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A Longitudinal Approach to Measuring

Income Mobility among Filipino Households

Arturo M. Martinez Jr.

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Abstract

This study takes a longitudinal approach to analysing household income distribution in the Philippines over the past decade using data from the redesigned Philippine Family Income and Expenditure Survey and Labour Force Survey. Using existing and newly-developed analytical tools, the study examined the income trajectories or income mobility of a sample of households tracked in 2003, 2006, and 2009 and found income mobility within this time period to be significant. However, income poverty rates and inequality levels over the past decade remained stagnant because significant positive and negative mobility existed across space and over time, thereby suggesting that the country's economic growth has created both winners and losers. In addition, positive changes in socio-economic capital were offset by reductions in economic returns to capital, highlighting that investments in socio-economic capital development should be complemented with effective management of economic returns to capital. Furthermore, there are some indications that households with lower income experienced slightly faster income growth. However, transitory income fluctuations contribute significantly suggesting that convergence of income of the poor and non-poor may be in part due to random variations. This result indicates that in order to achieve sustainable and inclusive growth, it is also important to provide economic risk-management tools for those who periodically move into and out of economic hardships.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

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Publications during candidature

Journal articles

Martinez, A., Western, M., Haynes, M., Tomaszewski, W. & Macarayan, E. (2014). Multiple Job Holding and Income Mobility in Indonesia**.** *Research in Social Stratification and Mobility, 37, pp. 91-104*. http://dx.doi.org/10.1016/j.rssm.2013.09.008

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Keywords

income mobility, poverty, income inequality, pseudo-panel, economic growth, social statistics, developing countries

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Contents

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List of Abbreviations used in the thesis

ADB – Asian Development Bank
APIS – Annual Poverty Indicators Survey
ARMM – Autonomous Region of Muslim Mindanao
ASEAN – Association of Southeast Asian Nations
BLES – (The Philippine) Bureau of Labour and Employment Statistics
CALABARZON – Cavite, Laguna, Batangas, Rizal and Quezon
CAR – Cordillera Administrative Region
CCT – Conditional Cash Transfer
CEDAW – Committee on the Elimination of Discrimination Against Women
DASP – Distribution Analysis Software Package
FGT – Foster, Greer and Thorbecke
FIES –Family Income and Expenditures Survey
GDP – Gross Domestic Product
GIC – Growth Incidence Curve
GMM – Generalized Method of Moments
GRC – Gradin, del Rio and Canto
HDI – Human Development Index
ILO – International Labour Organization
JR – Jalan and Ravallion
KILM- Key Indicators of the Labour market
LFS – Labour Force Survey
MDG – Millennium Development Goals
MIMAROPA – Mindoro, Marinduque, Romblon, Palawan
NCR – National Capital Region
NSCB – (The Philippine) National Statistical Coordination Board
NSO – (The Philippine) National Statistics Office
OECD – Organisation for Economic Co-operation and Development
PAG-ASA – Philippine Atmospheric Geophysical and Astronomical Services Administration
UNDP – United Nations Development Programme
UNESCAP – United Nations Economic and Social Commission for Asia and the Pacific
UNICEF – United Nations International Children’s Emergency Fund
UNSD – United Nations Statistical Division
WB – (The) World Bank
WHO – World Health Organization
WDI – World Development Indicators

Introduction

In response to the challenge of ensuring that socio-economic opportunities are evenly distributed, the United Nations (UN) along with its approximately two hundred member states have committed to reducing various forms of socio-economic deprivation and exclusion, particularly in developing countries. In this context, a list of targets between 1990 and 2015 were identified. The targets span multiple dimensions of socio-economic development such as income, health, education, employment and gender equality. These constitute the Millennium Development Goals (MDG).

Eradicating extreme hunger and poverty is the first of the eight MDGs that UN member states have committed to pursue by 2015. Under this goal, there are three specific targets: to halve the proportion of people living under US$1.25 a day, to achieve full and productive employment and decent work for all- including women and young people, and to halve the proportion of people who suffer from hunger (UN 2014). Although substantial gains have been made towards this goal — for instance in 2010, the global poverty rate has already fallen to less than half of the proportion of poor estimated in 1990 — much effort is still needed to improve the lives of the 1.2 billion people who remain extremely poor. As 2015 marks the deadline set for achieving the MDGs, it is important to evaluate where we stand and identify what else can be done for those who remain in the shackles of poverty. This serves as the main motivation of this research. In particular, the study focuses on income as a measure of socio-economic well-being.

The Philippines is an important case study for examining how income distribution evolves over time because of the seemingly weak impact of economic growth in reducing poverty and inequality. In general, a country's economic performance is usually measured in terms of its gross domestic product (GDP). From 2009 to 2012, the country's GDP per capita has grown rapidly, expanding by 4.1% annually which is among the highest growth trajectories in Asia (WDI 2014). Since 2000, GDP per capita grew at an annual rate of 3.1 (WDI 2014). Given the large contribution of the household sector to GDP, it is intuitive to think that the country's observed economic growth would have an impact on the mean and the variance of its household income distribution. However, a cursory look at conventional socio-economic indicators seems to suggest that the benefits of economic expansion have not had a significant impact on the income distribution with headcount poverty and inequality rates remaining high and barely moving (WDI 2014). There are several possible reasons why this could be the case. First, it is possible that the observed economic growth is accruing to the richest households only while the income of the remaining households is fixed. To some extent, the propensity of the richest households to be under-represented in household surveys may partially explain why economic growth does not seem to have a significant impact on the mean and variance of the household income distribution. Second, there is a growing gap between the coverage of national accounts and household surveys. For example, rents of homeowners and the value of financial services are imputed in the national accounts but not in household surveys (WB 2010). Third, it is possible to attribute this observation to the limitations of conventional indicators like average household income, cross-sectional poverty and inequality which simply quantify changes in the marginal distribution of income. Previous studies suggest that such an approach does not give a complete appraisal of the dynamics of the country's development process (Reyes, Tabuga, Mina, Asis & Datu 2011; Bayudan-Dacuycuy & Lim 2013). The objective of this study is to provide a benchmark for probing beyond indicators of marginal distributional income changes by adopting a longitudinal approach in examining income mobility patterns. This approach is intended to provide a better means of understanding the dynamics of living standards in the Philippines.

Although several studies have analysed growth, poverty and inequality in the Philippines (e.g., Balisacan & Fujisaki 1998; Balisacan & Pernia 2002; Pernia 2003; Schelzig 2005; Aldaba 2009), most have only provided static snapshots of poverty and inequality in the country. While these indicators are useful for studying how income distribution evolves over time, they are unable to identify whether those who are initially poor are able to get out of poverty and in what ways the persistently poor differ from the transiently poor. To address this shortcoming, I use conventional and newly developed statistical methods that are designed to take into account the temporal dimension of the income distribution using longitudinal data rather than a series of cross-sectional data. The use of a portfolio of statistical techniques allows us to examine the robustness of results, which in turn enhances the reliability of inferences for drawing policy implications.

The importance of providing a longitudinal perspective in income distributional analysis can be illustrated with the following simple example. Consider two scenarios for a two-individual society consisting of one income-poor and one non-poor individual. In the first scenario, incomes of both individuals did not change between the initial and final time periods. In the second scenario, the individuals switched incomes. Although there is a complete reversal of income ranks in the second scenario, the cross-sectional estimates will portray stagnant poverty distribution in both scenarios since this approach does not distinguish between persistent and transient forms of disadvantage. From a policy perspective, it is important to distinguish between these scenarios because they could require different policies. For instance, the first scenario calls for a policy that would address persistent forms of disadvantage while the second scenario calls for a policy that would minimize socio-economic vulnerabilities.

In general, socio-economic mobility attempts to measure how people's living standards change across space and over time. It describes the ability of people to partake in the socio-economic opportunities created by economic growth. In addition, it also determines which disparities in economic opportunities at a specific point in time can be used as a measure of welfare inequality over the long term (Fields 2008). If any person can work their way up the social hierarchy, then high inequality may be less consequential for a country's long-term growth trajectory. By exploiting longitudinal data and adopting richer methodologies, we can broaden our understanding of socio-economic mobility in the Philippines and eventually contribute to a more evidence-based policy-making.

The thesis is divided into three parts. The first part consists of two chapters that provide the building blocks needed for examining income mobility in the Philippines. In Chapter 1, I address the question '**how is income mobility measured?**'. Here, I discuss two important analytical considerations. First, I review several definitions of income mobility and explain how each concept is operationalized using empirical data. The discussion highlights that a good understanding of income mobility would require taking a multidimensional perspective. Secondly, I discuss why high levels of income mobility should not always represent a desirable outcome as conventionally perceived due to the inflationary impact of measurement errors and transient income fluctuation on mobility estimates. In Chapter 2, I provide a background of the socio-economic history of the Philippines over the past thirty years. The discussion is centred on answering the question '**has economic growth been pro-poor in the Philippines?**'. A simple simulation experiment showed that shifting from a cross-sectional to a longitudinal perspective could portray the economic development process in the Philippines in a different light than is conventionally perceived. This identifies the need to analyse income mobility patterns using actual panel data.

The second part of the study discusses the results from the empirical investigation of income mobility patterns in the Philippines. In Chapter 3, I describe the longitudinal data from the Philippine Family Income and Expenditure Survey and Labour Force Survey which serve as the main data sources for the succeeding analyses. The period of time covered in this study coincides with the decade that precedes the rapid economic growth episode currently experienced by the country. I split the analysis into two main periods with both similarities and differences in economic conditions. In Chapter 4, I ask the question '**is there income mobility in the Philippines?'**. As pointed out earlier, it is tempting to think that the income distribution in the country is stagnant based on cross-sectional trends of poverty and inequality. Contrary to this perception, I find that significant amounts of positive and negative mobility exist, but they tend to offset each other and result in small changes in the income distribution at the aggregated level. There is also some evidence that transitory fluctuations contribute significantly to the observed level of income mobility. After establishing that there is considerable amount of mobility in the country, I focus the discussion on mobility at the low-income range in Chapter 5. In particular, I ask the question '**how long do people stay in poverty?**'. The results suggest that poverty in the Philippines can be considered as mostly chronic or persistent in nature. Thus, the finding that the initially poor experienced slightly better income mobility outcomes may not be enough to eliminate poverty soon. Despite faster income growth, it may take generations for the poor to exit poverty if they are trapped in vicious cycles of socio-economic deprivation. Nevertheless, the results presented in Chapter 5 also suggest the relative importance of transient poverty increases as the poverty line decreases or the poverty measure under consideration becomes more sensitive to the illfare of the poorest of the poor. This result highlights the importance of examining the robustness of poverty estimates to measurement parameters and estimation methodology. After examining poverty dynamics, Chapter 6 discusses the relationship between inequality and income mobility where I ask the question '**who are the income-mobile?**'. The statistical analyses lead to mixed findings. While there is evidence that initially disadvantaged households experienced slightly better income mobility outcomes than initially high-income households, the differences in their income trajectories taper off when a proxy measure of permanent income rather than initial income is used to group households into different income groups. The results also suggest that advantaged households had the most erratic income fluctuations, experiencing the highest income gains (losses) in 2003-2006 and highest income losses (gains) in 2006-2009.

The third part of this thesis briefly discusses policy implications on and future directions for income mobility studies in the Philippines from both substantive and technical viewpoints. After providing a longitudinal perspective of poverty and income inequality and given the fact that a good understanding of the factors that contribute to income mobility is important in identifying appropriate policy intervention programs, I ask the question '**what drives income distribution dynamics in the Philippines?**' in Chapter 7. To address this question, I use an exact accounting procedure in measuring the contribution of socio-economic capital, socio-economic returns on capital and shocks on the observed changes in poverty and income inequality. The results indicate that the higher levels of ownership of assets and higher economic returns to formal and non-agricultural employment have contributed to lower poverty while human capital and access to basic services remain stagnant. However, the results also portray the impact of changes in socio-economic capital and changes in economic returns to capital as offsetting forces that contribute to slow poverty and inequality reduction despite the rapid economic growth that the Philippines has experienced since the beginning of the 21st century. Furthermore, the findings in this chapter also point to the importance of accounting for socio-economic shocks when outlining poverty-alleviation strategies. Given the importance of employment in inducing income mobility and the increasing prevalence of non-traditional employment, Chapter 8 investigates whether non-traditional employment can induce upward mobility using multiple job holding as a case study by asking the question, '**is multiple job holding correlated with income mobility?**'. Unlike in industrialized countries where pluriactivity is used to enhance one's skills to be able to move into better occupations, I find that multiple job holding in the Philippines is mainly used as a coping mechanism, a stark indicator of the high prevalence of underemployment and limited leverage against risks of income shortfall. This suggests that the emergence of non-standard employment arrangements which are not usually covered by labour policies can push workers trapped in precarious jobs to poverty. On the other hand, Chapter 9 takes a step further in investigating the future of income mobility literature in the Philippines (and other developing countries) with regard to data availability. To reconcile the need for providing a more dynamic perspective of the evolution of income distribution with the lack of panel data in developing countries, I ask the question '**how can we measure income mobility when there is no (or lack of) panel data?'**. I evaluate the performance of several pseudo-panel estimation techniques in measuring a wide array of income mobility indicators and find that methods with more flexible income model specifications perform better than those with highly parameterized models. More importantly, these flexible pseudo-panel procedures produced estimates of poverty dynamics and movement-based indices which are consistent with the estimates computed from the actual panel data. Nevertheless, further improvements are warranted to be able to develop a more satisfactory estimation procedure for indices measuring temporal dependence and the inequality-reducing effect of income mobility.

In summary, despite the faster economic growth rates that the country has experienced over the past decade, one of the main recurring findings of this study is the presence of a strong offsetting effect of income losses and income gains across space, over time and between socio-economic capital, socio-economic returns to capital and shocks. These offsetting forces have contributed to the seemingly stagnant income distribution in the country. In addition, I also find that the amount of mobility is significantly lower when permanent rather than current income is used. Overall, these results call for the need to identify a more aggressive mix of policy recommendations that will facilitate inclusive economic growth, minimize socio-economic vulnerabilities, and reduce poverty and long-term inequality in the Philippines more sustainably.

This research can be considered as a benchmark for future income mobility analysis in the Philippines. It surpasses conventional studies which have sketched poverty and inequality in the country as a one-time event and ignored the persistence and recurrence of such states over time. The analyses presented here strike a balance between improving (household) income distribution measurement theory and enhancing the accessibility of distributional statistics to policymaking. The topics covered in this study are quite broad because as a benchmark study, one of the main objectives of this research is to demonstrate the use of a wide range of analytical tools that enrich income distributional analysis by exploiting the longitudinal feature of household panel data. Although broad policy implications of the findings are discussed, very detailed policy recommendations are reserved for future studies. One of the potential shortcomings of this study is the lack of detailed analysis of the spatial disparities in income mobility. This is mainly driven by data limitations as the panel data used in this study can provide reliable estimates at the national and broad-regional levels only. Future research that will further explain this topic can consider using small area estimation techniques in order to provide more disaggregated estimates of income mobility. In addition, since the study covers three time periods only, the use of more sophisticated analytical tools (e.g., multi-level models) that require more time points is very limited. Nevertheless, while more research is warranted to address these limitations, I hope this thesis helps to shift the attention of policymakers away from static and towards more dynamic measures of well-being to better understand how this analytical approach will affect the direction of policies and programs on inclusive growth.

Chapter 1 Analytical Tools for the Analysis of Income Mobility

1.1 Introduction

The concept of well-being refers to human welfare in a wide range of aspects such as income, health, education, work, family, and other things that are important to people's lives. Implicitly related to this concept is the term socio-economic deprivation which refers to the lack of capability for valuable functionings that will allow one to tap opportunities needed to improve his/her living standards (Sen 1999). The measurement of well-being is an essential component of policy-making. For instance, a society's progress or socio-economic development is often gauged by how much people's well-being or living standards have improved and by how much socio-economic deprivation has been reduced over time. Measuring well-being also allows socio-economic planners to identify policy priorities that will put the needs of the people first and will address the challenges that societies face ahead (Organisation for Economic Co-operation and Development (OECD) 2013). A good example is the implementation of the MDGs which show a clear, global commitment to end the multiple dimensions of poverty and disadvantage.

There are different ways of measuring a country's overall well-being. Initially, traditional metrics have centred on the monetary aspects of well-being. Until 1970s, the use of GDP and other income-based measures flourished.[1] Later on, there had been emphasis in understanding how income is distributed throughout the population and this led to the emergence of various measures of income poverty (Foster, Greer & Thorbecke (FGT) 1984) and income inequality (Shorrocks 1982). However, narrow conceptualisations of disadvantage that are solely based on income ignore the fact that people have different capabilities to convert income into resources that improve living standards (Callander, Schofield & Shrestha 2011). For instance, people may have sufficient money to purchase food, but face difficulties in accessing markets that sell food because they live in remote areas. Conventional income-based measures of poverty would classify these individuals as non-poor. A better way to conceptualize disadvantage is in terms of the lack of capabilities, freedom or resources to participate in mainstream society (Nussbaum & Sen 1993; Sen 1999; United Nations Development Programme (UNDP) 2008). This implies a shift from conceiving disadvantage in terms of 'the

[1] Here, income is used as a general term to encompass different monetary measures of well-being. In Chapter 8, I use income in a more specific context to refer to the amount of money or its equivalent that accrue to an individual or group of individuals as a result of an economic transaction such as rendering labour, sale of goods or services, returns from investments. This definition distinguishes income from consumption expenditure. In other chapters, household expenditure is referred to as income.

means of living' people dispose of to the 'opportunities' they are given to choose the life that they want to live (McLachlan, Gilfillan & Gordon 2013). To shift the attention of policymakers away from conventional monetary-based measures of well-being and socio-economic deprivation in the 1980s, researchers started exploring more holistic measures of human development in the 1980s (McGillivray 2006). In 1990, the UN published its first Human Development Report which also launched the Human Development Index (HDI), a simple yardstick that expresses well-being in terms of income, health and education (UNDP 1990). Despite its limitations, HDI is still widely used to complement traditional income-based indicators in measuring socio-economic development among developing countries (UNDP 2013). On the other hand, more advances have been made in terms of developing holistic measures of well-being in industrialized countries due to its more advanced data collection systems. For instance, the Better Life Index (BLI) proposed by OECD covers eleven dimensions of well-being which include housing, income, jobs, community, education, environment, governance, health, life satisfaction, safety and work-life balance (OECD 2011).[2]

Although contemporary leading poverty researchers are unambiguous in declaring that disadvantage goes beyond income deprivation, with the debate progressively moving into the multi-faceted nature of socio-economic disadvantage, income remains a very important resource and a gatekeeper to participation in socio-economic transactions (Harding & Szukalska 2000). Furthermore, there is still much to learn about how to maximize the information provided by income data to better understand societal progress, particularly in developing countries where there are limited non-pecuniary socio-economic indicators. For instance, estimates of income poverty and inequality are conventionally presented as static cross-sectional aggregates which do not provide any information as to how persistent is poverty for different groups of people. Ignoring how people's incomes move over time may lead to inappropriate policy interventions. To illustrate how solely relying on these static indicators masks important features of a country's development process, consider a hypothetical population consisting of ten people. Of these ten people, four were rich and six were poor in the initial time period. Suppose in the subsequent period, all initially rich became poor and all initially poor became rich. Furthermore, suppose the incomes of the initially poor became

[2] Ravallion (2011) argues that the indices such as HDI and the Multidimensional Poverty Index (MPI) recently proposed by researchers from Oxford Poverty and Human Development Initiative (OPHI) (Alkire and Santos 2013), suffer from issues about marginal rates of substitution. In particular, according to Ravallion (2011), it is difficult to find an economic theory that can justify how multiple indicators should be weighted to form a singular index because there is no consistent valuation across different dimensions of well-being. Rather than a single multidimensional index, Ravallion (2011) thinks that developing a reliable set of multiple indicators of poverty and deprivation should be given more priority.

higher than the initial incomes of the initially rich. This scenario would lead to a twenty-percentage point reduction in poverty rate and an increase in inequality. Whether this turn of events is good or bad is subject to value judgment. On the good side, the development process has allowed the initially poor to catch up with the rest of the population. However, the complete reversal of incomes may also portray a very unstable income distribution. In general, while changes in the cross-sectional estimates of poverty and inequality are useful in providing a general picture of a developing country's socio-economic progress, they do not provide a complete appraisal of the temporal dynamics of the development process.

The study of income mobility is an emerging research paradigm in income distributional analysis which capitalizes on the increasing availability of panel data (Fields 2011). Unlike static cross-sectional measures which are based on changes in the marginal distribution of income, income mobility is measured based on the joint temporal distribution of income. A good understanding of income mobility trends is important for evidence-based policy planning because different income mobility regimes call for a different mix of policies. For instance, large increases in cross-sectional estimates of inequality may merit less concern when they are accompanied by high income mobility rates since it means that the poor can eventually get out of poverty. Analogously, a significant increase in cross-sectional poverty and inequality may be problematic when it is accompanied by low levels of income mobility. Nevertheless, high income mobility rates may not always be desirable. As pointed out in the example earlier, complete reversal of incomes wherein the richest swaps income with the poorest, second richest swaps income with the second poorest and so on, will still give the same cross-sectional estimates of poverty and inequality but at the same time will portray a highly unstable income distribution.

In summary, the main point that the discussions presented in this chapter seeks to convey is that while the analysis of income mobility provides a broader picture of the income distribution dynamics than conventional static socio-economic indicators, there are also additional technical considerations that have to be carefully taken into account. In general, the accompanying methodological decisions may lead to variations in research findings which in turn could cause confusion among non-technical audience. Policy responses to findings of income distributional analysis may lead to sub-optimal intervention programs when the estimates are not well explained to policymakers and other key stakeholders. In contrast, when the robustness of the results to measurement parameters are carefully examined, income mobility research can empower users and stakeholders by providing them with a better understanding of the impact of methodological decisions on research findings.

As a springboard for the analyses presented in the succeeding chapters, this chapter reviews the state of the art of examining income mobility by presenting the analytical tools that are used throughout this study. The rest of the discussion highlights that while examining income mobility patterns enriches our understanding of the evolution of poverty, inequality and income distribution, in general, there are additional technical considerations that have to be taken into account. A good understanding of these substantive and methodological issues will help us communicate the results of income distributional studies better so that it will feed into public discussion. This chapter addresses the following questions:

(i) Why it is important to probe beyond cross-sectional trends of poverty, inequality and economic growth when examining a country's income distribution?

(ii) How do we measure the different dimensions of income mobility?

(iii) What are the important considerations when examining income mobility?

1.2 What is Income Mobility and Why it is Important?

Income mobility can be likened to a concept of a ladder where the ladder represents the income distribution.[3] Some individuals climb up while others slide down. People also move from one step to another at different rates. Researchers have offered several interrelated reasons explaining the relevance of examining the patterns at which people are moving along the income distribution. First, income mobility is often regarded as a corrective tool for the negative impacts of high or increasing inequality. Friedman (1962 p.1971) articulated this hypothesis using an example, "*Consider two societies that have the same distribution of annual income. In one, there is great mobility and change so that the position of particular families in the income hierarchy varies widely from year to year. In the other, there is great rigidity so that each family stays in the same position year after year. Clearly, in any meaningful sense, the second would be the more unequal society*." To elucidate this idea further, it is helpful to first distinguish the two types of inequality: inequality of outcomes and inequality of opportunities.[4] Consider a simple scenario wherein a new job needs to be filled. Applying and being considered for this job represents an "opportunity" while being hired or denied represents an "outcome." In this example, there is inequality of opportunity when job applicants with the

[3] The concept of income mobility originated from the notion of social mobility. Broadly defined, social mobility refers to the shifting of individuals in social space (Sorokin 1927, 1959). Defining the segments of this social space is based on the stratification of individuals' well-being. There are several ways of doing this. Sociologists use occupations as the basis for social stratification while economists use income as their yardstick.

[4] The relationship of income mobility with inequality of outcomes and opportunities is more commonly discussed in an intergenerational context. Income mobility, when measured in terms of correlation between children's and parental income, is consistent with the meritocratic idea that an individual's well-being should depend on their own abilities and efforts rather than their parents' (Jenkins 2011). Nevertheless, this can also be extended in an intragenerational context.

same level of skills are discriminated on the basis of factors that do not have anything to do with their expected job performance and for which they do not have control of. Examples of these factors are sex, ethnicity, religion, among others. On the other hand, if selection is based solely on skills wherein the most skilled has the highest probability of getting the job, then any variation in employment outcomes would represent inequality of outcomes. More generally, when new opportunities in the form of wealth, income, socio-economic services, among others are created in the course of economic growth but the chance to access these new opportunities is mediated by factors that are beyond a person's control, we can say that there is inequality of opportunities. Otherwise, traditional view of inequality suggest that if outcomes reflect the level of effort, then inequality of outcomes will just be a result of variations in effort (Roemer 1998; Bardhan, Bowles & Gintis 2000).[5] Following this argument, increasing or high level of cross-sectional inequality need not have negative normative implications and should only be considered as a "distributional problem" if it is predominantly characterized by inequality of opportunities (Atkinson, Bourguignon and Morrison 1992).

By providing a wider perspective of how the distribution of income evolves over time, the examination of income mobility offers a way to distinguish inequality of opportunities from inequality of outcomes (Shorrocks 1978; Fields 2010). For instance, a scenario wherein cross-sectional inequality is increasing at the same time that the initially poor continuously experience low income mobility prospects may portray inequality of opportunities. On the other hand, a scenario wherein both initially poor and non-poor are enjoying high levels of income mobility may portray inequality of outcomes (Gottschalk 1997; Van Kerm 2006). Several studies provide empirical evidence of why inequality of outcomes could be of less concern than inequality of opportunities in the long-run. Using World Values Survey data for thirty OECD countries, Fisher (2009) finds that living in a perceived socio-economically mobile society uplifts individual life satisfaction. On the other hand, Tocqueville ([1856] 1986) surmised that when upward income mobility of others is unaccompanied by one's own, the initially poor who did not experience income mobility may resort to political actions (e.g., hold political rallies) which they think would help them become upwardly mobile like their non-poor counterparts (Hirschman & Rothschild 1973).

Different income mobility regimes call for a different mix of policies. A good understanding of the income mobility patterns enables policy planning and more efficient

[5] The works of Roemer, Bardhan, Bowles & Gintis provide excellent discussion about traditional and contemporary views of inequality. One of their main arguments is that it makes more sense to identify which mechanism of transmission of advantage is justified and which is unfair instead of pursuing an abstract objective of disconnecting initial levels of advantage and economic outcomes.

allocation of efforts and resources.[6] In theory, there are several possible types of income mobility regimes; zero mobility and perfect mobility are the two extreme cases. A society is said to have zero mobility if the income of every unit in the population is held fixed and there is perfect mobility if the conditional distribution of income destinations is the same for every income origin. In empirical application, the true income mobility regime often falls in between these two extreme cases. When initially poor people experience low income mobility, they become trapped in poverty and this could lead to the perception that there is no merit to work hard because the chance of getting out of poverty is limited. Without any mobility-enhancing intervention, such case could lead to a vicious cycle of poverty. This represents a significant waste of human resources (Asian Development Bank (ADB) 2012). Thus, finding an appropriate redistributive policy (e.g., conditional cash transfer) might be the way to counter this problem. Analogously, a scenario where high income range people experience low income mobility, portrays a system where socio-economic advantage accumulates over time. To be able to make the high income state more permeable to people from lower income segments, creation of additional high quality jobs and provision of trainings to meet the skill-requirement of these new jobs might be the way to move forward. In these two examples, low income mobility is portrayed as a problem that has to be addressed. However, the opposite case, i.e., having high income mobility, is not necessarily a desirable outcome. For instance, a high level of income mobility that is mainly driven by large fluctuations in transitory income could represent a very unstable economic system (Jarvis & Jenkins 1998). Analogously, low levels of income mobility may also be regarded as a good indicator if it represents a mature economy that has already achieved long-run equilibrium.

