA: serial correlation present at specified lags >q

```
-------------------------------------------------------------------------------
 H0: q=0 (serially uncorrelated)        | H0: q=specified lag-1
 HA: s.c. present at range specified    | HA: s.c. present at lag specified
---------------------------------------+---------------------------------
  lags   |     chi2      df     p-val | lag |     chi2      df     p-val
-----------+----------------------------+-----+----------------------------
  1 -  1 |     0.193      1    0.6606 |   1 |     0.193      1    0.6606
  1 -  2 |     0.449      2    0.7989 |   2 |     0.145      1    0.7034
  1 -  3 |     5.275      3    0.1527 |   3 |     3.416      1    0.0646
  1 -  4 |     7.931      4    0.0941 |   4 |     1.812      1    0.1782
  1 -  5 |     8.338      5    0.1385 |   5 |     1.841     1*    0.1748
-------------------------------------------------------------------------------
```

Normalized and Adjusted HF Cost

```
itsa cost_hf_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)  fig
> ure posttrend
       time variable:  time, -12 to 11
                delta:  1 unit
```

Regression with Newey-West standard errors Number of obs = 24

maximum lag: 1 F(7, 16) = 2.70

Prob > F = 0.0475

| Newey-West

cost_hf_norm | Coef. Std. Err. t P>|t| [95% Conf. Interval]

---+---

pc_male | -.0179709 .0247662 -0.73 0.479 -.0704728 .034531

pc_white | .1279522 .0390098 3.28 0.005 .0452551 .2106494

mean_cci | .8054308 .3764444 2.14 0.048 .0074044 1.603457

mean_age | -.1140815 .0696877 -1.64 0.121 -.2618127 .0336498

_t | .0006367 .0127914 0.05 0.961 -.0264799 .0277533

_x0 | .2297607 .1168394 1.97 0.067 -.0179277 .4774492

_x_t0 | -.0336032 .0189763 -1.77 0.096 -.0738311 .0066248

_cons | -6.259923 5.891737 -1.06 0.304 -18.74985 6.230001

Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

Linear Trend | Coeff Std. Err. t P>|t| [95% Conf. Interval]

---+---

Treated | -0.0330 0.0167 -1.9706 0.0663 -0.0684 0.0025

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

H0: variable is MA process up to order q

HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) | H0: q=specified lag-1

HA: s.c. present at range specified | HA: s.c. present at lag specified

---

lags	chi2	df	p-val	lag	chi2	df	p-val
1 - 1	4.839	1	0.0278	1	4.839	1	0.0278
1 - 2	5.121	2	0.0773	2	0.007	1	0.9336
1 - 3	5.885	3	0.1173	3	0.301	1	0.5835
1 - 4	7.393	4	0.1165	4	0.312	1	0.5763
1 - 5	8.381	5	0.1365	5	1.319	1*	0.2508

Normalized and Adjusted HF Surgical Costs

itsa cost_surgical_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1 >) figure posttrend