To be able to identify the ideal level of income mobility, it is first important to understand how mobility is conceptualized. The next section enumerates the different definitions of income mobility and discusses how various conceptualisations can lead to qualitatively different income mobility trends.

1.3 How Do We Measure Income Mobility?

Technically, income mobility can be regarded as a transformation between two income vectors over a period of time. However, there is a long standing debate as to which features of the vector transformation characterise low or high mobility (Maasoumi 1998; Fields & Ok

[6] It is often considered that static analysis of development is more suitable for treating symptoms of socio-economic disadvantage while a more dynamic analysis allows us to tease out causal relations among different factors and thus plan a more effective intervention of escaping disadvantage.

1999a; Fields 2008, 2009). The debate can be partially attributed to the different beliefs on which characteristic aspects of income are important to be examined over time. In addition to the different perspectives on what characterizes mobility, Ferreira et al. (2013) identified two other basic considerations that one needs to navigate to be able to measure income mobility: (i) concept of income and (ii) the time gap between the two income vectors. The first consideration entails choosing a specific type of income for which mobility should be measured. Hence, it answers the basic question *mobility of what*. As pointed out earlier, the term "income" is used throughout this study as a general term that encompasses different monetary measures of well-being and there are several types of income that could be of interest for mobility research. For instance, some researchers prefer to use earnings which includes regular cash income plus other income received from transfers while other researchers argue that consumption expenditure provides more insights into a person's economic well-being than the information provided by earnings. Chapter 3 discusses this issue further. The second consideration entails choosing the length of observation period for which income mobility is to be measured. It answers the question *how far apart in time the two income vectors are from one another* (Ferreira et al. 2013). In this context, there are two modes of measuring income mobility – intra-generational and intergenerational. Intra-generational income mobility corresponds to the historical income trajectories of the same set of people while intergenerational mobility refers to the income history of people from the same lineage across generations (i.e., parents and children) (Ferreira et al. 2013). The focus throughout the study is intra-generational mobility.[7]

The following section provides a general overview of some of the commonly used conceptual definitions of income mobility. In this review, I adopt the taxonomy proposed by Fields (2008) who defined income mobility in three perspectives: *mobility as movement*, *mobility as origin independence* and *mobility as equalizer of long term income.*[8] While the measures under these perspectives may differ in terms of functional forms, the choice of income mobility concept to be examined goes beyond the differences in formula and should be tailored to specific research questions that a study wants to answer (Ferreira et al. 2013).

[7] Although it is worthwhile to examine both intra-generational and intergenerational mobility as they capture short to medium-term and long-term changes in income distribution, respectively, the analyses presented in the succeeding chapters correspond to intra-generational mobility because information about parental income is not available.

[8] It can be argued that these three income mobility perspectives are not mutually exclusive. For instance, Jenkins (2011) categorized the concepts of income mobility into four broad groups: mobility as positional change, mobility as individual income growth, mobility as reduction of longer-term inequality and mobility as income risk. In his discussion, the mobility as origin-independence perspective proposed by Fields (2008) is subsumed under mobility as positional change.

For notation, the succeeding discussion assumes that the target population consists of N individual units whose incomes are observed for two different time points; the term Y_{it} is used to denote the i^{th} individual's income at time *t*.

1.3.1 What Characterizes Mobility of Incomes?

The first main perspective views mobility in terms of income movements. There are four sub-concepts within this perspective. First, income mobility may be gauged in terms of gross movements or what is commonly referred to as *income flux*. Mobility measures following this concept can be expressed as functions of the absolute income differences denoted by $|Y_{i2} - Y_{i1}|$. Second, mobility measures based on net income movements can be expressed as functions of actual differences in income levels denoted by $(Y_{i2} - Y_{i1})$. Unlike the first concept, the second concept distinguishes positive (or upward) from negative (or downward) income mobility and hence, other researchers also refer to the income flux and net income movement as non-directional and directional mobility, respectively. The third concept under the movement perspective views mobility in terms of changes in income shares denoted by $\frac{Y_{i1}}{\Sigma Y_{i1}} - \frac{Y_{i2}}{\Sigma Y_{i2}}$ while the fourth concept views mobility in terms of the changes in income ranks denoted by $\text{Rank}(Y_{i2}) - \text{Rank}(Y_{i1})$. In summary, the first two concepts measure changes in income levels (absolute mobility) while the last two concepts examine changes in an individual's income in relation to the incomes of everyone else in the society (relative mobility). Hence, the last two concepts of mobility depend not only on whether an individual's income changed over time but also on how the change alters his/her income share or income rank (Jenkins 2011).[9]

The second perspective views mobility in terms of the extent to which an individual's income in the past influences his/her current income (Lillard & Willis 1978). This is referred to as origin independence perspective. The basic property underpinning this perspective is that a more mobile society is one where an individual's first period-income is less important in predicting his/her income in the succeeding periods (Ferreira et al. 2013). In other words, mobility is high when an individual's income destination is weakly correlated to one's income origin and it is low when the correlation between the income origin and income destination is strong.

The third main perspective views mobility as an equalizer of long-term incomes. This perspective evaluates the extent to which long-term incomes are distributed more or less

[9] Under the positional movement concept, it is not possible for all individuals to be uniformly upwardly (or downwardly) mobile (Jenkins 2011).

equally over time. In general, an individual's income at any given time will differ from his/her average income taken over several successive time periods. Using temporal average income will smoothen the longitudinal variability in each individual's income as well as the variability across individuals.[10] The equalizer of long-term income perspective characterizes mobility in terms of the speed at which inequality is reduced as the observation period is lengthened (Shorrocks 1978, Jenkins 2011).[11] Under this perspective, mobility is high when the inequality in longitudinally-averaged income is less than the inequality at any particular point in time (Ferreira et al. 2013).

To impart meaning to the discussions above, consider the example provided in Table 1.1 which shows four income mobility scenarios labelled as S1, S2, S3 and S4, based on a hypothetical population consisting of four persons labelled as A, B, C and D. Each number corresponds to the amount of income units that each individual holds at a specific time point. First, we can use Scenario S1 to illustrate the difference between gross and net income changes. Under S1, the incomes of persons A and B increased by one unit each while that of persons C and D dropped by one unit. Summing up the absolute income differences across the four individuals is one of the many ways of measuring total income flux. In this example, the sum is four income units. On the other hand, summing up the individual income differences without taking the absolute value gives us a value of zero. Thus, whereas the first concept yields a non-zero estimate of mobility, the second concept leads to null mobility. The second scenario can be used to illustrate the difference between measuring income mobility in terms of changes in income levels and changes in either income share or income ranks. Under S2, the final incomes of persons A, B, C and D are twice their respective initial incomes. Summing up the income differences across all persons would give a non-zero estimate of mobility whereas summing up the changes in either income shares or income ranks gives a mobility estimate of zero. The third scenario illustrates the difference between movement-based and origin independence-based perspectives of income mobility. Under S3, person A swaps income with person D and person B swaps income with person C. In this scenario, the correlation between the initial and final income vectors is -1. Since the initial income vector perfectly predicts the values of the final income vector, we can say that there is no mobility based on the origin independence perspective. Similarly, since the observed increases in the income of the initially two poorest persons offset the observed income declines of the remaining two persons, we can also say that there is no directional income mobility under this scenario. However, since all persons

[10] The longitudinally averaged income can be used to approximate permanent or long-term income.
[11] The speed of inequality reduction depends on the chosen inequality measure (Schluter and Trede 2003).

observed change in both the actual income levels and income ranks, Scenario S3 portrays a mobile society in terms of non-directional income mobility and positional movement. Lastly, the fourth scenario illustrates the difference between mobility based on origin independence and mobility as equalizer of long-term income perspectives. The relatively high yet negative correlation (i.e., -0.8) between the two income vectors implies that there is low income mobility based on the origin independence perspective. However, since inequality in average income (4.5, 3, 4.5, 3) is lower compared to either the initial or final income vector, we can say that there is mobility based on the concept of equalizer of long-term income.

This section has discussed the differences between various concepts of income mobility that are commonly used in the literature. The concepts explained here are used intensively throughout the thesis, particularly when I describe the income mobility patterns in Chapter 4. The next section enumerates several analytical tools that can be used to compute these concepts using empirical data.

Table 1.1 Differences Between Income Mobility Perspectives

Scenario	Initial income vector	Final income vector
	A B C D	**A B C D**
S1	(1, 2, 3, 4)	(2, 3, 2, 3)
S2	(1, 2, 3, 4)	(2, 4, 6, 8)
S3	(1, 2, 3, 4)	(4, 3, 2, 1)
S4	(1, 2, 3, 4)	(8, 4, 6, 2)

1.3.2 Analytical Tools for Measuring Income Mobility

An income transition matrix is one of the most popular analytical tools used to summarize income mobility under the movement perspective. In particular, a transition matrix with boundaries between R income classes consists of each element $p_{k|j} = \frac{P(b_{j-1} \leq Y_{it-1} < b_j\,,\ b_{k-1} \leq Y_{it} < b_k)}{P(b_{j-1} \leq Y_{it-1} < b_j)}$ which is equal to the conditional probability that individual *i* moves to class *k* of income at time *t* given he/she was in class *j* at *t-1*, where $0 = b_0 < b_1 < \ldots < b_{R-1} < b_R$ (Table 1.2). When income mobility is low, one would expect that the diagonal elements of the transition matrix would be close to one. On the other hand, when income mobility is high, the diagonal elements of the transition matrix are likely to take equal values. Depending on one's research objective, the income classes can be specified in a number of ways. For example, it can be divided into R = 2 classes where the classes correspond to the state of being poor or non-poor. This is useful for measuring movements into and out of poverty. More generally, incomes could be divided into different income brackets according to absolute income cut-off points or income quantiles to measure absolute and relative mobility, respectively.

To be able to compare two transition matrices, it is useful to summarize the mobility implied from each transition matrix into a single scalar value. A simple approach is to count the number of classes for which an individual moved during an observation period. For example, if an individual moved from class 1 to class 3, then that individual is given a value of 2 because he/she moved by two classes. Equation (1.1) is computed by taking the average number of classes moved across all individuals. The immobility ratio is another simple summary measure that can be computed by counting the number of individuals who remained in the same class and dividing the count by the total number of individuals in the target population (1.2). However, one of the disadvantages of using an income transition matrix to provide a compact summary of the income mobility process is that it ignores the mobility experienced by individuals whose incomes changed yet remained in the same income class.

Table 1.2 Sample Income Transition Matrix

Quintile	Poorest Quintile	2nd Quintile	3rd Quintile	4th Quintile	Richest Quintile
Poorest Quintile	0.5	0.25	0.2	0.05	0
2nd Quintile	0.1	0.4	0.35	0.1	0.05
3rd Quintile	0.05	0.2	0.45	0.2	0.1
4th Quintile	0	0.05	0.35	0.45	0.15
Richest Quintile	0	0.05	0.15	0.25	0.55

$$ave\ \#\ states\ moved = \frac{\sum_i \left| \sum_{r=1}^{R} r * I\{b_{r-1} \le Y_{it-1} < b_r\} - \sum_{r=1}^{R} r * I\{b_{r-1} \le Y_{it} < b_r\} \right|}{N} \quad (1.1)$$

$$immobility\ ratio = \frac{cardinality(I\{b_{r-1} \le Y_{it-1} < b_r, b_{r-1} \le Y_{it} < b_r\})}{N} \quad (1.2)$$

In addition to using a transition matrix, there are a number of alternative ways of measuring income mobility. For instance, the class of indices proposed by Fields and Ok (1999b) can be used to measure the first two concepts of income mobility under the movement perspective. On the other hand, the average rank and King's (1983) indices are used to measure the third mobility concept under the movement perspective while Hart's (1976) index can be used to measure mobility based on the origin independence perspective. Furthermore, some examples of mobility indices that can be used when taking the equalizer of long-term income perspective include the measures proposed by Shorrocks (1978), Chakravarty, Dutta & Weywark (CDW) (1985) and Fields (2010). Table 1.3 provides the computational formula for each of these mobility indices.

While the list of concepts and empirical measures provided in this section is not exhaustive, these are the most commonly used tools in mobility studies.[12] It is important to note that the differences in mobility estimates based on varying concepts and analytical tools are not necessarily of limited practical interest because each concept corresponds to inherently distinct notions of what mobility is (Ferreira et al. 2013). Figure 1.1 illustrates this point. Using simulated data, I compare the relationship among different income mobility indices. While there is a general linear (either positive or negative) relationship among the indices considered, the strength of the correlation depends on the income mobility concept being measured. For instance, indices that do not differentiate between downward and upward income mobility (e.g., Fields-Ok's, King's, average rank jump, Hart's and Shorrocks' indices) are strongly correlated with each other but exhibit more variability when compared to equalization indices and poverty dynamics.

In providing a descriptive summary of the income mobility patterns in Chapter 4, measures related to the Fields-Ok's, average rank jump, Hart's, Shorrocks' indices and transition matrices are used intensively. This mix of indicators is chosen to provide an optimal insight to the different perspectives of mobility without having to use a very long-list of overlapping indicators.

1.4 Incorporating Income Mobility in the Analysis of Poverty, Inequality and Pro-Poor Growth

A number of studies have emphasized the usefulness of capturing the temporal dynamics of poverty, inequality and pro-poorness of growth for policy-targeting (Grimm 2007; Van Kerm 2009; Bourguignon 2011; Palmisano & Peragine 2014; Palmisano & Van de gaer 2013). Conventional measures of poverty, inequality and pro-poorness of growth are focused on understanding the pure cross-sectional effect of economic growth and ignores the identity of income recipients (Palmisano & Peragine 2014). In technical parlance, this is termed as the *temporal anonymity* property. However, people change their income positions over time. Today's poor (rich) is not necessarily the same set of people who were poor (rich) yesterday. Thus, if the objective is to understand how growth impacts the living conditions of the initially advantaged or disadvantaged, then it is important to capture income mobility. This section

[12] Fields (2008) provides a more comprehensive review of the various income mobility concepts used in the literature.

extends the discussion provided in Section 1.3 by reviewing the different ways of taking income mobility into account when measuring poverty, inequality and pro-poorness of growth. As in the previous section, the discussion highlights the differences between various methodologies to demonstrate the sensitivity of resulting estimates to the choice of measurement techniques.[13]

1.4.1 Measuring Intertemporal Poverty

Since the work of Sen (1976), many of the poverty estimation studies have centred on tracking snapshots of poverty by examining the trends of its incidence, depth and severity over time using repeated cross-sectional data collected at different time points. However, these poverty measures are not very useful in distinguishing a society where most of the poor have been trapped in socio-economic dearth for a long time from a society where many of the poor have been experiencing transient downturn in fortunes (Bane & Ellwood 1986). Given that a longitudinal perspective provides a broader picture of poverty and the panel data required to provide this broader picture is gradually becoming more available, several advances in measuring intertemporal poverty has been made over the years (Jalan & Ravallion 1998; Yaqub 2000; Foster 2009; Gradin, del Rio & Canto (GRC) 2012). Some of the ideal properties of an intertemporal poverty measure include continuity, focus, monotonicity, scale invariance, duration sensitivity and transfer axioms (GRC 2012).[14]

This section reviews several estimation tools for measuring persistent and transient poverty using two analytical frameworks – components approach and spells approach. The notations used in this section are slightly different from the notations used in Section 1.3. Here, Y_{it} is used to denote the i^{th} person's income at time t, normalized by the poverty line z. In other words, Y_{it} in this section is equal to the Y_{it} used in the previous section divided by the poverty line.

[13] For an introductory review of poverty and inequality measurement, readers are referred to Foster et al. (2013).
[14] According to GRC (2012), the continuity axiom states that any increase in household income at any time period when the household is non-poor should not change the value of the intertemporal poverty measure. The monotonicity axiom states that any decrease in household income during episode of poverty should increase the value of the intertemporal poverty measure. The scale invariance axiom states that rescaling the income and poverty line by the same factor should not change the value of the intertemporal poverty measure. The focus axiom states that any increase in the income of the non-poor should not affect the intertemporal poverty measure. The duration sensitivity axiom states that an intertemporal poverty measure should be able to differentiate the impact of shorter or longer poverty spells.

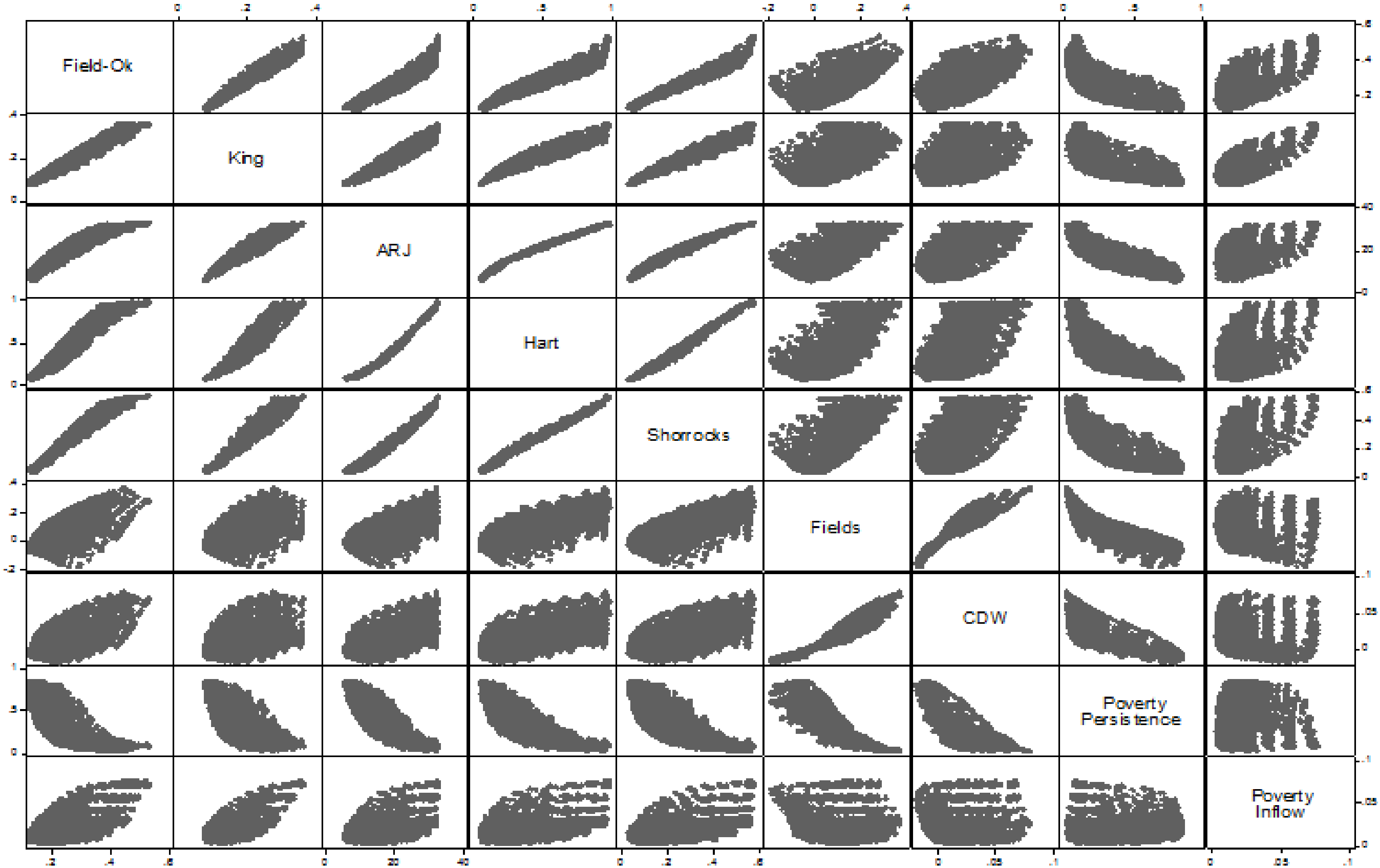
Table 1.3 Formula of Different Income Mobility Indices

Concept	Index	Formula
Income Movement	Fields-Ok	$\frac{1}{N}\sum_{i=1}^{N} \lvert \ln(\frac{Income_{it}}{Income_{it-1}}) \rvert$
	King	$1 - \frac{\gamma}{N}\sum_{i=1}^{N}(\frac{\lvert z_i - Income_{it}\rvert}{\overline{Income_i}})$
	Average Rank Jump	$\frac{1}{N}\sum_{i=1}^{N} \lvert rank(Income_{it}) - rank(Income_{it-1}) \rvert$
	Poverty Persistence	$\frac{1}{N_p}\sum_{i \in P}^{N_p} I\{Income_{it} \leq z,\} \quad where\ P \equiv \{i: Income_{it-1} \leq z\}$
	Poverty Inflow	$\frac{1}{N_C}\sum_{i \in C}^{N_C} I\{Income_{it} \leq z,\} \quad where\ C \equiv \{i: Income_{it-1} > z\}$
Time dependence	Hart	$1 - Correl(\ln(Income_{it}), \ln(Income_{it-1}))$
Mobility as Equalizer of Income	Shorrocks	$1 - \frac{I(\sum Income_{it})}{\sum_{t=1}^{T} w^t I(Income_{it})}$
	Fields	$1 - \frac{I(\sum Income_{it})}{I(Income_{it-1})}$
	Chakravarty, Dutta and Weywark (CDW)	$\frac{I(Income_{agg})}{I(Income_{it-1})} - 1$

Source: Fields (2008 and 2010)

Note: In the notations above, I{condition} is an indicator function which takes a value of 1 if the condition is satisfied and 0 otherwise. On the other hand, I( ) is an inequality index. Z is used to denote the poverty line.

Figure 1.1 Relationship between Different Income Mobility Indices



Source: Author's computations using simulated data and the Stata tools for income mobility analysis developed by Van Kerm (2002).

Measuring Intertemporal Poverty using the Components Approach

The components approach can be traced back to the permanent income hypothesis proposed by Friedman which states that over a person's lifecycle, each has his/her own permanent income stream but it can have short-term transitory fluctuations from time to time (Friedman 1957). The main interest of the components approach lies in disentangling the contribution of the short-term and long-term components to a person's income intertemporal poverty status.

Jalan & Ravallion (1998) Approach

Jalan & Ravallion (JR) (1998) proposed using the longitudinal average as an estimate of permanent income. In particular, suppose $\bar{Y}_i = \frac{\sum_{t=1}^{T} Y_{it}}{T}$, $g_{it} = max(1, Y_{it})$ and $\bar{g}_i = max(1, \bar{Y}_i)$. The measures of total poverty and poverty persistence are given by (1.3) and (1.4), respectively. On the other hand, transient poverty is estimated by subtracting poverty persistence from total poverty (1.5).

$$P_{\alpha}^{total} = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} g_{it}^{\alpha}}{NT} \tag{1.3}$$

$$P_{\alpha}^{persist} = \frac{\sum_{i=1}^{N} \bar{g}_i^{\alpha}}{N} \tag{1.4}$$

$$P_{\alpha}^{transient} = P_{\alpha}^{total} - P_{\alpha}^{persist} \tag{1.5}$$

These measures are identified by the parameter α and hence, they are analogous to the class of poverty indices proposed by Foster, Greer & Thorbecke (FGT) (1984). When α = 0, they measure the incidence of intertemporal poverty, depth when α = 1 and severity when α = 2. If all units have longitudinal average incomes that exceed the poverty line z, but income in some time periods fall below z, $P_{\alpha}^{persist}$ will be equal to 0 while $P_{\alpha}^{transient}$ will be equal to P_{α}. On the other hand, if all units have longitudinal average income falling below z, both P_{α}^{Total} and $P_{\alpha}^{persist}$ will take a value of 1 and consequently, $P_{\alpha}^{transient}$ will be 0.

One of the main caveats of the JR approach is that the values of the resulting poverty measures do not necessarily range between zero and one because the P_{α}^{total} is not always guaranteed to be higher than $P_{\alpha}^{persist}$ or $P_{\alpha}^{transient}$.

Duclos, Araar & Giles (2010) Approach

Duclos, Araar & Giles (DAG) (2010) also proposed using longitudinal average income as an estimate of permanent income. However, unlike the JR approach, the DAG approach differentiates a poor person whose income consistently fell below the poverty line throughout the observation period from a person with the same longitudinal average income but experienced both poverty and non-poverty. By doing so, the DAG approach takes into account a person's risk-aversion to unexpected income fluctuations. This is consistent with the notion that a person's (economic) disutility tends to increase as the variation in their income stream increases which also leads to higher transient poverty (Gottschalk 1982). The DAG approach entails computing the variability-adjusted poverty status of each person (1.6). The parameter α ≥ 1 represents a person's level of risk aversion to income variations wherein a value of unity means that the person is risk-neutral. On the other hand, the risk-premium that person *i* would be willing to pay to be able to remove the variability in its poverty gap status is given by $\gamma_{\alpha}(g_i)$ (1.7). Under the DAG approach, transient poverty is defined as the total cost that will be incurred due to variability in poverty gaps over time while total poverty is the sum of the average poverty gap in the population, the cost of inequality in equally-distributed poverty gaps among individuals and transient poverty.[15]

$$P_{i\alpha}(g_i)^{\frac{1}{\alpha}} = \left(\frac{\sum_{i=1}^{T} g_{it}^{\alpha}}{T}\right)^{\frac{1}{\alpha}} \quad (1.6)$$

$$\gamma_{\alpha}(g_i) = P_{i\alpha}(g_i) - P_{i1}(g_i) \quad (1.7)$$

$$P_{\alpha}^{total} = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T} g_{it}}{NT} + \left(\frac{\sum_{i=1}^{N}\sum_{t=1}^{T} g_{it}^{\alpha}}{NT}\right)^{\frac{1}{\alpha}} - \frac{\sum_{i=1}^{N}\sum_{t=1}^{T} g_{it}^{\alpha}}{NT} + \frac{\sum_{i=1}^{N} \gamma_{\alpha}(g_i)}{N} \quad (1.8)$$

$$P_{\alpha}^{transient} = \frac{\sum_{i=1}^{N} \gamma_{\alpha}(g_i)}{N} \quad (1.9)$$

$$P_{\alpha}^{persistent} = P_{\alpha}^{total} - P_{\alpha}^{transient} \quad (1.10)$$

Although the JR and DAG approaches both fall under the components framework of measuring poverty dynamics, the two approaches have remarkable differences. For instance, while the income movements above the poverty line influences a person's persistent poverty status under the JR approach, the same cannot be said about the DAG approach because it censors income movements at the poverty line. In other words, under the JR approach, a person experiencing numerous episodes of poverty may still be considered not persistently poor if his/her income for at least one time period is high enough to make the longitudinally-averaged income exceed the poverty line. On the other hand, since only poverty gaps are considered when using the DAG approach, high incomes for few time periods cannot compensate for the numerous episodes that a person spent in poverty. Another important difference between the two approaches lies on how transient poverty is conceptualized. In the JR approach, transient poverty is simply the difference between total poverty and poverty persistence whereas under

[15] When a household is risk neutral (α = 1), transient poverty will be equal to 0.

the DAG approach, transient poverty is intimately linked with the level of risk aversion a person has towards income fluctuations.

Measuring Intertemporal Poverty using the Spells Approach

Unlike the components approach, the spells approach treats a person's poverty status in each time period, independently. This approach is consistent with the arguments presented by Jappelli (1990) stating that it is not safe to assume that individuals can "borrow" income from different time periods when there are variations in the liquidity constraints over time.

Conventional Spells Approach

The conventional spells approach entails counting the number of time periods when the observed income of each person fell below the poverty line. Then, a specific frequency threshold $\tau \leq T$ is used to distinguish transient from persistent poverty (1.13). For example, in the study of Gaiha & Deolalikar (1993) covering nine years of data, the authors defined persistent poverty as those whose income fell below the poverty line for at least five years. On the other hand, in a study covering three survey years, Reyes et al. (2011) defined persistent poverty as those who experienced income shortfall for at least two years.

$$P^{persist} = \frac{\sum_{i=1}^{N} V_i}{N} \tag{1.11}$$

$$P^{transient} = \frac{\sum_{i=1}^{N} (1-V_i)}{N} \tag{1.12}$$

where

$$V_i = \begin{cases} 1 \ if \ \ \sum_{t=1}^{T} I(Y_{it} < 1) > \tau \\ 0, otherwise \end{cases} \tag{1.13}$$

The intertemporal poverty measures presented in (1.11) and (1.12) have several limitations. First, they only estimate the number of persistently and transiently poor and do not provide any information about the depth and severity of intertemporal poverty. These measures are not also absolutely sensitive to the duration of poverty. For example, a persistently poor person who stays in poverty for an additional year because of lower income, will not reflect an increase in $P^{persist}$. Similarly, a transiently poor person who stays in poverty for an additional year will not increase $P^{transient}$ as long as the time spent in poverty does not exceed τ.

Foster (2009) Approach

To address the limitations of the conventional spells-based measures of poverty dynamics, Foster (2009) introduced a class of intertemporal poverty measures that are sensitive to poverty duration and can be used to estimate incidence (1.14), depth (1.15) and severity of intertemporal poverty (1.16). The proposed measures are provided below:

$$K_0 = HD \tag{1.14}$$

$$K_1 = HDG \tag{1.15}$$

$$K_2 = HDGS \tag{1.16}$$

where H is the proportion of the persistently poor persons (i.e., $H = P^{persist}$), D is the average duration that persistently poor persons spent in poverty, G is the average proportional income shortfall of persistently poor persons and S is the average squared proportional income shortfall of persistently poor persons. From this, it is straightforward to estimate transient poverty. First, we estimate $K(Y, z, \tau = 0)$ using the same formula where all poverty spells are accounted for. Transient poverty is then estimated by subtracting poverty persistence from total poverty.

Although the Foster approach takes into account the number of episodes spent in poverty, it does not take into consideration whether some poverty episodes occurred consecutively. Hence, it fails to consider that continuous episodes of poverty can be more harmful than the same number of periods spent in poverty but spread in between several episodes of non-poverty (Bane & Ellwood 1986; Jappelli 1990).[16]

Gradin, del Rio and Canto (GRC) (2012) Approach

Gradin, del Rio & Canto (2012) noted that many of the techniques discussed above fail to satisfy several properties of an ideal intertemporal poverty measure. For instance, the conventional spells approach and Foster approach violate the poverty duration sensitivity property because these approaches only take into account the number of poverty episodes within the observation period but not the duration spent in consecutive episodes of poverty. On the other hand, components-based measures such as the JR approach violate the intertemporal focus, poverty spell duration sensitivity and regressive transfer axioms because periods of high income compensate for periods of low income. To address this issue, GRC proposed a class of intertemporal poverty measures which circumvent these limitations.

[16] This is consistent with the state dependence hypothesis about poverty which states that the longer a household stays in poverty, the lower the chance of escaping it.

$$p_i^{GR}(Y_i; z) = \frac{1}{T}\sum_{t=1}^{T} g_{it}^{\gamma} w_{it}^{\beta} \tag{1.17}$$

such that

$$g_{it}^{\gamma} = \begin{cases} \left(\frac{z_i - Y_{it}}{z_i}\right)^{\gamma} & if\ Y_{it} < z_t \\ 0 & otherwise \end{cases} \tag{1.18}$$

$$w_{it}^{\beta} = \left(\frac{s_{it}}{T}\right)^{\beta} \tag{1.19}$$

$$P_{GR}(Y; z) = \begin{cases} \frac{1}{N}\sum_{i=1}^{N} p_i^{GR}(Y_i; z) & if\ \alpha > 0 \\ \frac{q}{N} & if\ \alpha = 0 \end{cases} \tag{1.20}$$

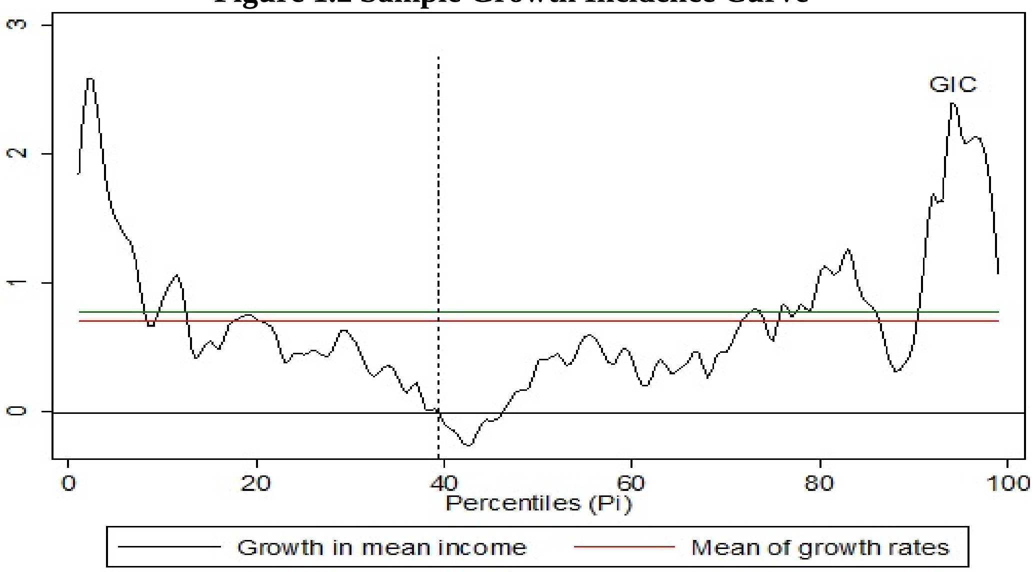
The term γ is analogous to the parameter used in the conventional poverty measures proposed by FGT (1984) which indicates index's sensitivity to the depth of poverty. The parameter β indicates the level of sensitivity of the poverty measure to the duration of the poverty spell. In particular, higher values of β provide more penalty to longer episodes of poverty.

In summary, the discussion in this section suggests that there are various ways of capturing the temporal dynamics of poverty. In Chapter 5, I examine the robustness of the intertemporal poverty trends by estimating poverty using all the approaches presented in this section.

1.4.2 Income Mobility-Adjusted Pro-Poor Growth Assessment

Economic growth is said to be pro-poor when it allows the disadvantaged to catch-up with the rest of the population by providing an impetus for them to reach their full economic potential. Hence, an economic growth that is pro-poor allows a country to maximize its available human resources. Given these benefits, it is not surprising to note that the pro-poor growth literature has flourished over the years and now, it offers a portfolio of methods for measuring pro-poor growth (Kakwani and Pernia 2000; Kakwani & Son 2004, 2008; Ravallion & Chen 2003; Araar et al. 2009; Duclos 2009; Essama-Nssah & Lambert 2009). However, like conventional static measures of poverty, most of the existing pro-poor growth measures are based on changes in the marginal distribution of income. As mentioned earlier, this is what is referred to as temporal anonymity. Income distributional measures that satisfy temporal anonymity property ignore any reordering of incomes among individual units. For example, if the individual units swap income with each other, any income distributional measure satisfying temporal anonymity should have the same value. Previous studies suggest that the level of pro-poorness of growth is usually lower under the temporal anonymity assumption than when the joint distribution of income is used (Fields & Puerta 2010). Furthermore, departing from the temporal anonymity principle when assessing pro-poorness of growth provides a way of evaluating the extent up to which the benefits of economic growth reach the initially poor and those who just entered poverty. Thus, some researchers argue that pro-poorness of growth is better measured using the joint income distribution. To elucidate this, consider the simple example provided by Grimm (2007) wherein the population is divided equally into two income groups – the poor and the non-poor. Suppose that between two time periods, all initially poor persons observed fast income growth such that by the end of the observation period, their incomes are equal to the initial income levels of the initially non-poor. At the same time, the income of the initially non-poor contracted to levels that are even lower than the initial income of the initially poor. Following the conventional pro-poor growth assessment tools which satisfy the temporal anonymity principle, one would conclude that the growth pattern has been anti-poor both in absolute and relative terms. In particular, since poverty gap increased, one could conclude that growth has not been pro-poor in absolute terms. Furthermore, since the bottom half of the population observed negative income growth while the average income of the other half remained constant, then growth will be judged as anti-poor in relative terms. However, if one evaluates the observed growth pattern on the basis of individuals' income group membership at the initial time period, this leads to the assumption that the growth process has been pro-poor.

Figure 1.2 Sample Growth Incidence Curve



Source: Author's computations using simulated data.
Note: In this figure, the GIC intersects the x-axis at approximately Pi = 40. If the poverty line is set at or lower than $Y_1(40)$, then growth is said to be absolutely pro-poor. Otherwise, it is not absolutely pro-poor. On the other hand, growth is said to be relatively pro-poor if the GIC of the poor uniformly lies above the green line.

The growth incidence curve (GIC) proposed by Ravallion & Chen (RC) (2003) is one of the most commonly used analytical tool for examining pro-poorness of growth. For notation, $Y_{t(pi)}$ is used to denote the income of the individual whose income rank at time *t* is p_i and z denotes the poverty line. The GIC plots the income growth (y-axis) at each percentile of the income distribution (*x*-axis) within the time period under consideration. Growth is considered to be "absolutely pro-poor" when the GIC lies above the x-axis up to the maximum value of p wherein $Y_1(p_i) < z$[17] while it is "not absolutely pro-poor" if the curve lies below the x-axis for the same range of p. However, when the curve switches sign before that maximum value of p wherein $Y_1(p_i) < z$, then GIC fails to provide an unambiguous pro-poor growth assessment. On the other hand, under the relative definition, growth is considered pro-poor when the GIC lies above the horizontal line corresponding to g or the growth in mean income up to maximum value of p wherein $Y_1(p_i) < z$. Again, GIC fails to provide a conclusive assessment when the curve switches signs before that maximum value of p wherein $Y_1(p_i) < z$. In general, unless the economic growth is uniformly distributed within the income distribution (i.e. income changes by the same amount at each percentile), a pro-poor growth pattern would exhibit a downward sloping GIC. Figure 1.2 illustrates these points.

When the GIC fails to yield an unambiguous pro-poor growth assessment, RC (2003) proposed to use the concept of rate of pro-poor growth (RPPG). The authors defined RPPG as the mean growth rate of the poor. Technically, RPPG is the area under the GIC up to the maximum value of *p* wherein $Y(p_i) < z$. To assess the pro-poorness of growth, the corresponding evaluation function can be expressed as the difference between the observed growth in mean incomes g and (21).[18] Thus, the evaluation function can be expressed as

$$W_{RPPG}(Y_1, Y_2, g, z) = g - \frac{\sum_{p_i=1}^{FGT(0)} g(p_i)}{FGT(0)} \qquad (1.21)$$

where FGT(0) is the headcount poverty index. Following the absolute definition, growth is said to be absolutely pro-poor when RPPG or the second term in W_{RPPG} is positive. On the other hand, growth is considered to be relatively pro-poor when RPPG is greater than g or when W_{RPPG} is negative.

[17] z denotes the poverty line. If the GIC lies above the x-axis for all p, then there is first-order poverty dominance (Atkinson 1987; Foster and Shorrocks 1988).

[18] It can be shown that the RPPG is equal to the ratio of the change in Watts poverty index to the headcount poverty rate. The Watts poverty index is computed as $\frac{1}{N}\sum_{i=1}^{N}(\ln z - In\ Y_i) I\{Y_i < z\}$. As will be seen later, the Watts index is typically used to estimate the average exit time from poverty. It is also one of the few poverty measures that satisfy the focus, monotonicity, transfer and decomposability properties (Foster et al. 2013).

Noticeably, the GIC approach proposed by RC (2003) is only based on the changes in the marginal distribution of income over time and does not take into account individual income movements. Grimm (2007) adjusted the GIC approach when the assumption of temporal anonymity is removed and the joint distribution of income is used to account for a person's income mobility. In particular, Grimm (2007) coined the term "individual growth incidence curve" (IGIC) and defined the individual rate of pro-poor growth index (IRPPG) as the area under the IGIC up to the maximum value of $p(Y_1)$ wherein $Y(p(Y_1)_i) < z$. Implicitly, this includes income growth rates of non-poor individuals at the final time period as long as they were classified as poor at the initial time period. The pro-poor growth evaluation function can be expressed as

$$W_{IRPPG}(Y_1, Y_2, g, z) = g - \frac{\sum_{p(Y_1)_i=1}^{FGT_1(0)} g(p(Y_1)_i)}{FGT_1(0)} \tag{1.22}$$

where

$$g(p(Y_1)_i) = (Y(p(Y_1)_i)_2 - Y(p(Y_1)_i)_1)/Y(p(Y_1)_i)_1 \tag{1.23}$$

Under Grimm's (2007) approach, growth is said to be absolutely pro-poor when either the IRPPG or the second term in W_{IRPPG} is positive. On the other hand, growth is considered to be relatively pro-poor when IRPPG is greater than g or when W_{IRPPG} is negative. The only difference of (1.22) from that of RC (2003) is that income growth rates are computed with respect to the income quantile in which a person belonged to during the initial time period.

1.4.3 Measuring Dynamics of Income Inequality

As pointed out in Section 1.3, one of the income mobility perspectives is based on the extent to which income dynamics contributes to a more equitable distribution of long-run income. This perspective is appealing because it directly links income mobility with inequality. For socio-economic researchers, it is important to examine whether an increase in income mobility can contribute to transitory variations in income so that permanent income inequality would be less than observed income inequality (Jarvis & Jenkins 1998). In other words, high income inequalities in fluid societies might be less problematic because the distribution of lifetime income would be generally even through income mobility (Krugman 1992). The indices proposed by Fields (2010), CDW (1985) and Shorrocks (1978) follow this approach.

Jenkins & Van Kerm (2006) decomposed the changes in cross-sectional income inequality, measured using the generalized Gini coefficient, as a function of two components: a measure of pro-poorness of growth and changes in individual incomes (redistribution or re-ranking), as shown in (24).

$$\Delta G(s) = Redistribution(v) - Propoor(v) \quad (1.24)$$

where

$$Redistribution(v) = \iint [w(\Phi_1 ; v) - w(\Phi_2; v)] \left(\frac{Y_2}{\bar{Y}_2}\right) f(Y_1; Y_2) dY_1 dY_2 \quad (1.25)$$

$$Propoor(v) = \iint w(\Phi_1 ; v) \left(\frac{Y_2}{\bar{Y}_2} - \frac{Y_1}{\bar{Y}_1}\right) f(Y_1; Y_2) dY_1 dY_2 \quad (1.26)$$

and *w()* is the weight of an individual which is a decreasing function of the individual's rank in the income distribution as identified by the parameter *v*, $f(Y_1, Y_2)$ is the joint probability density distribution of Y_1 and Y_2, Φ_t is the cumulative density distribution of Y_t and $\bar{Y}_t$ is the mean of the income distribution $\{Y_{it}\}$.

As the definition of pro-poor growth implies, the first component measures how much income growth benefits those on lower incomes relative to those on higher incomes while the second component measures how much re-ranking in income positions is associated with the income growth (Jenkins & Van Kerm 2009). Decomposing the temporal changes in inequality into pro-poor and redistribution components is particularly useful for comparing groups in which inequality is moving at the same pace (Jenkins & Van Kerm 2006).

I use Jenkins & Van Kerm's (2006) approach of decomposing changes in inequality in Chapter 4 to briefly examine whether there is equalizing mobility in the Philippines.

1.4.4 Identifying Correlates of Income Mobility

When identifying the factors that drive income mobility in the succeeding chapters, the proximate determinants of mobility will be broadly grouped in this thesis into (i) (geographic) location, (ii) household composition, (iii) education, (iv) employment, (v) access to (basic) services and (vi) physical assets.[19] Several studies have highlighted that specific locational endowments may prompt concentration of skills which in turn expands better economic opportunities while locational disadvantage such as remoteness tends to increase the cost of carrying out economic activities which in turn has an adverse impact on income mobility prospects (Lobao, Hooks & Tickamyer 2007; Aslam & Corrado 2012). Urban-rural disparities in various income and non-income measures of well-being have also been well-documented in

[19] There are other factors that can influence the household income distribution based on the existing literature. For example, health is directly correlated with productivity which in turn, is directly correlated with economic well-being (Baker 2004). In addition, social networks can also be used to access essential resources such as education, healthcare and other utilities more easily (Acock & Hurlbert 2011, Jain & Sonnen 2011). However, this study does not include these types of variables as they are not available in the data used here.

many empirical studies (WB 2013). For instance Fields et al. (2003) find that poverty is predominantly a rural phenomenon in Indonesia, South Africa, Spain and Venezuela. In the Philippines, socio-economic development landscape has a very distinctive spatial feature wherein people living in the National Capital Region (NCR) and its neighbouring provinces have significantly lower poverty rates compared to those living in central and southern Philippines (Balisacan 1994, 1997; Balisacan & Hill 2003; Barrios & Landagan 2004; Schelzig 2005). In general, geography can act as either a gateway to better living standards especially when a specific location is endowed with rich natural resources or to economic challenges when a location is too remote and has very limited access to various social services. In addition to geography, one of the recurring findings in the development literature is related to human production theory. In particular, a number of studies provide empirical support that increases in household size tend to be correlated with downward income mobility because the additional resources needed to sustain a larger household is not usually compensated by higher income flows (Fields et al. 2003). Furthermore, consistent with human capital theory, higher education often leads to higher productivity and therefore, upward economic mobility prospects (Morgan, Grusky & Fields 2006; Hout & DiPrete 2006; Greenstone et al. 2013). There are a number of case studies that have shown that higher educational attainment (of the household head) reduces the household's vulnerability to poverty (Azam & Imai 2009). The Philippines is one of the countries which have a high regard for education, and this perspective is deeply rooted in its culture. For many poor Filipino households, education is considered one of the most important legacies that parents can impart to their children to be able to move away from socio-economic deprivation (Maligalig et al. 2014). Furthermore, several studies find a strong link between poverty cycles and employment transitions. For instance, Dartanto & Nurkholis (2013) find that a transition from formal to informal employment can push a non-poor household into poverty in Indonesia. In the Philippines, ADB (2010) find that middle class households with more members working as own-account and casual workers have higher risk of falling into poverty. Analogously, access to (basic) services and assets are also found to be significant correlates of well-being (WB 2004). For instance, access to high-quality healthcare services helps workers avoid employment interruptions due to sickness which in turn, allows them to continue translating their labour into financial capital (Schelzig 2005). Similarly, many forms of physical assets (e.g., land) and technological innovations are also useful tools for extracting more wealth (Carter 2000; Schelzig 2005; Moser 2006). In particular, ownership of land minimizes the risk of long poverty spells (Adam and Jane 1995) while household losing land have higher risk of experiencing downward mobility (Justino & Verwimp 2013).

The explanatory variables that will be included in the statistical models in Chapters 5, 6 and 7 fall under the categories described in this section.

1.5 Analytical Considerations When Examining Income Mobility

This section highlights the importance of being cautious when interpreting mobility estimates at face value due to other confounding factors like measurement errors and transitory income fluctuations (Lillard and Willis 1978; Solon 2001; Fields et al. 2003; Antman & McKenzie 2007; Krebs, Krishna & Maloney 2012). For example, an income mobility pattern that portrays low-income individuals to be catching up with high-income individuals may be artificially driven by the downward bias in the reported incomes of individuals at the top of the income hierarchy. On the other hand, it is also possible that a significant portion of the observed income mobility is driven by transitory income shocks. Depending on the objective of the study, it may be important to carefully examine the impact of these factors on the income mobility estimates.

1.5.1 Correcting for Measurement Error and Data Contamination

The discussion in the previous sections assumes that income is measured accurately. However, previous studies suggest that income, particularly those derived from household surveys, are prone to measurement errors (Duncan & Hill 1985; Bound & Kruger 1991; Gottschalk and Huynh 2010; Glewwe 2012). If measurement errors are non-negligible, the results of income distributional analysis may produce biased results and thus, lead to misleading conclusions and policy implications. This section briefly examines the issue of measurement errors in the context of income mobility estimation.

What are the common sources of measurement errors? The most basic forms of data contamination may arise from randomly misreporting income or data encoding mistakes. Conventionally, these errors are assumed to average out (i.e., zero-mean) and are uncorrelated with the true income. This type of error is commonly referred to as classical measurement errors. On the other hand, non-classical measurement errors either have non-zero means or are correlated with the true income. Either way, both types of measurement errors contribute to additional noise in observed incomes and findings from previous studies suggest that they can lead to biased estimates of cross-sectional poverty and inequality (van Praag, Hagenaars & van Eck 1983; Chesher & Schluter 2002; Jenkins 2011).[20] However, there are only few studies that

[20] Ravallion (1994) and Chesher & Schluter (2002) proposed adjustment procedures to correct the bias induced by measurement errors on cross-sectional estimates of poverty and inequality.

have investigated the extent of measurement error bias on income mobility estimates. When income is measured with error, the true historical income profile is unobserved. Thus, the estimated mobility of observed income will reflect the changes in the joint distribution of the true income and measurement errors.

Measurement errors tend to make income less correlated over time. Hence, when income mobility is viewed in terms of origin-independence perspective, measurement errors can lead to over-estimation of mobility. This is supported by the findings of Glewwe (2012) who estimated that about 15% to 42% of observed mobility in Viet Nam in the 1990s can be considered as upward bias due to measurement errors present in the survey data used. Krebs et al. (2013) also noted a non-negligible upward bias on income mobility estimates in Mexico due to measurement errors. Overall, although there are limited studies which examine the impact of measurement errors on income mobility estimated in terms of other mobility perspectives, it is safe to assume that the effect are not necessarily trivial (Boheim & Jenkins 2006).

There are several ways to minimize the bias induced by measurement errors. For instance, when the main income data source is a household survey, the survey records may be matched with reports by the same respondents from administrative data that are assumed to be error-free. In turn, this supplementary data can be used to derive appropriate income adjustment factors. In particular, some studies use tax data records to correct for the potential bias present in the data on observed income.[21] On the other hand, some researchers minimize measurement error bias by restricting the sample to population groups that are less likely to misreport income. For example, Gottschalk & Huynh (2010) proposed excluding those who are self-employed or those whom a large portion of income is imputed from the analysis. Some researchers trim the data by removing the bottom and top 1% while others take out all outlying income values before estimating mobility. Furthermore, others rely on more sophisticated statistical modeling techniques. One example is the use of a latent class of Markov models to gauge the impact of measurement errors on income transition matrices (Breen & Moisio 2004; Worts, McDonough & Sacker 2010). Given sufficient length of longitudinal data, the main idea behind this approach is to assume that the true transition probabilities are stable over time and this can be estimated from the Markov model. The resulting residuals are then treated as measurement errors. The use of instrumental variables is an alternative tool that can be used to address the bias caused by measurement error and it is particularly useful when the concept of origin-

[21] However, this approach may not be feasible for many developing countries where such type of administrative tax data is usually inaccessible if not unavailable.

independence is being used. The idea behind instrumentation is to use a proxy variable that is highly correlated with the outcome of interest but is uncorrelated with the measurement error. Arellano & Bond (1991) recommended the use of the income lagged two periods while Holtz-Eakin, Newey & Rosen (1988) proposed using income lagged three or more periods as instruments. In a more general setting and/or in the absence of reliable instruments, one can conjecture different forms of measurement error and create synthetic data of measurement errors by drawing from its assumed distribution. In turn, this can be incorporated to the observed income and estimate different income mobility indicators. This approach is useful for identifying bounds for income mobility estimates.[22]

In this study, I approximate the impact of measurement error using a simple simulation exercise and find that the income mobility estimates presented here may be higher than the actual magnitude of income mobility. Nevertheless, the bias could be minimal depending on the form of the measurement error.[23]

1.5.2 Decomposing Income into Permanent and Transitory Components

As suggested earlier, a person's observed income can be decomposed into permanent and transitory components (Friedman 1957). Permanent income refers to a person's income over a long horizon while transitory income refers to income received from unanticipated sources. Although transitory income can be either positive or negative, it is expected to average out in the long-run.

In general, the relevance of decomposing income mobility due to the dynamics in permanent and transitory income, for policy planning is manifold. First, understanding whether the observed mobility is a result of movements in either permanent or transitory income is important for outlining poverty reduction programs. Without distinguishing poverty persistence from transient poverty, policy planners may not be able to properly target intended program recipients which could lead to the transiently poor receiving disproportionately more assistance than the persistently poor or in some cases, the persistently poor people receive assistance that is only enough to protect them from temporary economic risks (Jenkins 2011). In other words, programs with unclear targeting mechanisms are at risk of being poorly-

[22] The same approach was adopted by Khor & Pencavel (2008) when estimating income mobility in China using Chinese Household Income Project (CHIP) data. In particular, the authors find that when the mean of the simulated error is approximately 10% of the mean of measured income, the average quintile move in urban China increases by approximately 4% while immobility ratio increases by 5%.

[23] Assuming that there is classical measurement error which inflates the variance of the observed (log) income by 5%, the results of a simple simulation experiment that I carried out suggest that income mobility in the Philippines can be overestimated by 15%. On the other hand, a positive auto-correlation between the measurement errors can offset the bias-increasing effect of measurement errors on mobility estimates. However, it is difficult to infer the form of measurement errors.

implemented and prone to undercoverage and leakage (Dutrey 2007; Ravallion 2009). In general, poverty reduction programs are cost-inefficient when it is not clear what type of poverty is being addressed and who the intended recipients are. Nevertheless, while it makes sense to spend more effort to alleviate the living conditions of the persistently poor, it is also useful to institutionalize risk-coping mechanisms that will enhance the socio-economic security of the transiently poor (Deaton 1991). Furthermore, it is also important to examine the dynamics in the transitory component of income as the cumulative effects of temporary income fluctuations among the poor could eventually lead to poverty persistence, especially when there are irreversible asset losses (Baulch & Hoddinott 2000; Hoddinott 2006). More generally, disentangling the contribution of permanent and transitory components on income mobility allows us to understand the incentive and security aspects of income mobility. For instance, the prospect of upward or downward mobility in the long-run, provides incentives for individuals to be engaged in productive economic activities. This is referred to as the incentive aspect of income mobility and it is primarily concerned with the dynamics of permanent incomes (Jenkins 2011). On the other hand, the security aspect of income mobility is contextualized within the assumption in economic theory that individuals are risk averse (Kaufmann 1970 as cited in Sinn 1981). In other words, for an average person, the ability to predict future income is important when planning consumption behaviour. Thus, people become more concerned on the arrangement of expenditures when income streams are fluctuating due to mobility of transitory income (Fachinger & Himmelreicher 2012). Second, decomposing income mobility into its permanent and transitory components also allows us to distinguish income mobility as a desirable outcome from income mobility as an indicator of instability (Friedman & Kuznets 1954).[24] In particular, income mobility is desirable when the growth in a person's permanent income is negatively correlated with his initial level of income as such type of growth pattern allows the poor to catch-up with the rich (Benabou & Ok 2011). In this context, income mobility makes the distribution of opportunities more equitable in the long-run (Atkinson et al. 1992). On the other hand, income mobility may be perceived as an indicator of socio-economic insecurity when it is mostly driven by fluctuations in short-term income (Jarvis & Jenkins 1998; Creedy & Wilhelm 2002; Allanson 2008; Rohdes, Tang & Rao 2013).[25]

[24] Analogously, cross-sectional estimates of inequality may also be decomposed into inequality due to disparities in permanent income and inequality due to varying income fluctuations. Up to some extent, income inequalities arising from disparities in permanent income may be associated with inequality of opportunities.

[25] Jenkins (2011) argue that fluctuation in transitory income is not a perfect indicator of economic instability. This is because income fluctuations may arise from voluntary choices made by an individual. For example, if an individual voluntarily decides to work shorter hours, the resulting income fluctuations will not necessarily imply insecurity.