time variable: time, -12 to 11

delta: 1 unit

Regression with Newey-West standard errors Number of obs = 24

maximum lag: 1 F(7, 16) = 2.17

Prob > F = 0.0947

```
------------------------------------------------------------------------------
             |               Newey-West
cost_surgi~m |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    pc_male |  -.0011555    .007438    -0.16   0.878    -.0169235    .0146124
   pc_white |   .0009533   .0140324     0.07   0.947    -.0287941    .0307007
   mean_cci |  -.0212267   .1091551    -0.19   0.848    -.2526252    .2101718
   mean_age |  -.0243314   .0296652    -0.82   0.424    -.0872189     .038556
         _t |    .025299   .0232981     1.09   0.294    -.0240908    .0746889
        _x0 |  -.0349692   .1740704    -0.20   0.843    -.4039819    .3340435
      _x_t0 |  -.0678776   .0305108    -2.22   0.041    -.1325575   -.0031977
      _cons |    1.92134   1.526902     1.26   0.226    -1.315548    5.158229
------------------------------------------------------------------------------
                  Postintervention Linear Trend: 0
Treated: _b[_t]+_b[_x_t0]
------------------------------------------------------------------------------
Linear Trend |      Coeff   Std. Err.      t      P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Treated   |    -0.0426   0.0131   -3.2494    0.0050    -0.0704   -0.0148
Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)
  H0: variable is MA process up to order q
  HA: serial correlation present at specified lags >q
------------------------------------------------------------------------------
```

```
 H0: q=0 (serially uncorrelated)        |  H0: q=specified lag-1
 HA: s.c. present at range specified    |  HA: s.c. present at lag specified
----------------------------------------+----------------------------------
  lags   |     chi2      df     p-val | lag |     chi2      df     p-val
---------+---------------------------+-----+---------------------------
  1 -  1 |     0.000      1    0.9831 |   1 |     0.000      1    0.9831
  1 -  2 |     0.034      2    0.9831 |   2 |     0.033      1    0.8569
  1 -  3 |     4.940      3    0.1762 |   3 |     4.577      1    0.0324
  1 -  4 |     7.155      4    0.1279 |   4 |     0.537      1    0.4636
  1 -  5 |     8.042      5    0.1540 |   5 |     1.212      1    0.2710
-------------------------------------------------------------------------
```

Normalized and Adjusted HF Non-Surgical Costs

```
itsa cost_nonsurgical_norm pc_male pc_white mean_cci mean_age, single trperiod(0) la
> g(1)  figure posttrend
       time variable:  time, -12 to 11
             delta:  1 unit
Regression with Newey-West standard errors      Number of obs     =         24
maximum lag: 1                                  F(  7,        16) =       5.01
                                                Prob > F          =     0.0037
------------------------------------------------------------------------------
             |             Newey-West
cost_nonsu~m |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
    pc_male |   .0609993   .0378871     1.61   0.127    -.0193176    .1413163
   pc_white |   .0435495   .1037644     0.42   0.680    -.1764212    .2635202
   mean_cci |   .5176415   .4847526     1.07   0.301    -.5099881    1.545271
   mean_age |  -.1232884   .1191868    -1.03   0.316    -.3759532    .1293764
        _t |   .0009418    .017463     0.05   0.958     -.036078    .0379617
       _x0 |   .2536298   .1519112     1.67   0.114    -.0684075    .5756672
     _x_t0 |  -.0969052    .039319    -2.46   0.025    -.1802578   -.0135525
     _cons |  -1.997992   6.995061    -0.29   0.779    -16.82686    12.83087
------------------------------------------------------------------------------

                Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

------------------------------------------------------------------------------
Linear Trend |      Coeff    Std. Err.      t      P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Treated   |    -0.0960    0.0283   -3.3877    0.0038    -0.1560   -0.0359
Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)
  H0: variable is MA process up to order q
  HA: serial correlation present at specified lags >q
------------------------------------------------------------------------------
  H0: q=0 (serially uncorrelated)        |  H0: q=specified lag-1
  HA: s.c. present at range specified    |  HA: s.c. present at lag specified
---------------------------------------+--------------------------------
    lags   |      chi2      df     p-val | lag |      chi2      df     p-val
```

```
----------+----------------------------+-----+----------------------------
  1 -  1  |     0.319      1    0.5721 |  1  |     0.319      1    0.5721
  1 -  2  |     1.034      2    0.5964 |  2  |     0.436      1    0.5091
  1 -  3  |     7.148      3    0.0673 |  3  |     5.184      1    0.0228
  1 -  4  |    11.498      4    0.0215 |  4  |     0.146      1*   0.7020
  1 -  5  |    11.965      5    0.0353 |  5  |     0.003      1    0.9531
--------------------------------------------------------------------------------
```