There is a wide range of literature discussing the different methodologies for decomposing income into its permanent and transitory components. One of the most commonly used approach is to estimate variance-components models with varying complexity and conditioned on various covariates (Dickens 2000; Geweke & Keane 2000; Moffitt & Gottschalk 2002; Zandvakili 2002; Ramos 2003; Gustavsson 2007). While the econometric literature offer several estimation methods to fit the variance component models using longitudinal data, there are several issues regarding the use of parametric models. One of the potential issues of this method is that it requires panel data of adequate length to be able to estimate the model parameters consistently.[26] However, while panel data is regularly collected in many industrialized countries, it is not collected frequently in developing countries. On the average, developing countries with nationwide longitudinal data on income have three to four waves only. In such cases, a simpler alternative approach is warranted. A candidate measure of permanent income is the individual's or household's income averaged over a specific time period after adjusting for inflation. This approach averages out the measurement error over time. This is also the approach that I use to derive a proxy measure of permanent income in the succeeding chapters.

1.6 Summary

This chapter presented the building blocks for examining income mobility, many of which are heavily used in the succeeding chapters. First, it reviewed the different definitions of income mobility. The existing literature offers three broad perspectives of what mobility means: as movements, as origin independence and as equalizer of long-term incomes. Additionally, there are different indicators for measuring the various concepts of income mobility. These measures do not necessarily produce quantitatively and qualitatively similar results. In many cases, a satisfactory measure of one particular concept may be a poor measure of another. Thus, when the objective is to provide a more holistic picture of a country's underlying income mobility process, it is important to examine it under different perspectives due to its multidimensional nature. However, calculating too many income mobility measures may also result in a confusing array of numbers. Instead of providing a more comprehensive view of the income mobility process, this may just obscure the big picture. To strike a balance between these two considerations, a possible approach is to focus on a limited number of

[26] Even if long panel data is available, there are other issues in using variance components model. For instance, Shin & Solon (2009) argued that parametric models are in some sense, "arbitrary mechanical constructs" such that the estimates can be sensitive to variations in how the underlying model is specified. In addition, choosing which parametric model specification is the most appropriate in different contexts is not an easy task.

indicators capturing different aspects of income mobility. Thus, in examining the mobility patterns throughout the study, I choose an optimal mix of indicators to cover as many dimensions of income mobility as possible within the context of the research question under consideration.

As previous studies have shown that income data are prone to measurement errors, the chapter briefly discussed the impact of measurement errors on income mobility estimates. There are several ways to minimize the bias due to measurement errors. One is to use external data to measure the degree of measurement bias and derive appropriate adjustment factors; another is to rely on finding suitable instruments to estimate income mobility parameters consistently. In the absence of auxiliary information, a general approach that can be adopted is to simulate measurement errors using distributional assumptions. Such simulation studies can help constructing bounds for the proportion of the observed income mobility that can be attributed to measurement errors.

Third, the chapter also emphasized that the normative assumption of more income mobility being always a desirable outcome should be examined with caution. An income mobility regime that is mainly driven by fluctuations in the transitory component of income may represent socio-economic insecurity. For policy planning, it is important to determine whether the observed mobility is a result of changes in permanent or transitory income. In this context, the chapter reviewed several econometric methods to decompose observed income into its permanent and transitory components. Much of the proposed procedures rely on using parametric models. If the available panel data is not of sufficient length to allow (consistent) estimation of the parameters of these models, one can adopt simpler techniques such as longitudinal-averaging of individual incomes to approximate the permanent component.

In summary, the main point that the discussions presented in this chapter seeks to convey is that while the analysis of income mobility provides a broader picture of the income distribution dynamics than conventional static socio-economic indicators, there are also additional technical considerations that have to be carefully taken into account. In general, the accompanying methodological decisions may lead to variations in research findings which in turn could cause confusion among non-technical audience. Policy responses to findings of income distributional analysis may lead to sub-optimal intervention programs when the estimates are not well explained to policymakers and other key stakeholders. In contrast, when the robustness of the results to measurement parameters are carefully examined, income mobility research can empower users and stakeholders by providing them with a better understanding of the impact of methodological decisions on research findings.

Chapter 2 Has Economic Growth been Pro-Poor in the Philippines?

2.1 Introduction

The notion of an Asian Century has attracted the interest of the global community towards the region. As billions of Asians are expected to enjoy living standards similar to those in Europe today, few decades from now, the Asian Century is a term used to refer to the forecasted domination of the region in terms of the world's socio-economic and political landscape (ADB 2011a). This is not surprising considering that, over the past five decades, Asia has witnessed rapid economic growth, significant poverty reduction and improved living standards. If these trends continue, economists forecast that the region will account for half of the global output, trade and investment by 2050 (ADB 2007). Signs of the advent of the Asian Century are quite apparent today. With the sluggish economy currently experienced by Western countries, the engine of growth of the global economy is now being driven by China and India, Asia's powerhouse economies (Eichengreen, Gupta & Kumar 2010; Santos-Paulino & Wan 2010). Nevertheless, other developing Asian countries like the Philippines are also showing signs of growth momentum. Since 2009, the country's GDP per capita has been increasing at annual rate of 4.1%. In the first quarter of 2013, the GDP grew by 7.8% surpassing China's 7.7% (CEIC 2014).[27] Due to this solid performance, the country has been dubbed one of the emerging Asian Tigers (Coclanis 2013). However, a cursory review of the country's historical growth performance reveals that its economic development path has been characterized by several boom and bust cycles in the past (Aldaba 2009; Schelzig 2005). For many years, the Philippines had been labelled as the Sick Man of Asia due to its lagging economic performance and low growth elasticity of poverty when compared to its Asian neighbours (Kind 2000) (Table 2.1). Thus, the rapid economic growth regime currently experienced by the country is a critical juncture. If complemented by an appropriate mix of socio-economic policies, economic experts believe that this episode could serve as a window of opportunity for the country to accelerate its development and be freed from shackles of poverty and economic stagnation (WB 2013). Otherwise, when institutions continue to operate in the favour of a privileged few, the current strong growth episode could end up as just another part of its perennial boom-bust cycle (Bird & Hill 2009). The first step to be able to outline growth-sustaining policies is to understand the underlying factors that drive the economic prospects of the Philippines. Although there are several metrics that can be used to evaluate the economic prospects of the

[27] This also surpassed the growth rates of other key Asian countries such as Indonesia (6%), Thailand (5.3%) and Viet Nam (4.9%) (WDI 2014).

country, this study reviews the evolution of the household income distribution in the Philippines. Since an economic growth that reduces social exclusion and minimizes the gap between the poor and the rich contributes to a more sustainable development (Aldaba 2009; Canlas, Khan & Zhuang 2009), analysing the historical development path of the household income distribution allows us to evaluate the sustainability of the Philippines economic growth.

The main objective of this chapter is to review the trends in economic growth, poverty and inequality in the Philippines over the past thirty years leading to the current rapid economic regime experienced by the country. This is done by drawing from findings in the previous literature and by using data from WB's PovcalNet. PovcalNet is an online computational tool that contains grouped income distribution data that allows users to reproduce comparable estimates of average income, poverty and inequality that WB researchers use (WB 2012). The last part of the chapter briefly demonstrates how our perception of the evolution of the income distribution may change when income mobility is taken into account. To do this, I simulate synthetic unit-level income from PovcalNet's grouped distribution data for the Philippines for the years 1985 to 2009. Then, I create pseudo-panels by assuming different income reranking scenarios. The discussion of the results of the simulation experiment sets the tone for the detailed discussion of income mobility in the succeeding chapters. In particular, this chapter is outlined to answer the following questions:

i. How did the household income distribution in the Philippines evolve over the past thirty years?
ii. Have the poor Filipinos benefited from economic growth more than the non-poor?

Table 2.1 Socio-Economic Indicators for Selected Southeast Asian Countries

country	Period	GDP per capita			US$2/day Poverty Rate		Inequality (Gini, %)	
		initial year	final year	%growth	initial year	final year	initial year	final year
Indonesia	1984-2011	646.10	1650.52	3.47	88.40	43.33	30.50	38.14
Lao PDR	1992-2008	271.73	561.52	4.54	84.80	66.00	30.40	36.70
Malaysia	1984-2009	2713.11	5984.92	3.16	12.30	2.27	48.60	46.20
Philippines	1985-2009	907.09	1325.90	1.58	61.90	41.50	41.00	43.00
Thailand	1981-2010	915.45	3163.90	4.28	44.10	4.05	45.20	39.40
Viet Nam	1993-2008	317.12	775.76	5.96	85.70	43.40	35.70	35.60

Source: WDI (2014)

2.2 Brief History of Economic Growth in the Philippines Over the Past Three Decades

The Republic of the Philippines is an archipelago consisting of 7,107 islands located in the *Pacific Ring of Fire* within the Southeast Asian region.[28] The country is divided into three main geographical divisions: Luzon in the north, Visayas in the center and Mindanao in the south. Within each division, the country is further divided into 17 regions and 81 administrative provinces. In terms of population structure, the Philippines is the seventh most populated country in Asia with a population size of about 98.4 million (in 2013) and an average annual population growth of 1.7% (WDI 2014). The country has a relatively young population with a median age of 23.4 years; where 33.4% of the country's population are under 15 years of age and 6.8% are aged 60 years or over (NSO 2013). The average life expectancy (at birth) in the Philippines is approximately 65.2 years for men and 72.1 years for women (UNESCAP 2013). The Philippines is a rapidly urbanizing country. For instance, compared to 1980s where only 62.5% of the population lived in rural areas, current estimates suggest that about 49.1% of the population are now living in urban areas (UNESCAP 2013). In terms of employment structure, the Philippines's labour force mainly relies on services sector as its main source of employment where about 58.9% of the employed population work in services, 32.1% in agriculture while the rest are employed in industry (ADB 2013a).

In terms of the recent economic history, the 1980s have been regarded as the "lost decade" in the Philippines. Much of the unsatisfactory growth performance happened in the early part of the 1980s as the weakening demand for exports was compounded by difficulties in tapping funds from the international market and series of domestic political struggles. These events partially triggered the government during that period to declare a moratorium on its foreign debt servicing (ADB 2007). The economy revived its optimism as a new democratic government was established in 1986. In particular, from 1985 to 1988, the GDP per capita and household expenditure per capita, were growing at approximately the same pace, about 2 to 2.5% per year. However, this recovery was short-lived as political power struggle and natural calamities plagued the country. In 1990, a major earthquake hit the northern and central parts of the country while a volcano erupted in 1991. The severity of these natural disasters impeded growth. From 1988 to 1991, the GDP per capita grew by only 0.3% per year. Despite this, survey-based estimates suggest that household expenditure per capita continued to grow at a

[28] The Pacific Ring of Fire is an area within the Pacific ocean where there is a number of plate tectonic activities (e.g., earthquakes and volcanic eruptions). It is estimated that about nine in ten earthquakes occur in the Pacific Ring of Fire (Park 2007).

modest pace of 2.5% per year during the same period. There are two competing reasons for this apparent inconsistency. First, it is possible that the household sector is growing much more rapidly than the growth of enterprise or government sectors (WB 2001). On the other hand, it is also possible that there are measurement biases in both the national accounts and household surveys.[29] Nevertheless, the slow poverty reduction from 1988 to 1991 seems to be more congruent to the slow GDP growth experienced during this period.

The Philippines experienced a severe electric power crisis from early 1990s until 1994. During this period, the GDP per capita dropped by 0.08% per year while household expenditure increased by only 1.04% per year. The country's economy rebounded only after the electric power crisis was addressed in 1994. From this year until 1997, GDP per capita rose by 2.9% per year while household expenditure per capita grew more rapidly at an annual rate of 7.6%.

Overall, the gains that transpired from 1985 to 1997 have been largely concentrated on the first and last three years (WB 2001). Growth was impeded again when the Asian financial crisis struck in 1997. This was further aggravated by the severe drought that struck the country in 1998 which affected a significant number of poor agriculture-based households. Between 1997 and 2000, estimates of GDP and average household expenditure barely changed. In the first part of 2000, income from semi-conductors, one of the country's main exports, dropped significantly when the global economy weakened due partly to the dot-com bubble burst and speculations that the change of millennium will have a severe effect on technological products (Aldaba 2009). The country also experienced another political crisis when the president was ousted from office due to corruption-related allegations (Canlas et al. 2009). Nevertheless, the country's GDP per capita still expanded by 1.7% annually from 2000 to 2003 (WDI 2014). From 2003 to 2006, growth in the GDP per capita is relatively high based on historical standard. However, it slowed down until 2009 due to the global price hikes in oil and food in 2007 and financial crisis in 2008 (Canlas et al. 2009). On the average, GDP per capita improved by 2.2% while household expenditure per capita increased by 1.5% per year from 2006 to 2009 (WDI

[29] The WB (2010) report offers several reasons to explain this divergence. First, growth in GDP may be driven by flow of investments, the benefits of which usually accrue to the upper tail of the income distribution (WB 2010). Since very affluent households are not adequately represented in household surveys and are prone to report lower income and consumption, it is possible that the mean income and expenditure derived from household surveys are underestimated (Deaton & Dupriez 2011). However, some may argue that the poorest of the poor are also likely to be under-represented in household surveys. When housing units are used as ultimate sampling units, those who usually live in makeshift housing and in remote areas may not have chance of being in the sample. Consequently, this will contribute to the overestimation of mean income. Another possible reason is that there are consumption items included in national accounts but not in household surveys (WB 2010). The list includes: imputed rents to homeowners, indirectly imputed financial services, and consumption by non-profit institutions serving households (Deaton 2005). The exclusion of these items in household surveys may contribute to the divergence of national accounts and survey-based estimates.

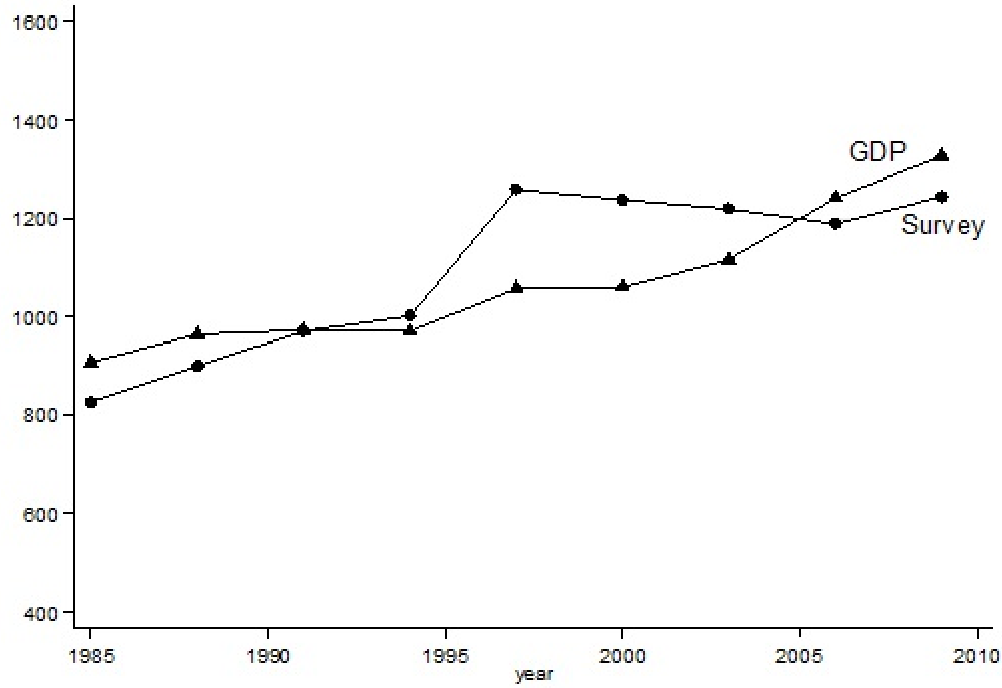
2014). Since 2009, the Philippines has posted remarkable economic gains. In 2012, the country's economy grew by 6.6% while estimates for the first quarter of 2013 place economic growth at around 7.8% (WDI 2014). With these recent developments, economic analysts are revising their growth forecast upwards to reflect the growth momentum transpiring in the Philippines (WB 2014). In addition, for the first half of 2013, various international credit rating agencies have also upgraded the country's investment grade (ADB 2013b).

2.3 Poverty, Inequality and Pro-poor Growth Patterns in the Philippines

2.3.1 Cross-Sectional Perspective

The Philippines has experienced stagnant economic growth until the late 1990s but since then, the country's economy has grown faster. This section reviews how economic growth has affected the household income distribution by examining poverty, inequality and pro-poor growth patterns in the Philippines. There are several studies that have done similar analysis (Balisacan & Fujisaki 1998; Balisacan & Pernia 2002; Schelzig 2005; Aldaba 2009). However, these studies used varying methodologies and looked at different time periods. Thus, for purposes of comparability across years when reviewing the country's poverty, inequality and pro-poor growth trends, I use the Povcalnet's database in the succeeding discussion. Comparisons are drawn from cross-sectional estimates for the period 1985 to 2009.

Figure 2.1 Comparison of Estimates of Growth from Survey and National Accounts



Source: WDI (2014) and Povcalnet (2014)

As pointed out earlier, survey-based estimates and those that are derived from national accounts do not necessarily produce qualitatively similar results. Figure 2.1 illustrates this point. From 1985 to 1997, the Philippines' GDP per capita and average household expenditure per capita generally moved in the same direction. Thereafter, GDP increased while average household expenditure went down. Some researchers argue that the GDP growth in the Philippines might have been overestimated in the recent years (Medalla and Jandoc 2008) while others contend that the estimates from national accounts compiled by government are statistically sound (Virola 2010).

Table 2.2 summarizes the trends in economic growth, poverty and inequality in the Philippines. Over the past three decades, the country's household expenditure per capita increased by 150% or approximately 1.7% annually between the periods 1985 and 2009. Prior to the peak of the 1997 Asian financial crisis, household expenditure experienced steady expansion. In particular, the household expenditure per capita grew by an average of 3.5% per year from 1985 to 1997 but it barely moved after the 1997 crisis. Despite the growth during this period, poverty reduction had been fairly slow. In particular, headcount poverty rate dropped by only 0.87 percentage points annually between periods 1985 and 2009 (from 62% in 1985 to 42% in 2009).

In the context of graduation from poverty, estimates of the Watts index predicts that if real income of all Filipinos in 1985 increased by 2% per year, then the average exit time from the US$2-poverty threshold was about 18 years.[30] However, due to the stagnating poverty rates after the Asian financial crisis, the average exit time from the US$2-poverty threshold dropped only to 9 years almost three decades later.

Table 2.2 also provides estimates of conventional measures of inequality such as the Gini coefficient and generalized entropy (GE) indices. The results suggest that regardless of the index under investigation, the inequality in the Philippines is persistently high. At the same time, there seems to be no significant change in the level of income inequality in the Philippines between 1984 and 2009. This can be partly attributed to the rise in income inequality from 1984 to 1997 being compensated by the decline in inequality between 1997 and 2009. The fastest increase in inequality transpired during the country's highest income growth period, during the years 1994 to 1997.

[30] This is computed by dividing by the value of the Watts index by the expected income growth rate. In this case, the Watts index value in 1985 is 36. Dividing this by an assumed annual income growth rate of 2% will yield 18 years. This means that in 1985, poverty was expected to be eradicated by 2003. However, in 2009, the Watts index suggests that the average poverty exit time is still 9 years.

Table 2.2 Distribution of Household Monthly Income Per Capita in the Philippines, 1985-2009 (in 2005 PPP US$)

Statistics	1985	1988	1991	1994	1997	2000	2003	2006	2009
GDP per capita (US$)	907.09	964.00	972.65	970.39	1,057.42	1,060.55	1,116.06	1,241.55	1,325.90
Mean	825.84	899.76	970.56	1001.4	1258.56	1237.92	1218.12	1187.88	1243.8
Lower Bound	809.4	882.6	950.04	981.24	1229.16	1209.36	1192.8	1163.76	1218.96
Upper Bound	842.28	916.92	991.08	1021.56	1287.96	1266.48	1243.44	1212	1268.64
Headcount poverty Index	0.62	0.57	0.56	0.53	0.44	0.45	0.44	0.46	0.42
Lower Bound	0.62	0.57	0.55	0.52	0.43	0.44	0.43	0.45	0.41
Upper Bound	0.63	0.58	0.57	0.54	0.45	0.46	0.45	0.46	0.42
Poverty Gap	0.25	0.22	0.22	0.2	0.16	0.16	0.16	0.16	0.14
Lower Bound	0.25	0.21	0.21	0.2	0.15	0.16	0.16	0.16	0.13
Upper Bound	0.25	0.22	0.22	0.21	0.16	0.17	0.16	0.17	0.14
Squared Poverty Gap	0.13	0.11	0.11	0.1	0.07	0.08	0.08	0.08	0.06
Lower Bound	0.12	0.1	0.11	0.1	0.07	0.07	0.07	0.07	0.06
Upper Bound	0.13	0.11	0.11	0.1	0.08	0.08	0.08	0.08	0.06
Watt's Index	0.36	0.31	0.31	0.29	0.22	0.23	0.22	0.23	0.18
Lower Bound	0.36	0.3	0.31	0.28	0.21	0.22	0.22	0.22	0.18
Upper Bound	0.37	0.32	0.32	0.29	0.22	0.23	0.23	0.23	0.19
Gini	0.41	0.41	0.44	0.43	0.46	0.46	0.45	0.44	0.43
Lower Bound	0.4	0.4	0.43	0.42	0.45	0.45	0.44	0.43	0.42
Upper Bound	0.42	0.41	0.45	0.44	0.47	0.47	0.45	0.45	0.44
GE(0)	0.28	0.27	0.32	0.3	0.36	0.35	0.33	0.32	0.3
Lower Bound	0.27	0.26	0.31	0.29	0.34	0.34	0.32	0.31	0.29
Upper Bound	0.29	0.28	0.33	0.32	0.37	0.37	0.34	0.33	0.31
GE(1)	0.32	0.3	0.36	0.34	0.41	0.4	0.36	0.35	0.34
Lower Bound	0.3	0.29	0.34	0.32	0.39	0.38	0.34	0.34	0.32
Upper Bound	0.33	0.32	0.38	0.35	0.43	0.42	0.38	0.37	0.35
GE(2)	0.51	0.47	0.58	0.53	0.71	0.69	0.56	0.54	0.52
Lower Bound	0.46	0.43	0.53	0.48	0.64	0.62	0.51	0.49	0.48
Upper Bound	0.56	0.52	0.64	0.57	0.78	0.76	0.61	0.59	0.56

Source: Author's computations using simulated data from Povcalnet and WDI data.

Note: The Povcalnet data are originally expressed as monthly estimates. I multiplied them by 12 to approximate annual figures. The headcount poverty index corresponds to the proportion of the population living below the poverty line. The poverty gap index refers to the average income shortfall of the poor in proportion to the poverty line. The squared poverty gap is the squared income shortfall of poor in proportion to the poverty line. The Watts index is an approximate measure of the average exit time out of poverty. All poverty indices are computed using the WB US$2/day poverty line. The Gini index is a measure of inequality that ranges between 0 and 1 with higher values indicating greater inequality. The Generalized Entropy (GE) index measures the redundancy or lack of randomness in the income distribution, with higher values corresponding to higher levels of inequality. The GE measures are more sensitive to differences in the lower income brackets if the value of the parameter α is close to 0 and they are more sensitive to differences in the higher income brackets if α is close to 1.The lower and upper bounds correspond to two standard errors below and above the point estimate of poverty and inequality. For details, readers may refer to Foster et al. 2013.

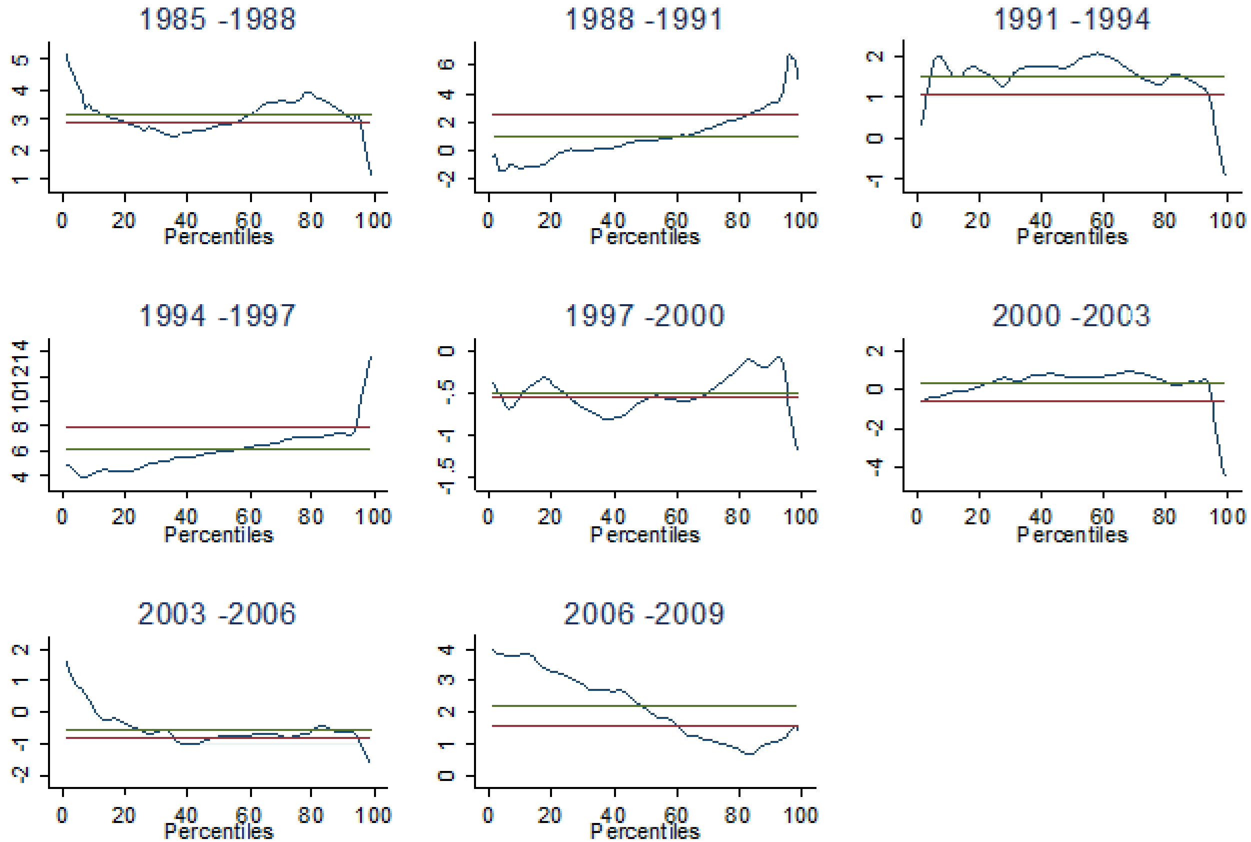
Figure 2.2 shows the GICs from 1985 to 2009. The GIC plots the income growth at each percentile. Growth is said to be absolutely pro-poor when it is above zero for all percentiles and it is relatively pro-poor when the growth of the income of the poor is higher than the growth in mean income (RC 2003). Following these definitions, I find mixed results about the pro-poor growth process that transpired in the country. For instance, growth has been absolutely pro-poor between 1985 and 2009, particularly during 1985-1988, 1991-1994, 1994-1997 and 2006-2009. However, there were periods when growth was not absolutely pro-poor. These periods include the episodes of decreasing household income between 1997 and 2006, and even during the modest growth periods in 1985-1988 and 1991-1994. On the other hand, it is clear that during high growth periods in 1988-1991 and 1994-1997, the income of the rich increased faster than the income of the poor suggesting that the respective growths during these periods were not pro-poor. Nevertheless, there is a sign that the poor benefited more from the observed growth than the non-poor during 2006-2009. Meanwhile for the other years, the GICs do not provide a clear pro-poor growth assessment.

The finding that income inequality remains pervasively high and the pace of poverty reduction slow leads socio-economists to conclude that an inclusive growth is yet to be a sustainable feature of the Philippines' economic development narrative even on the heels of a rosy macroeconomic picture. Several studies concluded that policies have been ineffective in redistributing the benefits of growth to the country's poorest of the poor (Schelzig 2005; Aldaba 2009). Poor Filipinos are trapped in precarious jobs due to the country's highly segmented labour markets (Usui 2011, 2012) and the poor's limited capacity to invest on education (Maligalig et al. 2014). Furthermore, many people who managed to get out of poverty at some point are immediately pulled back to economic dearth during crises due to their lack of access to risk management tools (Reyes & Tabuga 2012). Development experts offer various explanation why the pattern of growing inequality at the backdrop of rapid economic growth is also observed in many developing Asian countries. For instance, Zhuang, Kanbur and Rhee (2014) argue that globalization and market-oriented reforms which developing Asian countries are experiencing have inflationary impact on both growth and inequality. Nevertheless, amidst these substantive potential explanation, several technical issues remain. For instance, the data used for poverty, inequality and pro-poor growth calculations are based on analyses of repeated cross-sectional data. As pointed out in Chapter 1, repeated cross-sectional data overlook one vital point that should be of concern when one is examining the welfare of the poor. In particular, it does not give any information as to what happened to particular individuals. Individual incomes change from year to year but repeated cross-sectional data is unable to reveal whether particular individuals experienced income mobility. One of the things that have recently captured the interest of development experts in the Philippines is the extent to which our perception about poverty, inequality and pro-poorness of growth in the country could change when we shift from a static to a more dynamic perspective (Reyes et al. 2012; Bayudan-Dacuycuy & Lim 2013). The next section concludes the review of the Philippines' socio-economic history with a simple thought-experiment. Using several simulated pseudo-panel data sets, I will re-examine household income distribution trends with a more dynamic perspective.

2.3.2 Longitudinal Perspective

To account for individual income mobility when examining pro-poorness of growth, I construct several sets of pseudo-panel data following the methodology described in Appendix A2.1 because there is no actual panel data that cover the past three decades in the Philippines. In a nutshell, the approach entails considering different income re-ranking scenarios and for each scenario, computing dynamic measures of poverty and inequality as well as Grimm's (2007) individual rate of pro-poor growth as discussed in Chapter 1. Figure 2.3 provides a graphical summary of the various re-ranking scenarios considered. The first scenario is an extreme case corresponding to a static income ranking scenario wherein the income rank of each individual in 1985 remains the same in 2009. Another extreme case is the complete reversal of income ranks scenario wherein the individual with the lowest income in 1985 is the same individual with the highest income in 2009, the individual with the second lowest income in 1985 is the same individual with the second highest income in 2009, and so on. The other scenarios considered are generated by using different values for the correlation of the income ranks between the two time periods. Note that the neutral case corresponds to when an individual's income rank in 1985 is independent with his/her income rank in 2009.

Figure 2.2 Growth Incidence Curves in the Philippines, 1985-2009

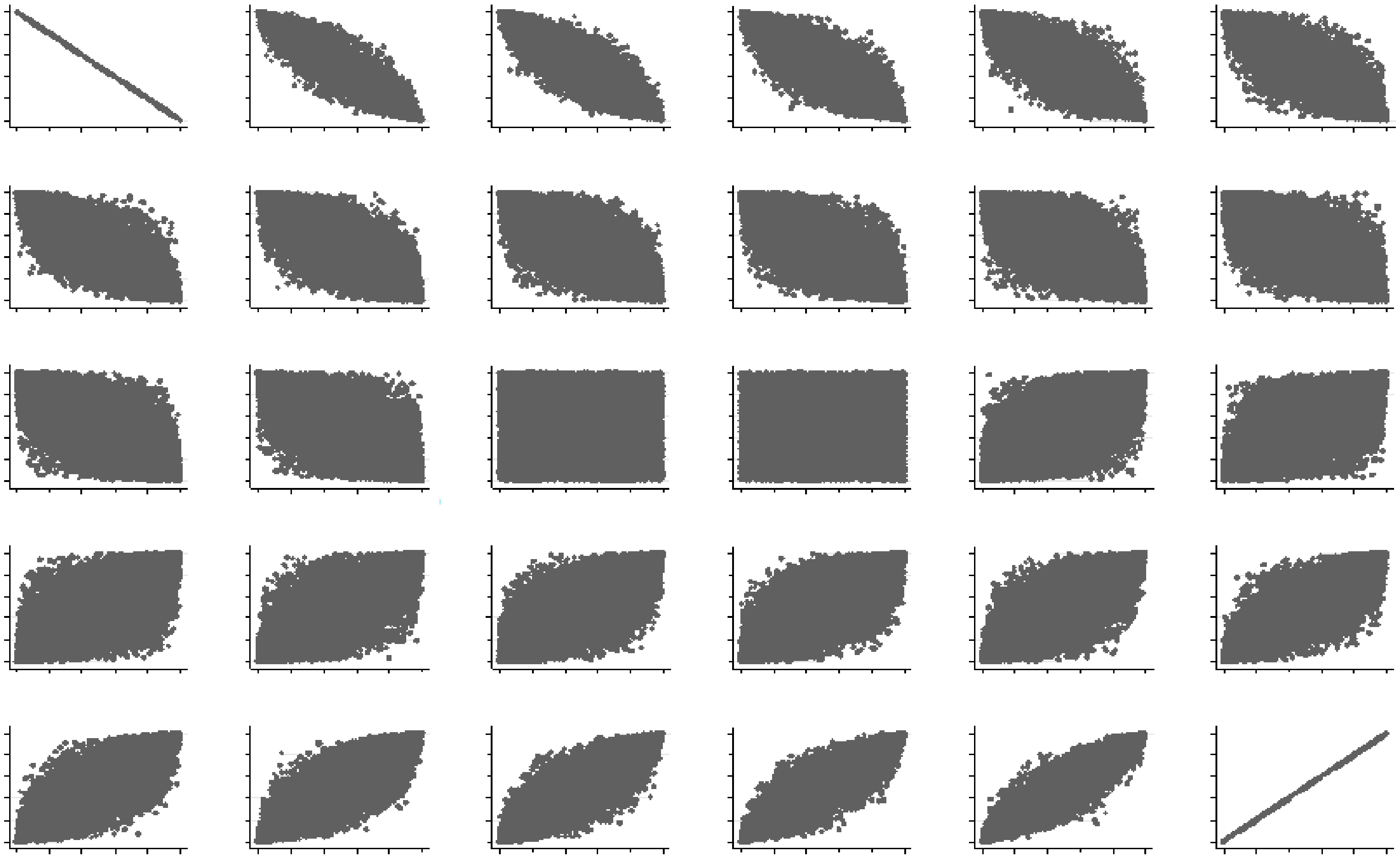


Source: Author's computations using simulated data from Povcalnet and DASP package of Stata.
Note: The green line represents the growth in mean income while the red line represents mean of growth rates.

Turning back to the estimates provided in Table 2.2, the US$2 headcount poverty rates in the country decreased from 62% in 1985 to 42% in 2009. If the income ranks are perfectly positively correlated, then the conventional perception about changes in cross-sectional poverty will not differ. Looking at movements into and out of poverty, one can conclude that 41% stayed in poverty and 21% got out of poverty. On the other hand, at the extreme case that income ranks are perfectly negatively correlated, about 5% of the population remained in poverty, 58% got out of poverty while 37% slid down into poverty. Moreover, if the incomes were absolutely driven by random fluctuations (i.e., income ranks in initial and final time periods are independent), the results of my simulation suggest that about 26% of the country's population were poor in both periods, 37% got out of poverty while 16% fell into poverty (left panel of Figure 2.4).

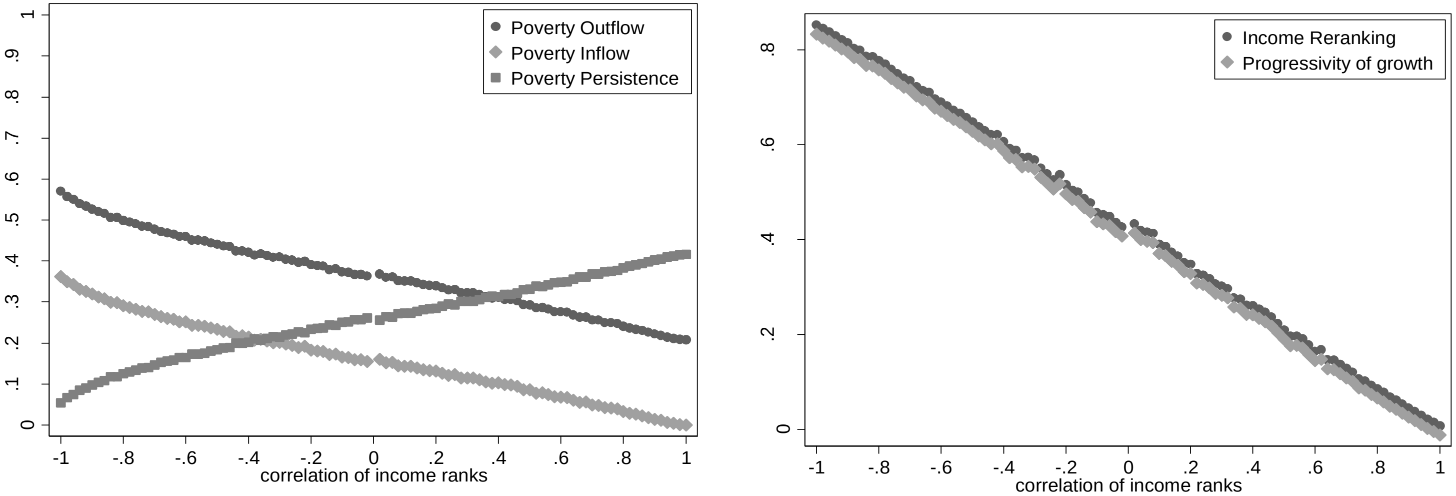
In terms of changes in inequality, it can also be observed from the right panel of Figure 2.3 that when the correlation of income ranks between the initial and final time period is close to (positive) one, the observed changes in income inequality can be primarily attributed to low level of pro-poor growth accompanying low income mobility. On the other hand, as the correlation moves away from (positive) one, the observed change in income inequality over the past thirty years becomes a portrait of offsetting forces of highly pro-poor growth and high income mobility. Furthermore, in terms of the estimated values of the IRPPG, Figure 2.5 shows that growth for the past three decades has been absolutely pro-poor because the average income growth of the poor is positive in every income reranking scenario considered. However, in relative terms, shifting from cross-sectional to longitudinal perspective paints a different picture. Specifically, the observed growth in the Philippines allows the poor to catch-up with the non-poor for majority of the scenarios considered except for instances when the income ranks between the initial and final time period are strongly positively correlated (Figure 2.5). Of course, whether a pro-poor growth on the basis of IRPPG should be considered as a desirable outcome or not is a value judgment. Nevertheless, the results presented here hint us on how our perception of trends in poverty, inequality and pro-poor growth based on cross-sectional estimates will change when income mobility is accounted for. This validates the argument that it is important to take income mobility into consideration when examining household income distribution.

Figure 2.3 Income Re-ranking Scenarios Considered for Constructing Pseudo-Panel Data Sets



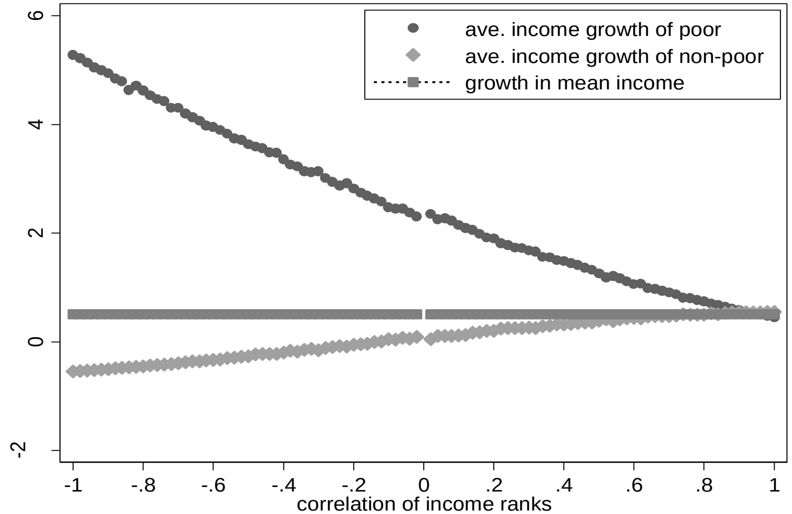
Source: Author’s computations using simulated data from Povcalnet.

Figure 2.4 Poverty and Inequality Dynamics in the Philippines, 1985-2009



Source: Author’s computations using simulated data from Povcalnet.

Figure 2.5 Individual Income Growth in the Philippines, 1985-2009



Source: Author’s computations using simulated data from Povcalnet.

2.4 Summary

Not everyone benefits from economic growth and not everyone falls behind when the economy contracts. In other words, the consequences of economic development do not accrue uniformly across all segments in the society. A historical analysis of economic growth pattern provides socio-economic planners the opportunity to examine the distribution of growth. This information is helpful when evaluating a country's ability to sustain rapid economic growth or identify binding constraints which hamper growth.

Using a range of analytical tools for examining pro-poor growth, this chapter reviewed the evolution of the income distribution of the Philippines from 1985 to 2009. Data on household expenditure per capita suggest that the economic growth observed in the country has been translated to a modest reduction in absolute poverty. However, the data do not provide sufficient empirical evidence to conclude that the gap between the rich and the poor is narrowing down. In other words, the income growth experienced by the poor does not seem to allow them to catch-up with the rich. The statistics presented in this chapter echo the findings of previous studies about the Philippines's dismal performance in terms of accelerating income growth, reducing poverty and closing the gap between the rich and the poor since the 1980s. Even during episodes of faster economic expansion, the pace of poverty reduction in the country has been persistently slow. In fact, compared to its other Asian neighbours, studies by Aldaba (2009), Balisacan (2001) and Schelzig (2005) conclude that the growth elasticity of poverty in the country has been significantly lower. Whether these results directly imply the persistence of cumulative advantage and poverty traps is worth rethinking for various reasons. For instance, the analytical tools used to draw these conclusions fail to account for the profile of people who moved into and out of poverty. Minimal changes in aggregate poverty rates do not imply that there have been no movements in and out of poverty. This provides an incomplete picture of the socio-economic development in the Philippines which in turn, makes it difficult for policymakers to identify appropriate intervention programs. In fact, through a simple simulation experiment, the analysis of pseudo-panel data has demonstrated that conclusions about changes in poverty, inequality and pro-poor growth patterns can be more dynamic than we conventionally think if mobility of individual incomes is explicitly taken into account.

The analysis presented in this chapter provides the motivation for examining income mobility in the succeeding chapters. If a country with a specific set of temporal changes in its marginal distribution of income portrays a multitude of possible income mobility regimes and in turn, different policy implications for making economic growth more beneficial for everyone, then it is important to shift our attention from a static to a more dynamic income distributional analysis. In the case of the Philippines, if the slow reduction in cross-sectional poverty and income inequality accompanying the rapid economic growth over the past decade has occurred in the context of high levels of income mobility, it would be indicative that upward mobility is achievable. Although such pattern cannot discount the difficulties that the poor still confront, it would encourage policymakers in the country to continue the existing programs that expand opportunities for income growth and promote greater access to absolute income mobility across the income distribution. On the other hand, if slow reduction in cross-sectional poverty and income inequality accompanying the rapid economic growth has occurred in the context of low income mobility, it could prompt policymakers to re-examine the effectiveness of existing programs in breaking the vicious cycles of poverty and disadvantage in the Philippines.

Appendix A2.1 Constructing Synthetic Pseudo-Panel Data of Income

The Povcalnet database is the main data source of the synthetic pseudo-panel data. It is an online poverty analysis tool developed by the WB which contains grouped distribution data in the form of income shares of different income quantiles aggregated for each country. The income data is expressed as either income or consumption expenditure in 2005 purchasing power parity (PPP) adjusted-US dollars.[31] This is done by inflating (deflating) the current year income into 2005 prices using national consumer price indices of each country and then applying the PPP conversion factors developed by International Comparison Program. The data available for the Philippines is based on household expenditure per capita and has periodicity of three years starting 1985 to 2009.

Using the grouped distribution data for the Philippines, I fit Lorenz parametric models to simulate individual-level incomes following the approach by Datt (1998). In general, a Lorenz function can be expressed as

$$L(y) = g(L(p), p, \theta) \qquad \text{(A2.1)}$$

where
y – income , μ_Y– average income, $f(y)$ – income density curve and $L(p)$ – share to total income of the bottom p percent of the population and θ are parameters of the Lorenz function. Generally, one can consider different parametric forms for the Lorenz function. The choice depends on which form will yield a valid Lorenz curve. In this study, I use the Log Normal form. Preliminary investigations suggest that results are generally robust under different parametric specifications.

From the grouped distribution data, one can estimate the parameter(s) θ using the grouped distribution data (p, $L(p)$). In addition, all Lorenz functions can be expressed as

$$L(p) = \frac{1}{\mu_y}\int_0^x yf(y)dy \qquad \text{(A2.2)}$$

$$p = \int_0^x f(y)dy \qquad \text{(A2.3)}$$

It follows that the derivative of a Lorenz function with respect to y evaluated at a point p_0 is equal to the ratio of the income quantile at p_0 to overall mean income.

$$L'(p = p_0) * \mu_y = y(p_0) \qquad \text{(A2.4)}$$

The last equation suggests that, a synthetic income quantile y_p can be imputed by multiplying the derivative of the Lorenz function (with respect to y) evaluated at $p = p_0$ by the average income. Where appropriate, I evaluate the derivative of $L(p)_{GQ}$ for 10,000 unique

[31] Prior to the use of 2005 PPP, the WB estimates poverty and inequality using the 1993 PPP. Milanovic (2009) find that the difference in poverty and inequality estimates between 1993 and 2005 PPP are not trivial.

values p_0 that were uniformly distributed within [0,1] range to simulate the entire parametric Lorenz-based income distribution. This produces an individual-level income dataset with 10,000 data points (i.e., "individuals") per year. Since the simulated individual-level income may not exactly match the underlying income distribution from which the grouped distribution data was derived, I implemented the adjustment procedure proposed by Shorrocks & Wan (2008) to ensure that the characteristics of the synthetic sample exactly match the actual Lorenz coordinates used in modelling.[32]

In the absence of genuine panel data of income for the past three decades, I adopt a naïve approach to be able to incorporate a longitudinal perspective in my analysis. To create a pseudo-panel data that will allow me to implement individual pro-poor growth assessment discussed in Chapter 1, the approach entails the following steps. First, I assume that the population is closed to births, deaths and migration throughout the observation period. Certainly, this assumption is somewhat unrealistic but not too far-stretched for the purpose of demonstrating how conclusions about income distribution trends may change when income mobility is incorporated. To construct pseudo-panel datasets, recall that from the grouped distribution data, 10,000 individual income data points are simulated for each (survey) year. Under the closed population assumption, each of the 10,000 points corresponds to a panel individual. Since there is no prior information that will enable me to match the identity of the individuals from 1985 to 2009, I consider a number of possible income re-ranking scenarios. Each scenario corresponds to one pseudo-panel data set. Figure 2.2 provides an illustration of the different scenarios considered. The leftmost panel on the first row of the figure depicts an income reversal scenario wherein the correlation between the initial and final income ranks is equal to one. In other words, the initially poorest becomes the richest, the initially second poorest becomes the second richest and so on. The third and fourth panels on the third row of the figure portray the scenario wherein an individual's income ranking at the initial time period is independent of his/her ranking at the final time period. The last panel on the last row illustrates the scenario wherein income ranks are absolutely persistent.

What are the feasible ranges of the correlation between the income ranks?

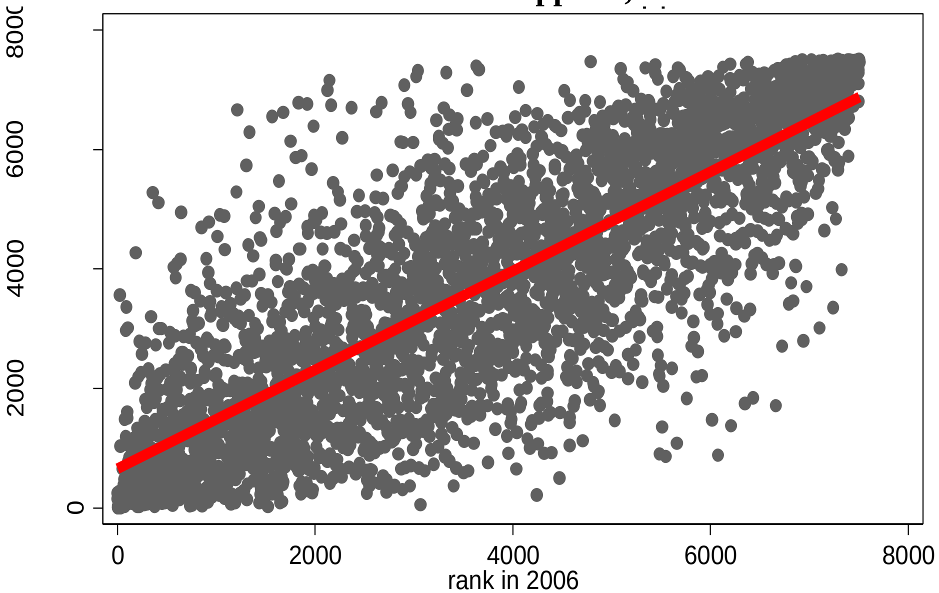
Most of the discussion provided in Section 2.4.2 operates under the assumption that there is no prior information about the correlation between the income ranks of individuals in the

[32] Often, the Lorenz coordinates provided in Povcalnet are based from published figures. Thus, employing Shorrocks and Wan's algorithm implies that the simulated unit-level income data will produce descriptive statistics that are consistent with the published figures.

initial and final time periods. Hence, the simulations consider different possible correlation values between -1 and 1. As mentioned earlier, a rank correlation equal to -1 implies that there is a complete reversal of individual income ranking while a value of +1 implies that income ranking is completely static. In estimating poverty dynamics based from cross-sectional data, Dang, Lanjouw, Luoto & McKenzie (DLLM) (2014) confronted the same dilemma. Instead of choosing a point estimate for the correlation between individuals' (real) incomes in the initial and final time periods, the authors used 0 and 1. These correlation values were then used to construct lower and upper bounds for different indices of poverty dynamics. Noticeably, DLLM (2014) did not consider negative correlations. They argued that while it is possible for some individuals to have negative correlation in incomes over time as a result of different socio-economic mechanisms, it is unlikely that the correlation will be negative for the entire population.

So what are the reasonable values for this correlation? As a form of validation exercise, I use actual panel data available from the Philippines between 2006 and 2009, the details of which are described in Chapter 3. Figure A2.1 shows the correlation between the rank of individuals' initial and final incomes in the Philippines. The Pearson's correlation index gives a value of 0.85. However, one could expect that the correlation of income ranks from 1985 to 2009 to be much lower as we believe that there would be more income mobility for a longer observation period. To validate this hypothesis, I also use panel data with a longer observation period for a country which is quite similar to Philippines. In this context, I refer to the Indonesia Family Life Survey. From 1993 to 2007, the estimated correlation of income ranks is 0.41. If the true income rank correlation from 1985 to 2009 is within the vicinity of this estimate, then Figure 2.4 would suggest that the initially poor are catching-up in the sense that their incomes are growing faster than that of the initially non-poor.

Appendix Figure A2.1 Correlation of Income Rank using Actual Panel Data in Philippines, 2006-2009



Source: Author's computations using simulated data from Povcalnet.

Chapter 3 Family Income and Expenditure Survey and Labour Force Survey

3.1 Introduction

In the previous chapters, I have briefly examined how the income distribution in the Philippines has evolved since the 1980s. One of the interesting patterns that emerged is that both poverty and inequality barely changed over the past decade despite moderate to rapid economic growth. More importantly, I have also discussed the importance of probing beyond conventional cross-sectional indicators of the income distribution to be able to better understand the dynamics of socio-economic development. After having shown that important features of the income distribution dynamics may be overlooked if the patterns of income mobility are not taken into account using a simple simulation experiment based on pseudo-panel data, the rest of this paper examines income mobility patterns in the Philippines using actual panel data. This chapter describes the Family Income and Expenditure Survey and Labour Force Survey which serve as the main data sources for the analyses presented in the succeeding chapters. The following discussion centres on the content of FIES and LFS, observation period, income measure and representativeness of survey data.

3.2 Survey Content and Administration

The Philippine National Statistics Office (NSO) conducts the FIES every three years to collect household income distribution data. The main data collection instrument is an approximately seventy-page questionnaire which includes detailed questions about different sources of household income and a comprehensive list of expenditure items. Data is collected through face-to-face interviews wherein the main respondent, typically the head of the household, is asked to answer the survey questionnaire. In addition to household earnings and expenditure, FIES also collects information about household characteristics such as the profile of household head, household composition, the dwelling unit characteristics, type of assets held and access to basic services. In particular, about 60% of the survey instrument is allotted to the consumption module, 15% for the earnings module and the remaining 25% is allotted for household characteristics and other information (Ericta & Fabian 2009).

The Labour Force Survey (LFS) is likewise collected by the NSO every quarter and it is the main data source for official employment statistics in the Philippines. It has a four-page questionnaire that collects information about the employment status of each household member. In particular, it asks questions such as labour force status, type of employment and sector of employment. The LFS also collects the basic socio-demographic characteristics such as age, sex and educational qualification of each household member (NSO 2012).

The FIES follows a semestral recall method wherein each sampled household is visited twice every year. The first visit is usually conducted in July of the reference year while the second visit is conducted in January following the reference year (Ericta & Fabian 2009). The NSO follows this scheme to capture the seasonal variations of household income and consumption (Ericta & Fabian 2009). On the other hand, the LFS is collected every April, July, October of the reference year and in January of the succeeding year (NSO 2012). The July and January rounds of LFS coincide with the semestral rounds of FIES making it possible to merge the household-level data collected from FIES with the individual-level data of LFS (NSO 2003).

Both FIES and LFS have undergone several revisions over the years (NSO 2003; Ericta & Fabian 2009). For instance, along with other household surveys conducted by NSO, both surveys started following the 2003 Master Sample Design for Philippines Household Surveys in 2003.[33] The 2003 Master Sample Design provides a scheme where a subsample of households used in previous survey waves are rotated back for the succeeding waves (Ericta & Fabian 2009).

3.3 Observation Period

The reference years for this study are 2003, 2006 and 2009. This period is quite interesting for both substantive and technical reasons. We have seen in Chapter 2 that compared to previous years, the Philippines experienced more rapid economic growth during this period. From 2003 to 2009, the country posted an annual average growth of 2.9% in terms of GDP per capita. This is about twice as fast as the country's average income growth rate two decades earlier (WDI 2014). In particular, the first period, 2003-2006, marks the transition from several decades of slow economic growth to faster economic expansion. However, the higher economic growth rates occurred in the context of a slight increase in cross-sectional poverty, which could be indicative that the poor have benefitted less from economic growth. The second period, 2006-2009, continues the rapid economic growth trend. Although this period coincides with the 2008 global financial crisis, both cross-sectional headcount poverty rates and income inequality did not change significantly during this period.

[33] In repeated cross-sectional surveys, a master sample is a sample from which subsamples can be drawn for the purpose of more than one (household) survey or more than one round of survey.

The study period also precedes the more rapid economic episode that is currently experienced by the Philippines. Although the transition into a faster economic growth regime could have paved way for more significant gains in reducing the number of poor and the gap between the poor and the rich, estimates of poverty rates and inequality levels barely changed during this period. The availability of panel data during this period through the redesigned FIES and LFS provides the opportunity to examine income mobility to give a more nuanced assessment of seemingly trivial changes in cross-sectional poverty and inequality and hence, a more comprehensive appraisal of the country's socio-economic development.