Normalized and Adjusted VAD Costs

```
itsa cost_vad_norm pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)  fi
> gure posttrend
       time variable:  time, -12 to 11
                delta:  1 unit
Regression with Newey-West standard errors      Number of obs     =         24
maximum lag: 1                                  F(  7,        16) =      15.00
                                                Prob > F          =     0.0000
------------------------------------------------------------------------------
             |               Newey-West
cost_vad_n~m |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    pc_male |  -.0014634   .0019724    -0.74   0.469    -.0056448    .0027179
   pc_white |  -.0014577   .0022058    -0.66   0.518    -.0061338    .0032183
   mean_cci |   .0758805   .0234349     3.24   0.005     .0262007    .1255602
   mean_age |   -.002439   .0060729    -0.40   0.693    -.0153129    .0104349
```

```
        _t |  -.0177346   .0122969    -1.44   0.169     -.043803    .0083337
       _x0 |  -.2272358   .1304271    -1.74   0.101    -.5037288    .0492572
      _x_t0 |   .0376478   .0213525     1.76   0.097    -.0076175    .0829131
      _cons |   .7122748     .19632     3.63   0.002     .296095    1.128455
------------------------------------------------------------------------------

 Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

------------------------------------------------------------------------------
Linear Trend |      Coeff    Std. Err.     t      P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Treated   |     0.0199   0.0173    1.1523    0.2661    -0.0167    0.0565
------------------------------------------------------------------------------

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

  H0: variable is MA process up to order q

  HA: serial correlation present at specified lags >q

--------------------------------------------------------------------------

  H0: q=0 (serially uncorrelated)        |  H0: q=specified lag-1

  HA: s.c. present at range specified    |  HA: s.c. present at lag specified

---------------------------------------+----------------------------------

    lags   |      chi2      df     p-val | lag |      chi2      df     p-val

-----------+---------------------------+-----+---------------------------

   1 -  1  |      0.377      1    0.5390 |   1 |      0.377      1    0.5390

   1 -  2  |      4.101      2    0.1287 |   2 |      4.027      1    0.0448
```

```
  1 -  3 |     4.939      3    0.1763 |   3 |     0.314      1    0.5753
  1 -  4 |     5.810      4    0.2138 |   4 |     0.035      1    0.8507
  1 -  5 |     6.070      5    0.2995 |   5 |     0.141      1*   0.7075
-------------------------------------------------------------------------
```

ED Visits Per 1000

itsa ed_per1000 pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1) figure posttrend

```
      time variable:  time, -12 to 11
            delta:  1 unit
Regression with Newey-West standard errors      Number of obs     =         24
maximum lag: 1                                  F(  7,        16) =       2.00
                                                Prob > F          =     0.1190
------------------------------------------------------------------------------
             |             Newey-West
 ed_per1000 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    pc_male |   .8503709   1.233565     0.69   0.500     -1.76467    3.465412
   pc_white |  -.3517546   2.340592    -0.15   0.882    -5.313588    4.610079
   mean_cci |  -19.17529   20.29494    -0.94   0.359    -62.19866    23.84807
   mean_age |  -1.341422    2.51351    -0.53   0.601    -6.669826    3.986982
         _t |   .8942306   .6333252     1.41   0.177    -.4483589     2.23682
        _x0 |  -8.611562   6.379412    -1.35   0.196    -22.13531    4.912187
      _x_t0 |  -1.751865   1.497513    -1.17   0.259    -4.926449     1.42272
```

```
      _cons |   174.3749   295.7684     0.59   0.564    -452.6262     801.376
------------------------------------------------------------------------------

                  Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

------------------------------------------------------------------------------
Linear Trend |      Coeff   Std. Err.      t    P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------------
   Treated   |    -0.8576   1.0977   -0.7813    0.4460    -3.1847    1.4695
------------------------------------------------------------------------------

. actest, lag(5)

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

  H0: variable is MA process up to order q

  HA: serial correlation present at specified lags >q

------------------------------------------------------------------------------

  H0: q=0 (serially uncorrelated)        |  H0: q=specified lag-1

  HA: s.c. present at range specified    |  HA: s.c. present at lag specified

---------------------------------------+--------------------------------

   lags   |     chi2      df     p-val | lag |     chi2      df     p-val

----------+----------------------------+-----+----------------------------

   1 -  1 |     1.154      1    0.2827 |   1 |     1.154      1    0.2827

   1 -  2 |     5.043      2    0.0803 |   2 |     3.482      1    0.0620

   1 -  3 |     8.392      3    0.0386 |   3 |     3.926      1    0.0475

   1 -  4 |     8.522      4    0.0742 |   4 |     0.302      1    0.5828
```

```
  1 -  5 |     12.187      5    0.0323 |   5 |      0.042      1    0.8367
----------------------------------------------------------------------------
 Test allows predetermined regressors/instruments
 Test requires conditional homoskedasticity


. ge adjusted= _s_ed_per1000_pred
. drop _t _x0 _x_t0 _s_ed_per1000_pred
----------------------------------------------------------------------------
```