3.4 Income Measure

There are several monetary measures that are of interest for income distributional analysis. Two of the most commonly used measures are income and consumption expenditure. Haughton and Khandker (2009) identified the advantages and disadvantages of using income or consumption expenditure. For instance, income data collected from surveys can be compared with administrative tax data records to check the reliability of the survey data. More importantly, examining the patterns of the distribution of different sources of income (e.g., employment, remittances, subsidies, etc.) is also relevant in policy analysis. In the Philippines, household income which is the sum of income from paid employment, self-employment, assets, transfers, remittances and other sources is used as basis for computing official poverty statistics (NSCB 2003).Nevertheless, a number of researchers examining income distribution in the country have increasingly favoured the use of consumption expenditure (David & Maligalig 2001; Balisacan & Pernia 2002) for various pragmatic and conceptual reasons. In particular, advocates of consumption expenditure-based measures argue that expenditure is more closely related to a person's living standards because it does not only reflect the welfare level that a person can achieve using its income but also captures one's ability to access savings or credit markets during episodes of low income. In addition, some argue that income data usually suffers from downward bias when survey respondents discount the extent to which they consume their own production, especially in developing countries that heavily depend on the informal economy in which various income sources are hard to capture and can have erratic fluctuations from time to time (Deaton & Zaidi 2002). In addition, consumption expenditure flow is generally smoother than income and thus, the former is considered a better measure of people's long-term economic prospects (Jefferson 2012). The other benefits of using consumption expenditure as a measure of material well-being include its ability to better reflect price change, private and government transfers as well as insurance value of government programs and credit markets (Meyer & Sullivan 2003). For further discussion, readers may refer to the work of Meyer & Sullivan (2003) who provided well-developed arguments in favour of using consumption expenditure rather than income when examining a country's income distribution.

Table 3.1 Regional Price Differences

Region		Region	
National Capital Region (NCR)	100	Region 7 - Central Visayas	105.4
Cordillera Administrative Region (CAR)	100.3	Region 8 - Eastern Visayas	90.3
Region 1 - Ilocos	93.4	Region 9 - Zamboanga Peninsula	94.1
Region 2 - Cagayan Valley	92.6	Region 10 - Northern Mindanao	89.2
Region 3 - Central Luzon	96.5	Region 11 - Davao	99.7
Region 4-A - CALABARZON	95.3	Region 12 - Soccsksargen	87.2
Region 4-B - MIMAROPA	96	Autonomous Region of Muslim Mindanao (ARMM)	107.6
Region 5 - Bicol	97.8	Caraga Region	88.9
Region 6 - Western Visayas	96.3		

Source: Sta. Ana and Varona (2012)
Note: 100 = reference category

Following the common practice in many developing countries (Deaton 1997), this study mainly uses consumption expenditure, unless stated otherwise. Household expenditure derived from FIES is the sum of expenditure on food, utilities, household operation, personal care, taxes and miscellaneous items. From this point onwards, the term income is used loosely to refer to this chosen monetary measure unless stated otherwise.[34] This income measure has been divided by the household size, assuming that there are no economies of scale in consumption (Lanjouw & Ravallion 1995). This is slightly different from the approach commonly used in industrialized countries which adopts an equivalence scale to take into account the possibility that children generally consume less than adults. Nevertheless, the choice of expressing the income measure in per capita terms is consistent with the usual practice in developing countries (Deaton 2004). Within each household, all household members are given the same income

[34] I have also done preliminary analysis of mobility of household income per capita. However, the results are qualitatively similar with the patterns depicted by the mobility of household expenditure per capita. To save space, I decided to focus on expenditure. Nevertheless, Appendix 4.1 presents some results based on household income per capita.

value. This is consistent with the notion that households act as the main budgetary units for which socio-economic decisions of individuals are made (WB 2014a). Unless stated otherwise, all estimates are expressed as monthly income per capita in constant 2005 PPP US$ to account for inflation. The income measure is further adjusted to account for differences in regional prices using the results based from the spatial price indices estimated by Sta. Ana & Varona (2012) (Table 3.1). In such cases, the prices in the National Capital Region is used as benchmark.

3.5 Sampling Design and Survey Weight Adjustments for Non-Coverage Bias

The FIES and LFS follow multistage stratified sampling design (NSO 2003). The target population of both surveys includes all households in the Philippines except institutional households and households from least accessible *barangays* (LAB) or villages (NSO 2003).[35] The villages (or combination of villages in some instances) were treated as the primary sampling units (PSUs). For each geographic region, the total number of sampled households were computed such that it would satisfy a pre-determined level of reliability.[36] Hence, the total number of sampled PSUs per region was computed by dividing the target number of sampled households per region by the desired sample size per PSU. The PSUs were selected using the probability proportional to size sampling scheme where size is gauged in terms of the number of households enumerated in the 2000 Census of Population and Housing. For each sampled PSU, housing units were selected with equal probability (NSO 2003). This resulted to a target sample of approximately 40,000 households for each survey wave.

The target sample was grouped into four replicates. In this study, I use the households from the fourth replicate only because these are the households that were tracked over time. There are three potential panel data sets that can be constructed: (i) households that are observed in both 2003 and 2006, (ii) households that are observed in both 2006 and 2009; and households that are observed in all three periods.[37]Table 3.2 shows the sample size for each of the panel data sets.

[35] A village is considered an LAB if (i) there is no regular means of transportation, (ii) the cost of one-way fare from the nearest accessible village is more than $10 to $15 based on 2003 prices or (iii) it takes more than 8 hours to reach the village. Of the 41,942 villages in the Philippines, 350 were classified as LABs and excluded from the target population (NSO 2003). On the other hand, institutional households refer to institutions that provide care to a group of people (e.g., health care institutions, etc.) (UNESCAP 2009).

[36] The regional sample size was computed so that the expected coefficient of variation of headcount poverty rate would not exceed 10% in NCR and 5% in areas outside NCR (NSO 2003).

[37] The full sample is designed to produce reliable estimates at the national and regional levels. On the other hand, the longitudinal sample is expected to provide reliable estimates at the national level.

Table 3.2 Sample Size

Regions	2003 (replicate #4)	2003-2006	2006-2009	2003, 2006, 2009
Philippines	**10,476**	**7,899**	**7,509**	**6,519**
National Capital Region (NCR)	954	611	724	449
Cordillera Administrative Region (CAR)	404	297	319	261
Region 1 - Ilocos	616	517	469	441
Region 2 - Cagayan Valley	523	421	406	372
Region 3 - Central Luzon	842	666	618	551
Region 4-A CALABARZON	1,021	745	681	604
Region 4-B MIMAROPA	450	331	297	266
Region 5 - Bicol	612	481	469	396
Region 6 - Western Visayas	736	623	558	525
Region 7 - Central Visayas	745	550	505	464
Region 8 - Eastern Visayas	560	424	381	353
Region 9 - Zamboanga Peninsula	451	338	334	299
Region 10 - Northern Mindanao	558	384	354	322
Region 11 - Davao	559	415	406	346
Region 12 - Soccsksargen	550	411	397	341
Autonomous Region of Muslim Mindanao (ARMM)	442	351	280	257
Caraga Region	453	334	311	272

Source: Author's computations using longitudinal subsample of FIES 2003, 2006 and 2009.

While the longitudinal subsample is expected to provide reliable estimates at the national level, it is not free from the risk of producing biased estimates. There are several sources of bias in this context. First, the survey does not follow households that moved out of its previous dwelling unit. Excluding them from the analysis could lead to the well-known non-coverage bias common in longitudinal studies. Second, bias may also arise from panel nonresponse when households that remained in the same dwelling unit refuse to participate in the succeeding survey waves. The consequences of these biases are major concerns in many longitudinal studies especially when the profile of sampling units that drop out are systematically correlated with the characteristic of being studied (Ashenfelter, Deaton & Solon 1986). To investigate this issue, I compare the measure of central tendency and dispersion of household expenditure per capita between the full cross-sectional sample and the longitudinal subsample. Preliminary investigation suggests that measures of central tendency and dispersion tend to be underestimated in the longitudinal subsample, especially when I examine households that appear in all three waves (Table 3.3).[38] To formally test whether the differences in the distributions are statistically significant, I use the Kolmogorov-Smirnov test. This test confirms that there are significant differences in the distributions of the full sample and longitudinal subsample. In this context, I am likely to produce biased estimates of income mobility if I do not introduce further adjustments.

Table 3.3 Comparison of Full Cross-Sectional and Longitudinal Subsample

Time period	**2003**		**2006**		**2009**	
	Mean Std Error	**Gini** Std Error	**Mean** Std Error	**Gini** Std Error	**Mean** Std Error	**Gini** Std Error
Full sample						
cross-sectional sample	1258.53	0.44	1228.05	0.441	1286.33	0.43
	9.43	0.002	10.88	0.003	12.79	0.002
Longitudinal subsample						
2003-2006	1158.34	0.434	1121.06	0.44		
	13.34	0.005	13.41	0.004		
2006-2009			1197.41	0.449	1223.23	0.426
			15.52	0.005	14.34	0.004
2003, 2006 and 2009	1138.48	0.428	1132.76	0.438	1159.69	0.414
	28.32	0.006	28.80	0.005	25.86	0.004

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Notes: For each year, the first column represents the average and its corresponding standard error while the estimates of the Gini coefficient and its standard error are provided in the second column. The mean is expressed in 2005 PPP US$.

Table 3.4 Features of Longitudinal Subsample Using Attrition-Adjusted Weights

Time period	2003		2006		2009	
	Mean	Gini	Mean	Gini	Mean	Gini
Longitudinal subsample (Adjusted)						
2003, 2006 and 2009	1234.84	0.431	1233.27	0.445	1267.91	0.423
	31.30	0.006	32.57	0.006	29.21	0.005

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Notes: For each year, the first column represents the average and its corresponding standard error while the estimates of the Gini coefficient and its standard error are provided in the second column. The mean is expressed in 2005 PPP US$.

[38] The same findings are drawn for household income per capita. Various software packages such as DASP (Araar & Duclos 2007), Stata's income mobility tools (Van Kerm 2002), ADECOMP (Azevedo, Nguyen & Sanfelice 2012) and MCLUST (Fraley & Raftery 2012) are used extensively in most of the computations.

Rubin (1987) proposed the use of weighting procedure to address attrition and non-coverage bias. Hence, I introduce weights for non-response by estimating logistic regression models for the probability of appearing in 2003, 2006 and 2009 waves, and specifying consumption, age of household head, sex of household head and urbanity as controls. The inverse of the predicted probabilities are multiplied with the existing survey weights. Table 3.4 shows the average household expenditure per capita and measure of inequality estimated using the adjusted survey weights. Although it is noticeable that the adjusted estimates are now more closely aligned with estimates based on the full sample, some studies suggest that the weighting procedure only corrects for observable characteristics related to dropping out of the sample (Fiztgerald, Gottschalk & Moffitt 1998). In other words, the longitudinal subsample may still be systematically different from the full sample in terms of unobservable characteristics. Nevertheless, it is important to note how this residual bias can affect the estimates. Given that households that moved from their original dwelling were not followed, it is possible that households with deteriorating socio-economic status and migrated between 2003 and 2006 and households with improved socio-economic status and migrated between 2006 and 2009 are systematically underrepresented. If we examine the numbers provided for the full cross-sectional sample in Table 3.3 and the numbers provided in the longitudinal subsample in Table 3.4, this would explain why the average income in 2003 and 2009 is lower in the longitudinal subsample but it is higher in 2006. Furthermore, it is apparent that the year-on-year differences in the mean and Gini coefficient are smaller using the longitudinal subsample than using the full cross-sectional sample. This could imply that the estimates provided in this study are likely to represent **lower bounds of the actual magnitude of income mobility in the Philippines**.

Throughout the rest of this study, all analysis incorporates weights adjusted for attrition and non-coverage. These weights are also multiplied by the household size. Hence, a household consisting of three family members is weighted thrice as high than a single-person household.[39]For convenience, I restrict the analysis to data for the 6,519 households that appear in all waves.[40]

As can be inferred from Table 3.5 and Figure 3.1, regions in the northern part, particularly the National Capital Region (NCR) have significantly higher income than the rest. Thus, I also

[39] Thus, the weights sum up to the total individual population.

[40] I decided against trimming the data (to remove the outliers) because the public use file of FIES has already undergone various data cleaning processes (Ericta & Fabian 2009).

provide subnational estimates in most of the succeeding analyses to capture the spatial variations in economic well-being within the country.

Table 3.5 Average Household Income Per Capita by Region

Location	Panel Sample					
	2003		2006		2009	
	mean	std err	mean	std err	mean	std err
LUZON						
National Capital Region (NCR)	2239.77	133.50	2297.86	158.83	2195.53	114.48
Cordillera Administrative Region (CAR)	1157.25	111.67	1065.41	133.72	1054.19	100.43
Region 1 - Ilocos	1133.38	100.41	1232.92	106.72	1300.44	92.23
Region 2 - Cagayan Valley	1216.74	90.40	1217.32	87.59	1295.92	100.16
Region 3 - Central Luzon	1337.95	62.13	1411.11	73.77	1403.81	74.00
Region 4-A - CALABARZON	1613.97	90.42	1545.10	92.11	1503.36	80.93
Region 4-B - MIMAROPA	757.33	88.42	744.52	62.63	930.42	136.97
Region 5 - Bicol	1192.61	190.30	1041.54	149.76	1041.21	122.31
VISAYAS						
Region 6 - Western Visayas	1045.55	74.98	1044.50	84.10	1137.46	80.80
Region 7 - Central Visayas	957.23	75.94	960.16	75.94	977.80	71.32
Region 8 - Eastern Visayas	972.25	79.49	994.93	73.74	1201.69	121.17
MINDANAO						
Region 9 - Zamboanga Peninsula	846.81	105.07	928.04	138.61	1032.59	140.25
Region 10 - Northern Mindanao	1039.68	102.08	1095.81	101.71	1095.94	74.97
Region 11 - Davao	1071.99	102.23	915.09	75.76	1046.81	99.60
Region 12 - Soccsksargen	836.42	58.55	825.25	62.58	995.79	71.98
Autonomous Region of Muslim Mindanao (ARMM)	576.56	52.03	516.88	30.00	567.09	34.35
Caraga Region	742.23	55.29	746.05	53.21	777.95	61.96

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

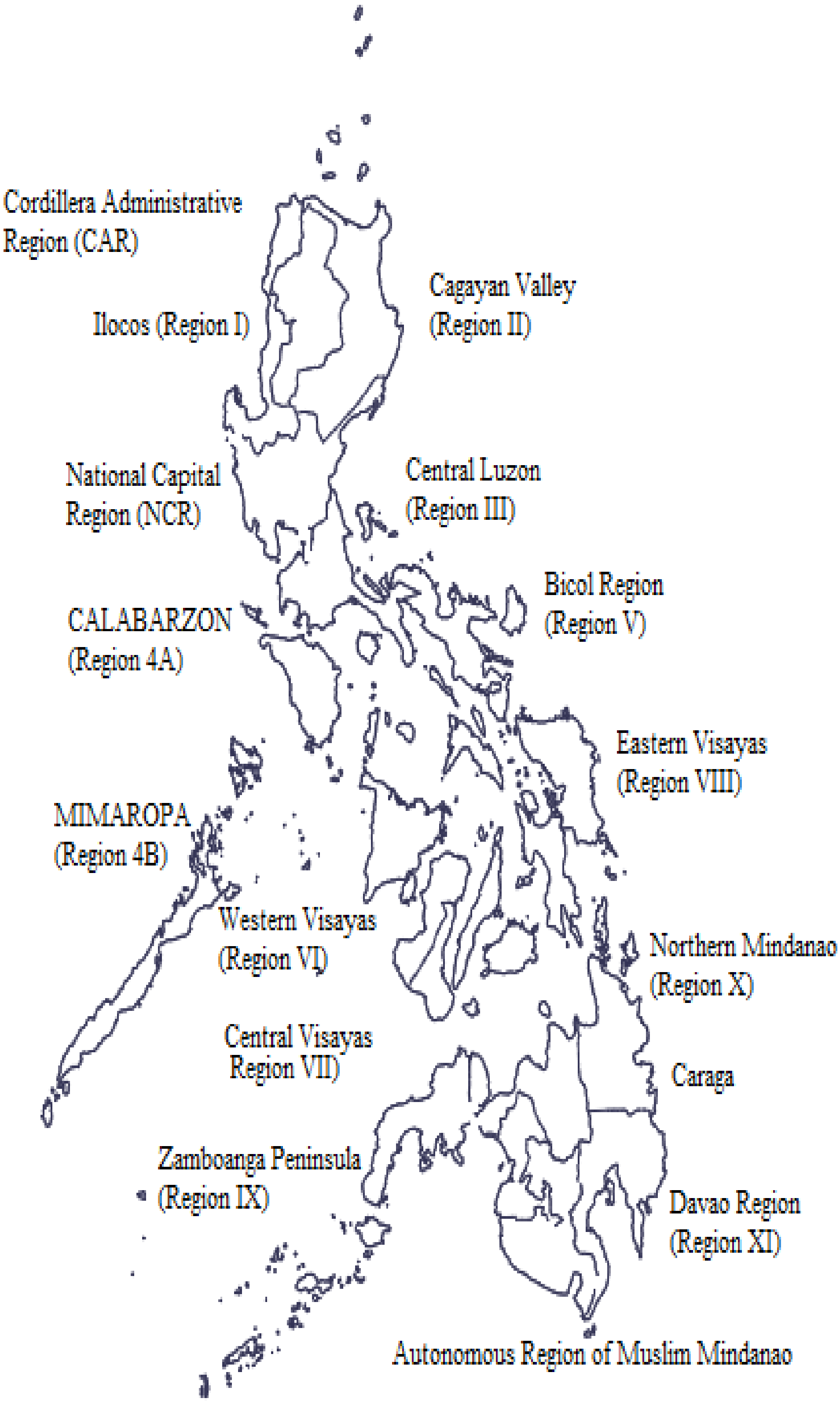
3.6 Poverty Lines

In the succeeding discussion, poverty is measured using four sets of poverty lines. Three of them are absolute poverty thresholds in the sense that the poverty status of a household does not depend on the incomes of other households. These are the US1.25/day (US$456/year), US$2/day (US$729.6/year) poverty line proposed by WB and the official poverty line compiled by the NSCB. Unlike the US$1.25 and US$2/day poverty lines which take a single scalar value, the national poverty line differs across provinces. On the other hand, the half-of-median threshold is a relative poverty line in the sense that it implicitly depends on the distribution of the incomes of all households. Because the half-of-median yields the smallest poverty threshold followed by the official poverty line while the US$2-a-day produces the highest poverty threshold, one would expect that poverty estimates will be highest based on the US$2-a-day poverty line. Thus, the US$1.25/day and US$2/day-based estimates can be considered as lower and upper bound of poverty, respectively.

3.7 Summary

This chapter described the features of the main survey data that are pertinent to the measurement of income mobility. The succeeding chapters cover various topics about income mobility patterns in the Philippines.

Figure 3.1 Regional Map of the Philippines



Appendix Table A3.1 Descriptive Statistics for Household Expenditure Per Capita (in 2005 PPP US$)

Household characteristic	2003				2006				2009			
	Mean	Median	Std Dev	Obs	Mean	Median	Std Dev	Obs	Mean	Median	Std Dev	Obs
Philippines												
Urbanity												
Rural	856.28	617.55	1,299.57	4,047.00	836.55	600.63	785.56	4,047.00	904.00	663.42	809.76	4,047.00
Urban	1,625.43	1,222.39	1,435.02	2,472.00	1,642.59	1,158.03	1,706.54	2,472.00	1,643.38	1,178.89	1,589.99	2,472.00
Major Island Group												
NCR	2,239.77	1,631.83	1,896.19	449.00	2,297.86	1,572.89	2,497.04	449.00	2,195.53	1,624.21	1,906.35	449.00
Luzon excl. NCR	1,316.74	966.99	1,591.75	2,891.00	1,305.11	942.77	1,286.49	2,891.00	1,318.59	982.37	1,261.51	2,891.00
Visayas	996.47	696.19	972.32	1,342.00	1,001.86	662.25	1,023.92	1,342.00	1,089.44	723.04	1,156.18	1,342.00
Mindanao	879.85	587.52	860.63	1,837.00	867.17	572.20	889.19	1,837.00	950.81	633.62	1,017.51	1,837.00
Gender of household head												
Female	1,819.13	1,267.04	2,620.60	951.00	1,665.71	1,200.25	1,586.66	1,080.00	1,689.69	1,268.03	1,513.39	1,273.00
Male	1,147.69	817.39	1,112.64	5,568.00	1,156.94	773.37	1,327.74	5,439.00	1,177.44	821.74	1,242.52	5,246.00
Age of household head												
Hhld head's age ≤ 35	1,057.62	752.26	1,090.41	1,379.00	1,041.69	659.66	1,455.68	900.00	1,029.78	699.56	1,251.77	636.00
35 < Hhld head's age ≤ 44	1,111.98	786.26	1,711.71	1,614.00	1,043.42	726.19	1,016.28	1,618.00	1,113.45	783.60	1,075.31	1,421.00
Hhld head's age > 44	1,405.34	993.76	1,362.68	3,526.00	1,393.73	947.58	1,504.67	4,001.00	1,377.38	966.49	1,395.28	4,462.00
Education of household head												
Primary school	799.02	617.40	651.25	3,253.00	776.75	581.63	668.01	3,228.00	816.58	639.14	606.71	3,181.00
Secondary school	1,336.65	1,041.70	1,045.21	2,728.00	1,314.64	991.63	1,116.67	2,734.00	1,335.08	1,024.85	1,105.46	2,757.00
College	2,930.43	2,237.76	3,343.99	538.00	3,018.15	2,257.93	2,843.42	557.00	2,990.61	2,392.24	2,524.09	581.00
Family size												
Family size ≤ 3	1,906.94	1,285.16	2,666.63	1,470.00	2,058.65	1,334.69	2,518.04	1,529.00	2,103.07	1,424.34	2,327.92	1,693.00
3 < Family size ≤ 5	1,348.82	1,001.87	1,130.78	2,448.00	1,354.42	979.91	1,188.48	2,467.00	1,430.39	1,044.28	1,249.85	2,443.00
5 < Family size ≤ 7	1,045.05	759.88	922.57	1,679.00	1,023.06	726.19	946.29	1,615.00	1,064.79	770.61	928.09	1,571.00
7 < Family size ≤ 9	793.15	571.46	653.19	657.00	802.88	574.13	709.83	669.00	903.24	683.06	775.46	588.00
Family size > 9	841.58	523.23	1,169.48	265.00	761.18	523.87	928.67	239.00	718.34	583.01	480.59	224.00
Main source of Income												
Agriculture	1,464.68	1,071.22	1,576.83	4,473.00	1,451.08	1,027.53	1,476.05	4,483.00	1,460.32	1,057.88	1,416.70	4,704.00
Non-Agriculture	595.30	490.58	402.41	2,046.00	625.45	480.11	808.81	2,036.00	645.69	528.90	507.97	1,815.00

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Chapter 4 Is there Income Mobility in the Philippines?

4.1 Introduction

I noted in Chapter 2 that the economic development in the Philippines has been characterized by boom and bust cycles until the 2000s. However, starting 2000, the country experienced a more rapid growth episode and estimates suggest that it is gaining more momentum in the recent years (WDI 2014). Modest to rapid economic growth can be expected to raise household income. However, this link seems to be weak in the Philippines. Household survey estimates suggest that from 2003 to 2009, average household income per capita increased by only 0.36% annually. Further, despite 4.1% annual GDP growth from 2009 to 2012, average household income barely moved (NSCB 2013a). Estimates from household surveys also suggest that income inequality remained high over the past decade. For instance, the Gini coefficient based on household income per capita hardly changed from 0.44 in 2003 to 0.43 in 2009. Nevertheless, the minimal changes in the cross-sectional estimates of poverty and inequality do not necessarily imply that the country's income distribution is stagnant. As mentioned in Chapter 1, examination of income mobility could provide additional information on the underlying mechanisms that drive the income distribution to change. Thus, the main objective of this chapter is to provide a descriptive analysis of the income mobility that transpired over the past decade in the Philippines. In particular, the chapter addresses the following questions:

(i) Why is average household income not growing at the same pace as the country's overall economy?

(ii) What does a small change in cross-sectional inequality mean?

(iii) Are all households' incomes static over time or are they changing at different rates?

(iv) If there is mobility, is it characterized by genuine income movements?

To answer these questions, I use a portfolio of analytical methods, both conventional and new in the income mobility literature to document the income mobility patterns. Acquiring this knowledge is the first step to being able to provide inputs for policymakers in developing policies that will foster more inclusive economic growth. Throughout the chapter, I use household expenditure per capita as the main income measure.

4.2 Is there income mobility in the Philippines?

4.2.1 Is there relative income mobility?

We learned from Chapter 1 that relative mobility refers to how the income of each unit changes in comparison with the changes observed in other units of the population. A simple way to gauge the level of relative mobility is to estimate the proportion of the population moving from one income quantile to another over time using an income transition matrix. Using household expenditure per capita data derived from the FIES, the results from this exercise show that in 2009, about 85% of the household population were found in a vingtile different from its origin in 2003, 72% were found in a different decile; and 52% were found in a different quintile.[41] Nevertheless, income persistence was also strong. From 2003 to 2009, about 55% of the population did not move beyond two vingtiles from 2003 to 2009.

With respect to directional mobility, I find that about 11% of the population moved one vingtile up while 17% moved one decile up. Long-distance upward moves were also not trivial. For instance, the proportion of the population moving in a higher quintile from 2003 to 2009 was 26.3%. Because relative mobility is based on income ranks, one could expect that downward mobility is as frequent as upward mobility. This is because in a fixed population, for a person to be able to move up an income rank, another person has to go down portraying a zero-sum game. For instance, I find that about 25.7% moved into a lower quintile during the observation period.

Another way of measuring the extent of relative mobility is to look at how income ranks among the population units have changed over time. To what extent does current income rank dictate one's ranking in the future? In general, a stagnant household income distribution will imply that people that were initially at the bottom of the income hierarchy will remain at the bottom, while the rich will continue occupying the top spot. If we plot the ranks of the initial and final-period incomes, a stagnant distribution will resemble a perfect unit-slope diagonal line. The rank correlation calculated is relatively high with the Pearson correlation estimated at 0.80. Regressing the income rank in 2009 on the income rank in 2003, I find that the slope coefficient is close to one, which indicates income rigidity. Nevertheless, while income ranks are persistent, there is also considerable relative mobility in the sense that a significant fraction of the population experienced higher or lower income ranks in 2009 compared to their initial ranks in 2003. In addition, based on the results of the simple linear regression analysis, 40% of the variation in income ranking in 2009 cannot be explained by the income rank in 2003.

[41] (Income) vingtiles divide the population into twenty groups according to income, ten groups for deciles and five groups for quintiles.

Table 4.1 provides a summary of the amount of relative mobility that occurred from 2003 to 2009. Overall, the results show that despite the strong persistence of income ranking, the income dynamics that transpired during this period is also characterized by considerable medium and long-distance movements of income ranks.

Table 4.1 Summary of Relative Income Mobility Measures

Income mobility indicator	**2003-2009**
Average number of vingtiles moved (non-directional)	2.77 0.03
Average number of vingtiles moved (directional)	0 0.05
Proportion of population remaining in leading diagonals	0.15 0.005
Proportion of population moving one vingtile up	0.11 0.005
Proportion of population moving one vingtile down	0.12 0.005
Proportion of population moving two vingtiles up	0.08 0.004
Proportion of population moving two vingtiles down	0.09 0.004
Proportion of population moving at least three vingtiles up	0.23 0.006
Proportion of population moving at least three vingtiles down	0.22 0.006
Correlation of income ranks	0.8***

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Note: The numbers in smaller font size are standard errors.

4.2.2 Is there absolute income mobility?

If all incomes increased by a constant proportional factor, the relative mobility measures presented in the previous section would indicate that there is no mobility. This is because relative mobility indicators only capture variations in income shares or rank orders of the population units over time. In other words, relative mobility measures are more sensitive to the changes in the shape of the income distribution rather than the changes in location. In contrast, absolute mobility gauges how income levels change from one time period to another. In this context, absolute mobility captures the growth dimension of income dynamics.

Nevertheless, there is still much mobility going on. For instance, following the approach used in ADB (2010a), I group each household according to its income levels to determine

Table 4.2 (Absolute) Income Transition Matrix, 2003-2009

		2009					
		extreme poverty	moderate poverty	low middle income	middle income	upper middle income	rich
2003	extreme poverty	0.4942	0.3951	0.1045	0.0062	0.0000	0.0000
	moderate poverty	0.2185	0.4219	0.3341	0.0243	0.0007	0.0004
	low middle income	0.0423	0.1983	0.5660	0.1860	0.0074	0.0000
	middle income	0.0040	0.0231	0.2933	0.5776	0.0934	0.0085
	upper middle income	0.0000	0.0000	0.0487	0.5298	0.3644	0.0572
	rich	0.0000	0.0000	0.0221	0.2665	0.4836	0.2279

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

whether it is extremely poor, moderately poor, lower middle income, middle income, upper middle income and rich.[42]

The results are summarized in the income transition matrix presented in Table 4.2. From 2003 to 2009, about 49% of the household population changed income status. Interestingly, I find that both positive and negative mobility are prominent features of the income dynamics observed during this period. More importantly, it appears that there is as much positive mobility as there is negative mobility. Noticeably, five out of ten Filipinos who lived in extreme poverty in 2003 were still in the same situation in 2009; four moved to moderate poverty and the remaining 10% reached low middle income status. About 40% of those who lived in moderate poverty in 2003 remained in the same income status in 2009 while more than 20% fell to extreme poverty. In addition, those who were in either middle or upper middle-income status in 2003 were less likely to experience income increase than those who were initially in lower middle-income strata. Although not shown in Table 4.2, the number of units found at the right of the off-diagonal section of the transition matrix is slightly higher than number of units at the left off-diagonal. In particular, about 26% of the population moved up to a higher income status while 22% moved down.

Thus far, the inferences based on (absolute) transition matrix have implicitly relied on the following measures of positive and negative mobility denoted by M_U and M_D where M_U

[42] The first group consists of incomes not exceeding US$1.25/day which is considered as an extreme form of income poverty, the second group consists of incomes falling in between US$1.25 and US$2 (moderate poverty), third group consists of incomes falling in between US$2 and US$4 (lower middle income), fourth group consists of incomes falling in between US$4 and US$10 (middle income), fifth group consists of incomes falling in between US$10 and US$20 (upper middle income) and last group consists of incomes exceeding US$20/day (rich). The cut-off points are expressed as daily expenditure per capita in 2005 PPP US$.

represents the proportion of the population whose income went up a certain income threshold c while M_D represents the proportion of the population whose income went down with respect to c.

$$M_U = \frac{1}{n}\sum I(Y_{i1} \leq c)I(Y_{i2} > c) \qquad (4.1)$$

$$M_D = \frac{1}{n}\sum I(Y_{i1} > c)I(Y_{i2} \leq c) \qquad (4.2)$$

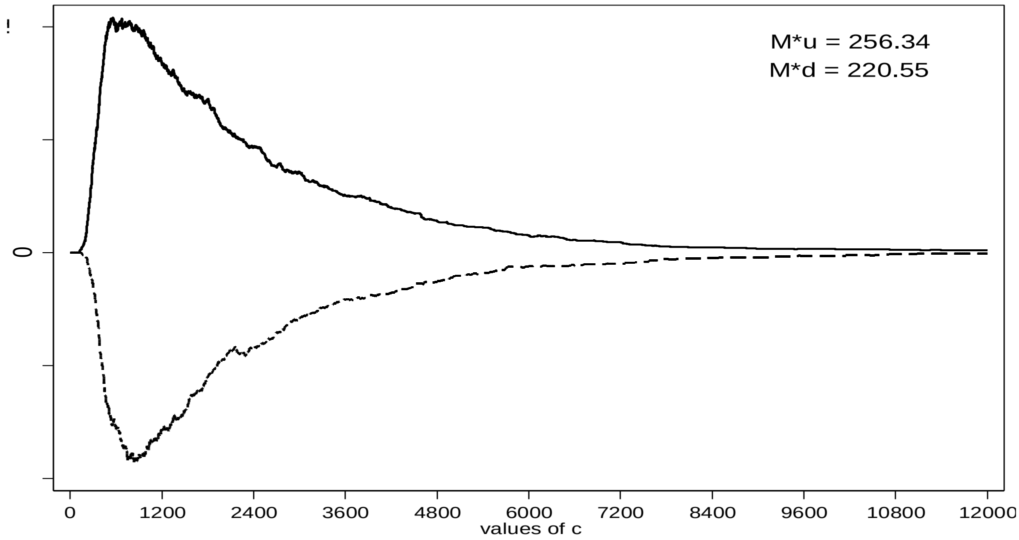
Noticeably, the value of these measures depend on the pre-specified cut-off point c. In this context, the transition matrix above treats all households with the same income status as identical. In other words, this transition matrix and other scalar measures derived from it, fail to capture positive and negative income movements occurring within the same income group. Recently, Foster & Rothbaum (2012) proposed a more general approach in comparing positive and negative income mobility rates. In particular, the authors defined M_U^* and M_D^* such that

$$M_U^* = \int_0^{C_H} \frac{1}{n}\sum I(Y_{i1} \leq c)I(Y_{i2} > c)\, dc \qquad (4.3)$$

$$M_D^* = \int_0^{C_H} \frac{1}{n}\sum I(Y_{i1} > c)I(Y_{i2} \leq c)\, dc \qquad (4.4)$$

The mobility measures M_U^* and M_D^* are integrated for all values of c, $0 \leq c \leq c_H$, where c_H can be set to be equal to the maximum income observed throughout the observation period. Hence, these mobility measures are not sensitive to a predetermined income threshold. Such a mobility measure provides an analytical tool for examining income mobility that incorporates the distribution sensitivity approach of the income transition matrix but is not pegged with respect to some predetermined income cut-off points (Foster & Rothbaum 2012). Figure 4.1 summarizes the upward and negative mobility estimates based on these mobility measures. The y-axis of the income mobility curve represents the values of M_U and M_D while the x-axis represents the different cut-off points c. We can see that for cut-off points less than the mean income, mobility rates increase uniformly and peak around the mean income. Thereafter, mobility rates gradually decrease. Consistent with the findings from the income transition matrices, I find that the total amount of positive income mobility is slightly higher than negative mobility. However, the difference between the two does not seem to be significant. Remarkably, the pattern of positive and negative mobility is quite symmetric across different cut-off points. The symmetry implies that for every household that experienced a positive (absolute) income increase at any point in the income distribution, there is a household that experienced a reduction in its (absolute) income level. Table 4.3 provides a summary of the amount of absolute mobility that occurred from 2003 to 2009.

Figure 4.1 Income Mobility Curve, 2003-2009



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 4.3 Summary of Income Mobility Measures

Income mobility indicator	Estimate
Average absolute change $\|Income_{2009} - Income_{2003}\|$	492.68 13.69
Average absolute percentage change $\|Income_{2009} - Income_{2003}\|/Income_{2003}$	0.41 0.006
Average income change $(Income_{2009} - Income_{2003})$	33.07 15.32
Average percentage change $(Income_{2009} - Income_{2003})/Income_{2003}$	0.16 0.008

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Note: The numbers in smaller font size are standard errors.

4.2.3 Is there equalizing mobility?

The level of income inequality in the Philippines is one of the highest in Southeast Asia (WDI 2014). Despite slight indications of a decreasing trend over the recent years, estimates suggest that income inequality in the country has remained very high. Because the observation that it has remained high is based on cross-sectional trends, we can only conclude that the gap between the rich and the poor has remained wide. However, as noted from the previous section, households are not necessarily static with respect to their position in the income distribution. In other words, those who are poor today are not necessarily the same households who were poor yesterday. The same is true for the middle class and the rich households. In particular, if poorer households have higher upward mobility prospects, then it is possible that despite the high levels of cross-sectional inequality, we would still observe lower inequality in the long-run.

Examining the relationship between long-run inequality and income mobility is the main theme of this section. Unlike the measures used in the previous section which view mobility in terms of income movements, this section investigates the extent to which income inequality that exists at any given time, is offset when household incomes are averaged over time and whether there is greater or less mobility at the lower income segments relative to mobility in higher income ranges.

Table 4.4 Inequality-Reducing Effect of Income Mobility

	GE(0)	GE(1)	Gini	GE(2)
2003-2009				
Single year income	0.3081	0.3449	0.4309	0.6074
Average income	0.2773	0.3049	0.4115	0.4710
Shorrocks' R	0.0870	0.0980	0.0390	0.2246

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Note: GE(a) – is the generalized entropy index for measuring inequality. The index is more sensitive to changes in the lower incomes for lower values of a and it is more sensitive to changes in the upper incomes for higher values of a.

One of the long-standing views about mobility is that it is a channel for making economic opportunities more evenly distributed. In other words, income mobility is seen as equalizer of incomes in the long-run. I begin the empirical investigation with the computation of the stability index proposed by Shorrocks (1978). This index directly links the concept of mobility with income inequality by providing an estimate of the relative reduction of cross-sectional inequality achieved through mobility of incomes. Table 4.4 presents the average inequality based on single-period incomes, the inequality of permanent incomes computed by taking the longitudinal average income of each household and the Shorrocks's rigidity or stability index.[43] Values of this index depend on the level of sensitivity of the underlying inequality measure to incomes in different parts of the distribution. Depending on the inequality measure being used, the results show that about 5% to 20% of cross-sectional inequality is reduced when household incomes are averaged from 2003 to 2009. The relative reduction in income inequality is lowest when inequality is measured based on the Gini coefficient and it increases as one uses an inequality measure that is more sensitive to the changes in the lower or higher income range.

[43] As shown in Chapter 1, the Shorrocks' rigidity or stability index is equal to one minus the ratio of the inequality of longitudinally averaged incomes to the average inequality over time.

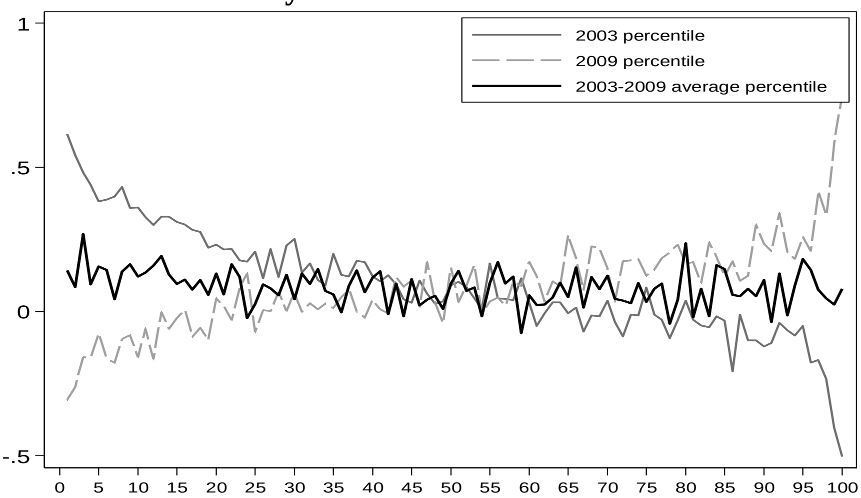
However, the reduced inequality is still considerably higher than the level of inequality in other neighbouring countries, based on current estimates (Table 4.5).

Table 4.5 Comparison of Philippines' Income Inequality With Other Southeast Asian Countries

Country	Year	Gini
Cambodia	2009	0.3603
Indonesia	2010	0.3557
Lao PDR	2008	0.3674
Philippines	2003 to 2009	0.4115
Thailand	2010	0.3937
Vietnam	2008	0.3557

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009 and WDI.
Notes: The estimate for Philippines is based on longitudinally-Averaged income while the rest are based on current year incomes.

Figure 4.2 Change in the Logarithm of Income between 2003 and 2009, by Income Percentile



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

In the previous section, we have seen that the mobility patterns observed in the country are not homogeneous. For instance, the income mobility that occurred from 2003 to 2009 is not uniformly positive nor negative. But how does the observed income mobility vary across the different segments of the income distribution? Have the incomes of the initially poor households increased faster? To answer this question, I first group the initial incomes of the household population into percentiles. I then take the average logarithmic change between the initial and final period-incomes of all people for each percentile, as illustrated by the downward sloping line in Figure 4.2. The results suggest that the majority of the richest 40% of the household population in the Philippines experienced income reduction from 2003 to 2009 and those who experienced larger income increases started with lower initial incomes. In fact, if I regress the logarithmic change from 2003 to 2009 on the percentile of income in 2003, I find that 10 higher percentile points on the 2003 income distribution is associated with a 0.9 percentage points lower average income growth from 2003 to 2009. Whether this implies that the poor benefitted more from the economic growth or not merits further investigation. However, the observed income changes may either be driven by changes in permanent or transitory income. In other words, if some of the households in 2009 experienced transitory shocks in their income, the income fluctuations may have placed them below or above their permanent (that is, steady-state) income. Khor & Pencavel (2008) argued that those who were below their steady-state income in the final period were more likely to have experienced smaller income increase between the initial and final periods, while the opposite holds for those who were above their steady-state income in the final period. This pattern is illustrated by the upward sloping line in Figure 4.2 wherein the average logarithmic change in income is plotted with respect to the income percentile in 2009. In other words, income growth from 2003 to 2009 was lower for households with lower income in 2009. The results of the regression model(s) depicted in Table 4.6 suggest that 10 higher percentile points on the 2009 income distribution is associated with a 0.6 percentage points faster income growth from 2003 to 2009.

To address the issue, I also compute the income growth for households grouped according to their average income throughout the observation period. Obviously, using incomes averaged over a six-year period as a measure of permanent income is not without question. Nevertheless, it is still helpful to use this approximate measure of steady-state income when answering whether the observed income growth pattern benefitted the poor more than the rich. The solid line in Figure 4.2 exhibits a slightly downward pattern for the bottom 20% of the population. Thereafter, there is not a dominant positive or negative slope. This is consistent with the regression estimates in Table 4.6, which suggest that 10 higher percentiles on average income is associated with only 0.01 percentage points lower income growth from 2003 to 2009.

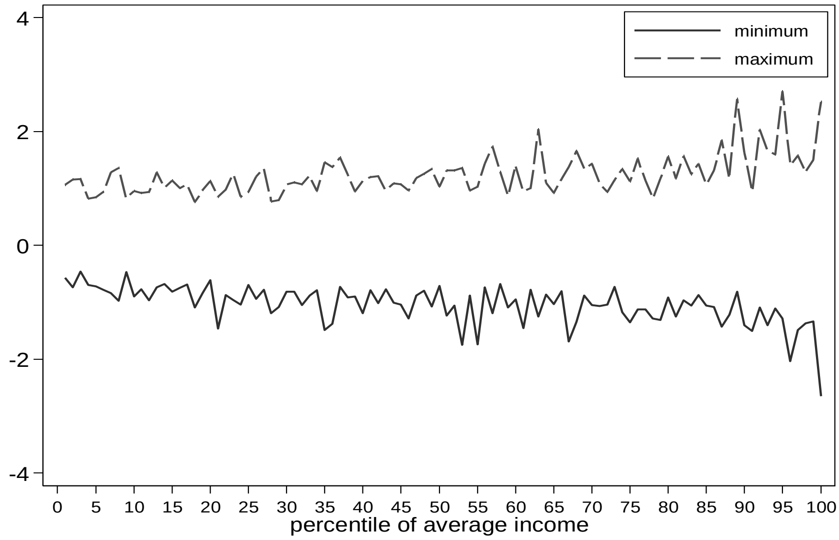
The results provided in Figure 4.2 are based on observed income growth averaged across all units within each percentile. However, units within each percentile have varied income growth experiences. Figure 4.3 plots the minimum and maximum income growth for each percentile where the percentile is based from the average of incomes over the six years. The typical lowest income growth is approximately 17% annual income reduction, while the typical highest income growth is approximately 20% annual income increase. While these variations in income growth experiences are generally independent of income position, there is slight evidence suggesting that the ultra-rich tend to experience both the highest and lowest income growth.

Table 4.6 Regression Estimates of the Relation between Changes in Income and Percentiles of Income

	2003-2009		
	(I)	**(II)**	**(III)**
Percentile of initial income	-0.0009***		
Percentile of final income		0.0006***	
Percentile of averaged income			-0.0001***
Intercept	0.0536***	-0.0259***	0.0143***
R^2	0.1197	0.0586	0.0029

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Figure 4.3 Range of Values of the Change in the Logarithm of Income between 2003 and 2009, by Percentile of Average Income



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Overall, the panel data suggest that incomes of poor people are increasing slightly faster than those who were initially non-poor. However, the advantage does not seem to be remarkable and more effort is needed for the poor to be able to catch-up. Moreover, the considerable proportion of the household population experiencing negative mobility tend to offset the inequality-reducing effect of faster income growth among the poor. This observation can be further validated when I decompose the changes in inequality levels from 2003 to 2009 into pro-poor and re-ranking components following the approach proposed by Jenkins & Van

Kerm (2009). In particular, suppose the change in inequality from time t to $t+1$ is denoted by $\Delta G(s)$. As discussed in Chapter 1, Jenkins & Van Kerm (2009) showed that this can be expressed as the difference between the amount of income re-ranking and pro-poor income dynamics that transpired during the observation period. The results are presented in Table 4.7. The first two rows correspond to the values of the S-Gini index for 2003 and 2009, respectively. The third row corresponds to the contribution of income mobility or redistribution to the change in inequality while the last row corresponds to the contribution of the progressivity of growth or the extent to which growth benefits the poor. The results show that while many of the initially poor households experienced improvements in terms of the share of income held, this is offset by income re-ranking that contributes to wider income gaps. The consequence is the observed slow pace of the reduction in income inequality.

Table 4.7 Decomposition of Change in Inequality into Re-ranking and Pro-poor Components

	v= 1.5	**v=2**	**v=3**	**v=4**
Initial S-Gini	0.298	0.428	0.551	0.612
Final S-Gini	0.294	0.422	0.54	0.598
Change	-0.004	-0.007	-0.011	-0.014
R-component	0.058	0.071	0.078	0.082
P-component	0.062	0.078	0.09	0.096
Kakawani index	2.38	2.98	3.433	3.67

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

As pointed out at the beginning of this section, the estimates provide weak evidence that household incomes have increased significantly, which suggests a stagnant income distribution. To summarize the findings in this section, I find that income persistence or income immobility is indeed strong. For instance, the numbers presented in Table 4.2 suggest that about half of the household population who were in extreme poverty in 2003 remained in the same status in 2009, while some 23% of the households that were classified rich in 2003 remained in the same position six years after. Stronger income status persistence emerge when one looks at the transition matrix based on income quintiles. In most of these cases, the entries in the main diagonal tend to be the largest in any row, suggesting substantial immobility. Nevertheless, the distribution of household income in the Philippines is much more dynamic than conventionally perceived based on the growth of average per capita household income. In both absolute and relative terms, I find that a considerable number of initially poor people have managed to move out of poverty while some initially rich people experienced negative income movements. In addition, a considerable number of middle class households have either fallen into poverty or have managed to move up the income ranks. Remarkably, for a given number of people that experienced positive income movements at any point in the income distribution, a commensurate number of people observed negative income movements. This behaviour contributed to a slow pace of improvement in average incomes. However, income mobility is contributing to a gradual reduction in long-run inequality. For instance, I find that those who are in the bottom 20% experienced slightly better mobility. However, for the remainder of the population, the observed mobility has a mean-reversion effect, which suggests that a significant portion of the observed mobility is driven by transitory fluctuations. I turn to this issue in the next section.

4.3 Discussion

Is the observed income mobility driven by permanent income dynamics or transitory income fluctuations? For instance, it is possible that the global financial crisis that began in 2008 might have caused a transitory income shock, especially for the richest segment of the population. This would explain why many rich people experienced significant income declines in 2009. To answer this question, I replicate Table 4.2 using 2003-2006 and 2006-2009 as reference periods, which allows us to examine income mobility before and after the global financial crisis. The results show that income persistence was stronger before the crisis especially in the bottom and top income tiers. Unlike the poor and rich people, middle income people were less mobile from 2006 to 2009. It is possible that during this period, middle income people were using their savings as buffer against the economic shocks.

From 2003 to 2006, the country's economy measured in terms of GDP per capita increased by an annual rate of 2.04%. Despite this, (absolute) poverty increased during this period. Several studies point to potential contributing factors. For instance, Reyes et al. (2011) noted that the family size of chronically poor households increased faster than their real incomes. Consequently, the reduced income per member pushed these households into more severe poverty. Estimates from labour force survey also reveal that labour outcomes seem to have deteriorated during this period. In particular, labour participation rate decreased from 66.7% in 2003 to 64.2% in 2006 (WDI 2013) while the proportion of employed persons working less than 40 hours per week rose by 1.5 percentage points based from my estimates using the labour force survey. The share of the employed population engaged in unpaid family employment also increased from 10% to 11.5% over the three year period. Because households of lower economic status rely mostly on income from labour, it is not surprising to note that the inferior job quality has been accompanied by increased poverty. Santos (2008) surmised that the expanded coverage of the value tax, which began in 2005, may have also resulted in higher poverty rates as the resulting inflation reduced the real income of the poor. Virola (2008) identified climate-induced shocks as another factor contributing to the downward mobility experienced by households in the low-income range.

The results presented in Tables 4.8 and 4.9 portray a stronger income persistence at the top of the income pyramid before the financial crisis. This may be attributed to the fact that much of the economic growth observed during this period occurred in high productivity sectors while the growth in the agriculture sector where the poor households are concentrated remained sluggish (Canlas et al. 2009).

From 2006 to 2009, GDP per capita increased at an annual rate of 2.19%, slightly higher than the 2003-2006 growth rate. Relative to 2003-2006, poverty persistence was significantly lower during this latter period. This outcome may be partially attributed to the expansion of poverty reduction efforts by the national government. For instance, the coverage of the Conditional Cash Transfer program expanded from covering 161 municipalities in 2008 to 277 municipalities in 2009 (Virola 2008). Like the poor, middle income households also experienced more positive income mobility prospects. This may also be explained by the improvement in quality of employment in various labour market indicators during this period. For instance, vulnerable employment decreased from 44.5% in 2003 to 42.6% in 2006 (WDI 2014), while the proportion of employed persons working less than 40 hours per week decreased from 38% in 2006 to 35.4% in 2009. Wages, particularly in the government sector, also increased significantly during this period with the enactment of the Salary Standardization Law.[44] However, the gains observed during this period were partially offset by the food price and global financial crises in 2008. In particular, the significant increase in food prices in 2008 pushed vulnerable households into poverty while the global financial crisis depressed the value of assets of middle income and rich households (Yap, Reyes & Cuenca 2009). Nevertheless, compared to other countries, the Philippines had shown more resilience to the adverse impact of the 2008 global financial crisis (ADB 2012a)[45]; which may explain why low to middle

[44] The Salary Standardization Law increased government employees' salary to make it at par with their counterparts who are doing similar jobs in the private sector (TUCP 2009).

[45] A report from ADB (2012a) identified several factors why the Philippines was not significantly affected by the financial crisis relative to other countries, especially those which also have a large number of households with at least one (international) migrant family member. First, ADB (2012a) surmised that since Filipino migrants were spread across the world, the negative impact of the crisis was less stark than in other countries whose migrant workers were mainly concentrated on the heavily affected countries. Second, the buoyant demand for Filipino workers from a broad range of fields such as domestic services, health care, engineering and computer hardware and software development, lead to an increased deployment of Filipino migrant workers even during the financial crisis.

income households still experienced better income mobility prospects from 2006 to 2009 than the 2003-2006 period.

Table 4.8 (Absolute) Income Transition Matrix, 2003-2006

		2006					
		extreme poverty	moderate poverty	low middle income	middle income	upper middle income	rich
2003	extreme poverty	0.6730	0.2757	0.0497	0.0016	0.0000	0.0000
	moderate poverty	0.2591	0.5033	0.2207	0.0164	0.0004	0.0000
	low middle income	0.0331	0.2219	0.5840	0.1564	0.0041	0.0006
	middle income	0.0035	0.0258	0.2801	0.5887	0.0923	0.0096
	upper middle income	0.0000	0.0000	0.0313	0.4975	0.3845	0.0868
	rich	0.0000	0.0000	0.0000	0.2271	0.4458	0.3271

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Notes: Extreme poverty - US$1.25/day or lower; moderate poverty - US$1.25 to US$2; lower middle income – US$2 to US$4; middle income – US$4 to US$10; upper middle income –US$10 to US$20; rich - exceeding US$20/day (rich).

Table 4.9 (Absolute) Income Transition Matrix, 2006-2009

		2009					
		extreme poverty	moderate poverty	low middle income	middle income	upper middle income	rich
2006	extreme poverty	0.5581	0.3518	0.0893	0.0008	0.0000	0.0000
	moderate poverty	0.1687	0.4752	0.3361	0.0197	0.0002	0.0000
	low middle income	0.0171	0.1622	0.6295	0.1845	0.0064	0.0003
	middle income	0.0010	0.0170	0.2446	0.6373	0.0945	0.0057
	upper middle income	0.0000	0.0000	0.0490	0.5305	0.3564	0.0641
	rich	0.0000	0.0000	0.0000	0.2704	0.5089	0.2207

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Notes: Extreme poverty - US$1.25/day or lower; moderate poverty - US$1.25 to US$2; lower middle income – US$2 to US$4; middle income – US$4 to US$10; upper middle income –US$10 to US$20; rich - exceeding US$20/day (rich).

While household income distribution in the Philippines is much more dynamic than conventionally perceived, income mobility has been lacklustre compared with other developing countries. Latin American countries such as Brazil, Chile, Colombia and Costa Rica also have high levels of income inequality. However, in the past 15 years, these countries have experienced significantly more upward mobility (Ferreira et al. 2013). In contrast, income mobility in the Philippines has been characterized by offsetting forces of upward and downward mobility. While high economic growth contributed to upward mobility of some households, many man-made and natural crises and the lack of inclusive growth have pushed a large number of households into poverty. This finding is consistent with findings from previous studies suggesting that the country has been ineffective in minimizing poverty inflows during income shocks because of the lack of social protection services and inefficient redistribution policies (Manasan 2009; Balisacan et al. 2010).

4.4 Summary

Recent estimates of macroeconomic indicators paint a vibrant Philippine economy. For instance, from 2009 to 2012, real GDP per capita grew by 4.1% annually. In the first quarter of 2013, total GDP expanded by 7.8%, faster than China (7.7%), Indonesia (6%), Thailand (5.3%) and Viet Nam (4.9%) (NEDA 2013). This outcome is in sharp contrast to the economic contraction that the country experienced in the 1980s and much higher than its modest growth performance in the 1990s and first half of 2000s. However, the rapid economic growth has yet to be manifest in the distribution of household income in the Philippines based on conventional indicators. For instance from 2009 to 2012, average real per capita household income barely moved (NSCB 2013b). At the same time, income inequality has remained persistently high over the past decade (ADB 2012b). Together, these indicators portray a stagnant household income distribution.

This chapter has investigated this puzzle by examining the mobility patterns of household incomes in the Philippines. The contribution of examining household income dynamics in the Philippines is twofold. First, studying household income mobility addresses the limitations of the conventional indicators that focus only on the features of the marginal distributions and how they change over time. However, marginal distributions usually fail to provide a good representation of the dynamic features of a country's growth process. Second, measuring how much income mobility is present is important in gauging the impact of economic growth on living standards.

The analyses provide a broad snapshot of the income mobility patterns in the Philippines from 2003 to 2009. The investigation provides three main findings. First, the distribution of household incomes in the Philippines is much more dynamic than conventionally thought. For instance, about 72% of the population moved into a different income decile and 53% moved into a different quintile during the observation period. The average annual percentage change of income per capita is about 21%. Nevertheless, income persistence is strong. For instance, the correlation between the ranks in 2003 and 2009 is approximately 0.8. Second, the observed income mobility is characterized by high positive and negative mobility rates. Interestingly, the patterns of positive mobility are quite symmetric with the patterns of negative mobility throughout the income distribution. In other words, for every person who experienced an income increase at any point in the income distribution, there is another individual (or a commensurate number of individuals) who experienced an income decline. This finding means that the income gains experienced by a significant number of Filipinos during this period of economic of growth has been neutralized by the income reductions experienced by others. This offsetting of positive and negative income mobility heavily contributes to the static nature of the indicators of the income distribution at the aggregate level. Third, the empirical investigation also reveals that a non-negligible portion of the observed mobility is driven by fluctuations in the transitory component of income. This puts into question the sustainability of the observed economic mobility.