Admissions Per 1000

```
itsa admit_per1000 pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)
figure posttrend
       time variable:  time, -12 to 11
             delta:  1 unit


Regression with Newey-West standard errors      Number of obs     =         24
maximum lag: 1                                  F(  7,        16) =       0.52
                                                Prob > F          =     0.8103
------------------------------------------------------------------------------
             |             Newey-West
admit_p~1000 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    pc_male |  -.1235779   2.511661    -0.05   0.961    -5.448062    5.200906
   pc_white |    7.00518   6.412629     1.09   0.291    -6.588986    20.59935
```

```
   mean_cci |   39.37776   50.59206     0.78   0.448    -67.87261    146.6281
   mean_age |  -4.232948   9.132943    -0.46   0.649    -23.59392    15.12803
        _t |   -1.27521   1.031745    -1.24   0.234    -3.462411    .9119911
       _x0 |   15.73977   13.53132     1.16   0.262    -12.94535    44.42489
     _x_t0 |   .2868107   3.226127     0.09   0.930    -6.552274    7.125895
     _cons |  -368.9929   741.5517    -0.50   0.626    -1941.012    1203.027
------------------------------------------------------------------------------

                Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

------------------------------------------------------------------------------
Linear Trend |      Coeff    Std. Err.     t      P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------------
  Treated    |    -0.9884   2.7224   -0.3631    0.7213    -6.7597    4.7829
------------------------------------------------------------------------------

. actest, lag(5)

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

  H0: variable is MA process up to order q

  HA: serial correlation present at specified lags >q

------------------------------------------------------------------------------

  H0: q=0 (serially uncorrelated)        |  H0: q=specified lag-1

  HA: s.c. present at range specified    |  HA: s.c. present at lag specified

-----------------------------------------+------------------------------------

    lags   |      chi2      df     p-val | lag |      chi2      df     p-val
```

```
----------+----------------------------+-----+----------------------------
  1 -  1  |    0.001     1    0.9765 |  1  |    0.001     1    0.9765
  1 -  2  |    0.082     2    0.9599 |  2  |    0.080     1    0.7776
  1 -  3  |    3.895     3    0.2730 |  3  |    3.863     1    0.0494
  1 -  4  |    3.910     4    0.4183 |  4  |    0.046     1    0.8303
  1 -  5  |    4.520     5    0.4772 |  5  |    0.118     1    0.7315
----------------------------------------------------------------------------
  Test allows predetermined regressors/instruments
  Test requires conditional homoskedasticity
. ge adjusted=_s_admit_per1000_pred
. drop _t _x0 _x_t0 _s_admit_per1000_pred
----------------------------------------------------------------------------
```

Readmits Per 1000

```
itsa readmit_rate pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)  figure
posttrend
        time variable:  time, -12 to 11
                delta:  1 unit
Regression with Newey-West standard errors      Number of obs     =         24
maximum lag: 1                                  F(  7,        16) =       0.58
                                                Prob > F          =     0.7588
------------------------------------------------------------------------------
             |             Newey-West
readmit_rate |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

```
------------+----------------------------------------------------------------
     pc_male |  -.0058888   .0080034    -0.74   0.473    -.0228553    .0110776
    pc_white |   .0160214   .0139683     1.15   0.268    -.0135901    .0456329
    mean_cci |  -.0547663   .0935184    -0.59   0.566    -.2530164    .1434838
    mean_age |   .0034991   .0149554     0.23   0.818     -.028205    .0352032
          _t |  -.0005907   .0026267    -0.22   0.825     -.006159    .0049776
         _x0 |    .005454    .027001     0.20   0.842    -.0517857    .0626937
       _x_t0 |   .0081468   .0090746     0.90   0.383    -.0110904    .0273841
       _cons |  -.7448158     1.4998    -0.50   0.626     -3.92425    2.434619
------------------------------------------------------------------------------

                Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

------------------------------------------------------------------------------
Linear Trend |      Coeff    Std. Err.     t      P>|t|    [95% Conf. Interval]
------------+----------------------------------------------------------------
   Treated   |     0.0076   0.0073    1.0285    0.3190    -0.0080    0.0231
------------------------------------------------------------------------------

. actest, lag(5)

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

  H0: variable is MA process up to order q

  HA: serial correlation present at specified lags >q

------------------------------------------------------------------------------

  H0: q=0 (serially uncorrelated)        |  H0: q=specified lag-1
```

HA: s.c. present at range specified | HA: s.c. present at lag specified

lags	chi2	df	p-val	lag	chi2	df	p-val
1 - 1	1.163	1	0.2808	1	1.163	1	0.2808
1 - 2	1.163	2	0.5590	2	0.001	1	0.9726
1 - 3	5.623	3	0.1315	3	3.947	1	0.0470
1 - 4	5.683	4	0.2241	4	0.370	1*	0.5428
1 - 5	8.327	5	0.1391	5	0.539	1	0.4630

Test allows predetermined regressors/instruments

Test requires conditional homoskedasticity

* Eigenvalues adjusted to make matrix positive semidefinite

```
. ge adjusted=_s_readmit_rate_pred
. drop _t _x0 _x_t0 _s_readmit_rate_pred
```

Mean LOS

```
itsa mean_los pc_male pc_white mean_cci mean_age, single trperiod(0) lag(1)  figure
posttrend
      time variable:  time, -12 to 11
            delta:  1 unit
```

Regression with Newey-West standard errors Number of obs = 24

maximum lag: 1 F(7, 16) = 2.61

Prob > F = 0.0532

| Newey-West

mean_los | Coef. Std. Err. t P>|t| [95% Conf. Interval]

---+---

pc_male | -.2270253 .1899313 -1.20 0.249 -.6296615 .175611

pc_white | .370852 .3211162 1.15 0.265 -.3098839 1.051588

mean_cci | 3.534379 3.549748 1.00 0.334 -3.990751 11.05951

mean_age | -.4097409 .4059074 -1.01 0.328 -1.270226 .4507444

_t | -.0045016 .0640854 -0.07 0.945 -.1403565 .1313534

_x0 | .6685449 .6366554 1.05 0.309 -.6811041 2.018194

_x_t0 | -.1168599 .175714 -0.67 0.515 -.489357 .2556371

_cons | -.674593 50.2011 -0.01 0.989 -107.0962 105.747

Postintervention Linear Trend: 0

Treated: _b[_t]+_b[_x_t0]

Linear Trend | Coeff Std. Err. t P>|t| [95% Conf. Interval]

---+---

Treated | -0.1214 0.1339 -0.9061 0.3783 -0.4053 0.1626

```
. actest, lag(5)

Cumby-Huizinga test for autocorrelation (Breusch-Godfrey)

  H0: variable is MA process up to order q

  HA: serial correlation present at specified lags >q

------------------------------------------------------------------------------

  H0: q=0 (serially uncorrelated)        |  H0: q=specified lag-1

  HA: s.c. present at range specified    |  HA: s.c. present at lag specified

---------------------------------------+----------------------------------

   lags   |     chi2      df     p-val | lag |     chi2      df     p-val

----------+---------------------------+-----+---------------------------

   1 -  1 |     5.582      1    0.0182 |   1 |     5.582      1    0.0182

   1 -  2 |     7.493      2    0.0236 |   2 |     0.009      1    0.9251

   1 -  3 |     9.153      3    0.0273 |   3 |     0.002      1    0.9669

   1 -  4 |    10.286      4    0.0359 |   4 |     0.693      1    0.4053

   1 -  5 |    11.183      5    0.0479 |   5 |     0.111      1    0.7390

------------------------------------------------------------------------------

  Test allows predetermined regressors/instruments

  Test requires conditional homoskedasticity

. ge adjusted=_s_mean_los_pred

. drop _t _x0 _x_t0 _s_mean_los_pred
```