The findings from this chapter serve as roadmap for the remainder of this study. First, it is operationally useful to differentiate persistent and transient poverty to be able provide optimal intervention programs for the varying needs of the poor. Thus, Chapter 5 examines the duration of poverty experiences of Filipinos. Second, while I find evidence that the country's poor have experienced slightly better income mobility prospects, an important task for policy-targeting is to be able examine the profile of upwardly and downwardly income mobile individuals. Chapter 6 discusses this topic. Third, a good understanding of the factors that contribute to income mobility is instructive for devising policies that would distribute the benefits of economic growth more equitably. Thus, Chapter 7 identifies the proximate determinants of income mobility in the Philippines. Fourth, as households in the Philippines heavily rely on earnings from employment, there is a need to investigate the status of quality of employment in the country and its role in fostering more sustainable positive mobility. An examination of the effectiveness of existing social safety nets in minimizing economic vulnerabilities is also warranted as the results of this chapter show that both positive and negative mobility are common features of the country's income dynamics. This topic is examined in Chapter 8. Fifth, it is operationally useful to provide a longitudinal perspective when examining the evolution of income or any other measure of living standards. In general, while static indicators of development are useful for a quick analytical assessment of economic progress, they hide a number of important features of the underlying development process.

However, to be able to provide a longitudinal perspective, panel data that track income or other measures of living standards of the same set of individuals are needed. However, many developing countries do not have adequate panel data because it is often costly to collect. The pseudo-panel estimation approach discussed in Chapter 9 is a good example of a methodology for exploiting the information available from repeated cross-sectional survey data more optimally to answer questions that are conventionally answered by longitudinal data.

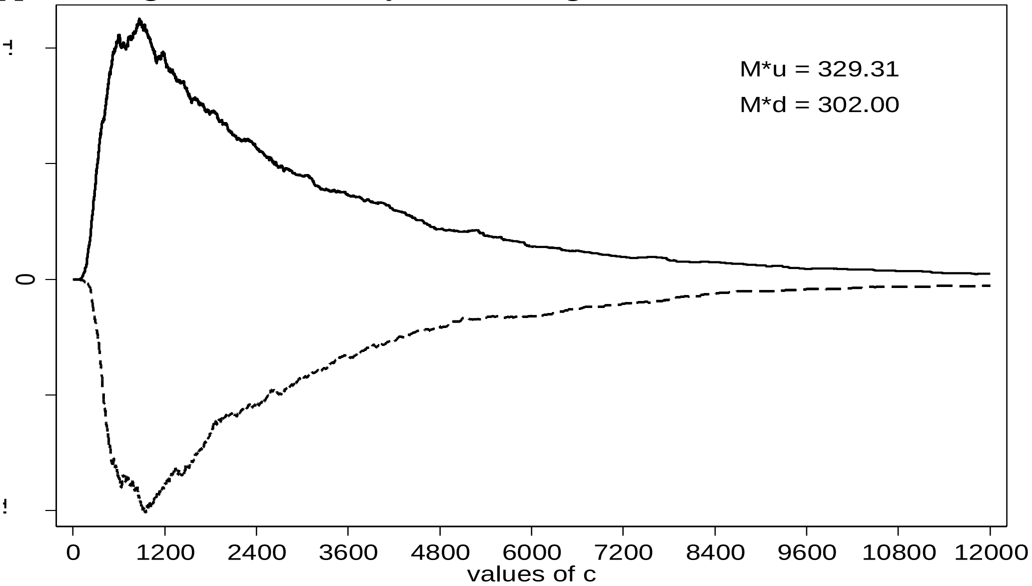
Appendix 4.1 Mobility of Household Incomes

In this section, I briefly examine the mobility patterns in the Philippines using household income data. There are some advantages in using household income rather than expenditure to measure poverty, inequality and mobility. For instance, it is arguably easier to link income with socio-economic policies because income can be decomposed into components such as earnings from employment and receipts from government transfers -- things that concern socio-economic planners. Furthermore, it is also possible to measure poverty, inequality and mobility at finer levels of disaggregation using income data collected from administrative systems. However, using income as a welfare measure has disadvantages too. For instance, since income is generally more sensitive to erratic fluctuations (Jefferson 2012), it is intuitive to expect more mobility using household income data than expenditure-based estimates. Additionally, the proportion of people who are classified as poverty-vulnerable tend to be higher using income-based measures. Nevertheless, this conclusion is not impeccable as there are studies that found more mobility using expenditure data (Gradin, Canto & del Rio 2008). The objective of this section is to briefly compare the differences in mobility patterns between household expenditure and income in the Philippines.

Appendix Figure 4.1 presents the mobility curve based on household income data. The mobility pattern is remarkably similar when it is compared with the expenditure-based mobility curve shown in Figure 4.2. The upward mobility curve presented in Appendix Figure 4.1 is generally symmetric with the downward mobility curve which implies that downward mobility offsets upward mobility. As expected, I also observe higher mobility rates using income data as evidenced by higher values of Foster & Rothbaum's (2012) mobility indices. This is also confirmed from the various mobility indicators presented in Appendix Table 4.2.

Using the same income thresholds to distinguish extreme poverty, moderate poverty, low middle income, middle income, upper middle income and rich, I replicate the absolute mobility matrix presented in Table 4.2 using household income. The results are shown in Appendix Table 4.1. About half of the people living in extreme poverty in 2003 still remained extremely poor in 2009, 35% moved to moderate poverty while the rest entered middle income status. This is approximately the same with the estimate that I calculated using expenditure data. Interestingly, income persistence among the rich seems to be stronger when using income data. In particular, 31% of the initially rich in 2003 remained rich in 2009 which is higher than the 23% estimated using expenditure data.

Appendix Figure A0.1 Mobility Curve Using Household Income Data, 2003-2009



Source: Author's computations using household income per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Appendix Table A0.1 (Absolute) Household Income Transition Matrix, 2003-2009

		2009					
		extreme poverty	moderate poverty	low middle income	middle income	upper middle income	rich
2003	extreme poverty	0.4952	0.3530	0.1406	0.01	0.0000	0.0012
	moderate poverty	0.2257	0.4047	0.3147	0.0536	0.0012	0.0000
	low middle income	0.0553	0.1927	0.5288	0.2126	0.0090	0.0016
	middle income	0.0052	0.0359	0.2893	0.5384	0.1156	0.0156
	upper middle income	0.0000	0.0030	0.0411	0.5056	0.3616	0.0887
	rich	0.0000	0.0000	0.0366	0.3163	0.3359	0.3113

Source: Author's computations using household income per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009

Appendix Table A4.2. Selected Indicators of Mobility, 2003-2009

Income mobility indicator	Income	Expenditure
Average number of vingtiles moved (non-directional)	2.91 0.04	2.77 0.03
Average number of vingtiles moved (directional)	0 0.06	0 0.05
Proportion of population remaining in leading diagonals	0.14 0.005	0.15 0.005
Proportion of population moving one vingtile up	0.11 0.005	0.11 0.005
Proportion of population moving one vingtile down	0.11 0.005	0.12 0.005
Proportion of population moving two vingtiles up	0.09 0.004	0.08 0.004
Proportion of population moving two vingtiles down	0.09 0.004	0.09 0.004
Proportion of population moving at least three vingtiles up	0.23 0.006	0.23 0.006
Proportion of population moving at least three vingtiles down	0.23 0.006	0.22 0.006
Correlation of income ranks	0.77***	0.8***
Average absolute change $\lvert Income_{2009} - Income_{2003} \rvert$	672.61 20.04	492.68 13.69
Average absolute percentage change $\lvert Income_{2009} - Income_{2003} \rvert / Income_{2003}$	0.49 0.01	0.41 0.006
Average income change $(Income_{2009} - Income_{2003})$	25.98 22.11	33.07 15.32
Average percentage change $(Income_{2009} - Income_{2003})/Income_{2003}$	0.21 0.01	0.16 0.008

Source: Author's computations using household income and expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Chapter 5 How Long Do the Poor Stay in Poverty?

5.1 Introduction

Official headline statistics of poverty in the Philippines are usually presented as a cross-sectional snapshot picture of disadvantage (NSCB 2013a). These static measures describe poverty in the country as a one-time event, and ignore the persistence and recurrence of poverty over time. However, the poor are not all the same: some experience disadvantage as a temporary once-off event, others experience recurring episodes of disadvantage, and others endure longer spells of socio-economic deprivation and the associated long-lasting grip of social exclusion. Overall, emerging from poverty is not a simple rags to riches story because moving out of poverty today does not completely remove the risk of falling back into economic dearth in the future. This chapter further probes the results from Chapter 4 suggesting that households with lower incomes in the Philippines have experienced slightly better income mobility prospects than the rest of the population but this may not be enough to set forth a virtuous cycle of development that will permanently improve the lives of more than four million poor Filipino households (NSCB 2013b) and put the Philippines on-track of its goal of becoming the next Asian Tiger. This is done by examining the factors that characterize intertemporal income poverty, i.e., duration and frequency of episodes that households spend below the poverty line.

A household's intertemporal poverty experience can either be persistent (chronic) or transient. Persistent poverty could be further transmitted across generations giving way to vicious cycles of socio-economic hardship while transient poverty is characterized by a household's inability of meeting its minimum basic needs from time to time. High levels of persistent poverty are harmful to a country's long-term growth prospects and thus, governments and international development community alike, aim to eradicate persistent poverty. This commitment is exemplified in the MDGs which identify eradication of extreme poverty as its first objective (UN 2014). Nevertheless, tackling transient poverty is also important because it can also slow down a country's growth momentum (Jalan & Ravallion 2000). When outlining intervention programs, it is important that policy planners differentiate between persistent and transient poverty as the policy interventions necessary to ameliorate these different types of disadvantage may be very different. For instance, providing social safety nets to minimize the adverse impact of socio-economic shocks may not be an optimal strategy to reduce disadvantage amongst people who have experienced uninterrupted, even intergenerational, spells of disadvantage. Similarly, providing long-term social assistance to those who are transiently poor may not be cost-effective. The key message is that no poverty and disadvantage reduction programs will serve as a "one-size-fits-all" policy lever, and hence probing beyond cross-sectional measures of poverty and examining its intertemporal patterns can guide efficient and cost-effective policymaking decisions.

Given the importance of examining intertemporal poverty for policy-making, several studies have attempted to incorporate a longitudinal perspective in the analysis of poverty in the Philippines using either actual panel or pseudo-panel data (Balisacan & Pernia 2002; Tabunda & Albert 2002; Albacea & Gironella 2003; Reyes et al. 2011; Bayudan-Dacuycuy and Lim 2013). However, they fall short of examining the sensitivity of their estimates to different methodologies, different types of poverty indices and different poverty line specifications, to which I hereafter refer as measurement parameters. Examining the robustness of intertemporal poverty estimates is important because previous poverty estimates highly depend on the measurement parameters used (Kurosaki 2006). In addition, knowledge on the robustness of estimates provides more nuanced insight into poverty and disadvantage patterns which in turn, could help researchers to better communicate key policy messages.

The discussion in this chapter contributes to the existing poverty literature in the Philippines by providing a broader examination of intertemporal poverty using a more complete set of analytical tools. In particular, the chapter addresses the following substantive and methodological questions:

Substantive

(i) Is poverty in the Philippines characterized by long episodes of poverty spells or transitory movements around the poverty line?

(ii) What is the spatial distribution of intertemporal poverty in the Philippines?

(iii) Aside from geography, what are the characteristics of intertemporally poor?

Methodological

(iv) Are the observed patterns sensitive to the estimation parameters?

(v) How robust are the poverty rankings to the parameters used in the estimation process?

5.2 Intertemporal Poverty in the Philippines

Like many developing countries, poverty reduction is explicitly articulated in the Philippines's development plan (Reyes et al. 2011). Over several decades, the country has been working to reduce poverty by implementing a multitude of anti-poverty programs which aim to improve the quality of life of the poor (Schelzig 2005; Aldaba 2009; Bayudan-Dacuycuy & Lim 2013). From 1986 to 1992, the administration of then President Corazon Aquino implemented three major intervention programs which include the *Tulong sa Tao* (Help for the People), the Comprehensive Agrarian Reform Program (CARP) and the Community Employment and Development. From 1992 to 1998, the Ramos administration implemented the Social Reform Agenda which focused on the development of the twenty poorest provinces and the poorest sectors. From 1998 to 2001, the Estrada Administration launched the *Lingap Para sa Mahirap* (Care for the Poor) which provided assistance to the poorest families from each local government unit. From 2006 to 2010, the Arroyo administration started the *Kapit Bisig Laban sa Kahirapan* (KBLK) (Linking Arms Against Poverty Program) which offered socio-economic services to the poor. The current Aquino administration is implementing the Social Reform Program (SRP) which provides conditional cash transfers to families that satisfy certain criteria. While most of these programs occupy the centrepiece of each administration's platform, each program has its own thrust. For instance, the CARP focused on agricultural development, KBLK paid attention on improving delivery of social services (Schelzig 2005) while SRP is spending effort on institution-building and promoting effective participation in governance (NEDA 2011).

During the period that these programs were implemented, the Philippines noted a reduction in poverty rates. For instance, I noted from Chapter 2 that the proportion of the population living below US$2 a day dropped by approximately 20 percentage points between 1985 and 2009. However, it can also be noted that the pace of poverty reduction in the Philippines is significantly lower than other countries' pace and this process has been painfully slow despite faster economic growth that the Philippines experienced during the past decade (Aldaba 2009). There are several possible reasons that could explain why poverty is barely declining amidst faster economic growth rates in the country. First, it is possible that most of the poor have incomes far below the poverty line and it takes a very long time before the benefits of economic growth trickle down to the persistently poor. Second, it is possible that the poor don't contribute much to economic growth because they are concentrated on low productivity sectors due to their limited skills. Third, as suggested in Chapter 4, even if many low income people are moving into and out of poverty transiently, the number of people falling into poverty may offset the number of people moving out of poverty at any given time. These scenarios call for different policy response; the first two should focus on long-term human capital development programs because it will be hard for the persistently poor to get out of poverty by solely relying on their efforts while the other scenario should be geared towards minimizing recurring socio-economic vulnerabilities. However, Reyes (2002) identified that one of the bottlenecks in policy planning that has contributed to the slow poverty reduction is that the previous intervention programs were not well-targeted and tend to discount the heterogeneous needs of the poor. That study argued that there was no clear guideline where long-term human development efforts and short-term risk management initiatives should be channelled. This issue could be attributed to the lack of intertemporal poverty data that can be used to inform policies. As pointed out in Chapter 3, socio-economic planners in the Philippines had to rely on poverty data collected from cross-sectional surveys for many years and it was only in 2003 when the FIES, the data source of official poverty estimates, was redesigned to collect nationally-representative panel data. With cross-sectional surveys, researchers were unable to measure intertemporal poverty directly. Nevertheless, there were some efforts to examine the intertemporal patterns of poverty even before FIES was redesigned by analysing either pseudo-panel data (e.g., Balisacan and Pernia 2002; Albacea & Gironella 2003) or actual longitudinal data from one-shot surveys (e.g., Reyes 2002a; Tabunda & Albert 2002), however, the data limitations made it hard for these studies to generalize their results to larger populations.

More recently, Reyes et al. (2011) and Bayudan-Dacuycuy & Lim (2013) and used the panel data from the redesigned FIES to provide a more dynamic perspective of intertemporal poverty in the Philippines. Both studies characterize the country's poverty to be mostly persistent in nature. However, while they have addressed the limitations of previous research by providing direct survey estimates of persistent and transient poverty at the national-level, they also have critical limitations. First, both studies employed confining methodology as they solely relied on the spells approach only for measuring intertemporal poverty. As explained in Chapter 1, the spells approach narrowly focuses on frequency of poverty episodes over time and ignore the fact that people can "borrow" income from different time periods. Second, both studies restrictively measured poverty in terms of incidence or head count of poor. Third, both studies used the official poverty lines compiled by the government, the use of which remains debatable because the official poverty thresholds are based on different regional food menus which tend to make the resulting estimates inconsistent across regions (Bersales 2009).

This chapter contributes to the existing literature by measuring intertemporal poverty using a more comprehensive set of analytical tools and measurement parameters. To do this, I adopt the spells and components approaches as described in Chapter 1. In addition, I measure intertemporal poverty in terms of incidence, depth and severity. Four different sets of poverty lines are used to examine the robustness of estimates to poverty line specifications. Examining robustness of intertemporal poverty estimates is important for both methodological and substantive reasons. The existing literature suggests that the poverty estimates may vary significantly depending on measurement parameters (Grootaert & Kanbur 1995; JR 1998, McCulloch & Baulch 1999; Kurosaki 2006; Christiaesen & Shorrocks 2012). If robustness of the parameter estimates is not guaranteed, it is possible that the poverty levels reported are arbitrary leading to inaccurate interpretations and outcomes.[46] For example, if the magnitude of poverty reported is higher or stagnant than it actually is, the business community may be dissuaded from investing in the country (Balisacan 1997).

There are several examples of poverty reduction programs in the Philippines that rely on the reliability of poverty rankings. For example, only households living in selected municipalities from the 20 poorest provinces are eligible for the national government's conditional cash transfer program during the first stages of its inception (Reyes & Tabuga 2012). Other government agencies such as PhilHealth, a government-owned corporation that provides health insurance, as well as non-government agencies also use poverty rankings to identify areas that need priority assistance (Addawe, Martinez & Perez 2007). With the use of narrow estimation methodologies, it will be difficult to gauge whether these intervention programs that rely on poverty rankings are implemented optimally.

Another important contribution of this study is to provide estimates of intertemporal poverty at the sub-national level. Locating where the poor are is important for socio-economic planning. For one, it makes the delivery of social services more efficient and cost-effective (Kanbur 1987). It also helps exploit dynamic externalities and geographic spill-over effects of economic growth (Ravallion & Jalan 1996). However, previous studies such as that of Reyes et al. 2011 and Bayudan-Dacuycuy & Lim 2013 do not clarify whether the areas with the highest levels of total poverty are also the same location as those areas with the highest levels of persistent or transient poverty. This is important to know because policymakers may be more concerned on channelling resources to areas with slightly lower levels of total poverty but with more prevalent persistent poverty than areas with higher levels of total poverty but significantly lower poverty persistence. Considering that persistent and transient poverty call for different policy mix, this type of research will also improve the efficiency of poverty reduction programs by being able to target appropriate interventions to where these are needed.

[46] Recently, ADB (2014) released a report suggesting that poverty in Asia increased from 1.6 billion in 2005 to 1.8 billion in 2010. This result contradicts a number of poverty assessments that were published by various international development agencies which suggest that poverty in the region has declined. Ravallion (2014) surmised that this contradiction stems from the measurement parameters used by ADB.

5.3 Methodology

To provide a more comprehensive picture of the intertemporal poverty in the Philippines compared to previous studies, this chapter measures intertemporal poverty using the methodologies proposed by Jalan & Ravallion (JR) (1998), Duclos, Araar & Giles (DAG) (2010), Foster (2009) and Gradin, del Rio and Canto (GRC) (2012) as discussed in Chapter 1.[47] The second part of this chapter differentiates the characteristics of the persistently poor, transiently poor and non-poor by estimating multinomial logistic models. The dependent variable measures the intertemporal poverty status of each household and takes two forms as shown in (5.1). The first form evaluates poverty status using the components approach while the second form uses the spells approach. As pointed out in Chapter 1, under the components approach, a household is considered persistently poor if its longitudinally-averaged income falls below the specified poverty line, transiently poor if its longitudinally-averaged income is higher than the poverty line but at least one of its cross-sectional incomes fell below the poverty line and non-poor if the household never experienced income shortfall (below the poverty line). Under the spells approach, a household is considered persistently poor if at least two of its cross-sectional incomes fell below the poverty line, transiently poor if only one of its cross-sectional incomes fell below the poverty line and non-poor if the household never experienced income shortfall. Each outcome of interest is regressed on several household characteristics such as the human capital available to the household, assets held by the household, access to basic services and geographic characteristics in the initial time period. These variables are included in the model because as discussed in Chapter 1, higher levels of human capital and assets, greater access to basic services and favourable geographic characteristics reduce poverty risk. For instance, it is well-established in the literature that higher levels of education expand socio-economic opportunities of poor Filipinos and thus, minimize the risk of staying in poverty for a long time (Maligalig et al. 2014). As discussed in Chapter 1 too, access to productive assets, basic services and spatial endowments can also be used to minimize the risk of long poverty spells (WB 2004; Schelzig 2005; WB 2013). Changes in these factors are also included as control variables in the regression models to capture for demographic and economic events (5.1). This is further discussed in Chapter 6.

[47] There are some limitations with regards to the measurement of poverty from the data. In particular, I do not have information about the poverty status of the households before the beginning of the observation period. Moreover, since I am using survey data conducted every three years, there is no way to know how people moved into and out of poverty in between the survey years. For instance, a household that is classified as poor in two consecutive survey years may have been non-poor in between. In other words, there is incomplete information about the duration of poverty because the data is censored. For simplicity, the discussion assumes that the observation periods follow a continuum.

(a) $W_1 = \begin{cases} 0, & hhld\ is\ nonpoor \\ 1, & hhld\ is\ persistently\ poor \\ 2, & hhld\ is\ transiently\ poor \end{cases}$ where poverty status is gauged based on longitudinally-averaged income

(b) $W_2 = \begin{cases} 0, & hhld\ is\ nonpoor \\ 1, & hhld\ is\ persistently\ poor \\ 2, & hhld\ is\ transiently\ poor \end{cases}$ where poverty status is gauged based on the number of episodes spent in poverty

$$W_i = \beta_1 Human\ Capital + \beta_2 Asset + \beta_3 Access\ to\ Services + \beta_4 Geography$$
$$+\beta_5 \Delta\ Human\ Capital + \beta_6 \Delta Assets + \beta_7 \Delta Access\ to\ Services + \varepsilon_{it} \qquad (5.1)$$

5.4 Empirical Results

5.4.1 Intertemporal Poverty in the Philippines

I begin with a presentation of cross-sectional estimates of poverty. Figure 5.1 plots the headcount poverty rate or the proportion of poor people in y-axis against different low income thresholds in the x-axis. I placed two vertical lines in the same figure to represent the lowest and highest poverty line under consideration in this study. Depending on the poverty line used, it is estimated that about 13% to 39% of the population can be considered poor in 2009 (Figure 5.1). Furthermore, Table 5.1 presents headcount poverty rate, poverty gap, severity of poverty and Watts index using the four sets of poverty lines. Separate estimates are also provided for urban and rural areas. The estimates suggest that the poverty gap or average income shortfall is about 3% to 13% while the severity of poverty or average squared income shortfall is roughly 1% to 5% of the poverty line in 2009. If all household incomes per capita were increased by 2% per year, the estimates of Watts index suggest that poverty is expected to be eradicated after 8 to 9 years from 2009.[48] Table 5.1 also indicates that poverty in the Philippines has a remarkable geographic feature. In particular, the proportion of poor in rural areas is about two to four times the headcount poverty rate in urban areas. The magnitude of income shortfall and the inequality among the poor are also significantly higher in rural areas than in urban areas. Hence, it is not surprising to note that from 2009, it will take about 13 years for all households in rural areas to exit US$2/day poverty compared to the 4 years needed for households from urban areas to accomplish the same feat, assuming a uniform 2% annual income growth.

Although the numbers presented in Table 5.1 are useful for gauging how significant poverty is in the Philippines, they provide limited information about poverty dynamics over

[48] As explained earlier, the average exit time needed to exit poverty is computed by dividing the value of the Watts index by the expected income growth rate. For example, the Watts index value in 2009 using the US$2/day poverty line is 16.64. Dividing this by an assumed annual income growth rate of 2% will yield 8.32. This means that, under the assumption that all incomes grow at a uniform rate of 2% per year, US$2 poverty rate will be eradicated after 8.32 years.

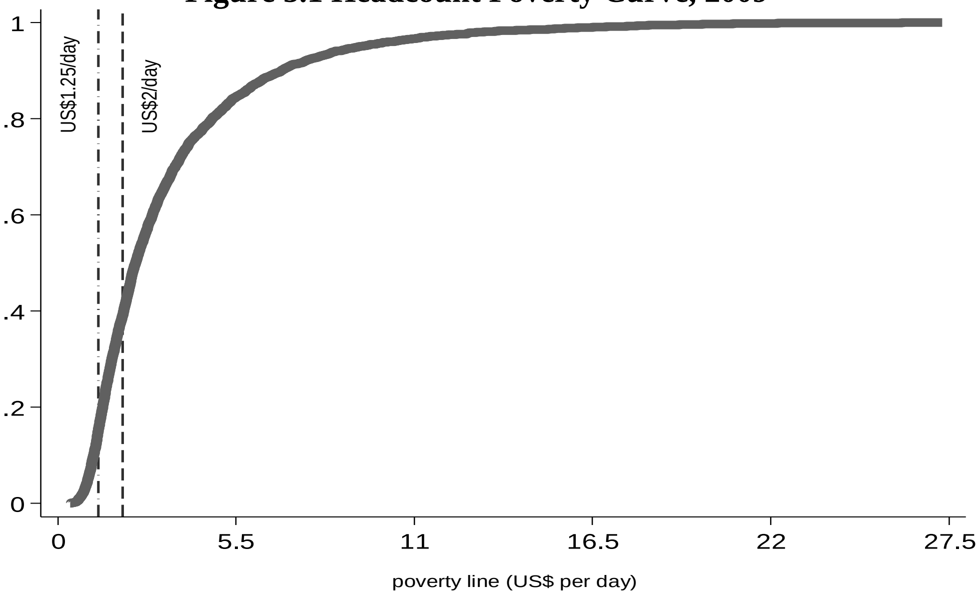
time. For instance, the slight increase in poverty from 2003 to 2006 and minimal reduction between 2006 and 2009, do not readily imply limited movements into and out of poverty (Reyes et al. 2011). This can be proved by examining poverty transition rates presented in Tables 5.2 to 5.5. The rows in each table are divided into three main panels, from top to bottom, poverty transition rates between 2003 and 2006; 2006 and 2009; 2003 and 2009 while the columns present estimates for the national level as well as for urban and rural areas.

The estimated poverty transition rates show a large degree of poverty inflow and outflow despite the minimal changes in the cross-sectional measures of poverty. For example, 75% of the population with incomes below US$2/day in 2003 were non-poor in 2009 while the other 25% remained (US$2/day) poor. This highlights the importance of providing a longitudinal perspective when examining poverty.

Poverty Estimates using the Components Approach

In this section, I present the estimates of persistent and transient poverty using the JR and DAG approaches. As explained in Chapter 1, although both methodologies follow the components approach of measuring intertemporal poverty, they conceptualize transient poverty differently. The JR approach defines transient poverty as the residual when persistent poverty is subtracted from total poverty whereas DAG links transient poverty in terms of a person's level of risk aversion.

Figure 5.1 Headcount Poverty Curve, 2009



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 5.1 Cross-Sectional Measures of Poverty in the Philippines, 2003-2009

Poverty Measure	2003			2006			2009		
	Phils	Urban	Rural	Phils	Urban	Rural	Phils	Urban	Rural
US$1.25/day Poverty Line									
Headcount poverty rate	18.29	6.54	29.67	19.25	7.32	30.80	15.40	6.54	23.97
	0.55	0.59	0.85	0.06	0.62	0.86	0.54	0.63	0.82
Poverty gap	4.47	1.19	7.65	4.74	1.53	7.85	3.15	1.17	5.07
	0.17	0.14	0.29	0.18	0.17	0.29	0.14	0.14	0.24
Severity of Poverty	1.63	0.36	2.86	1.66	0.47	2.81	0.99	0.31	1.65
	0.08	0.06	0.15	0.08	0.07	0.14	0.06	0.05	0.11
Watts Index	5.68	1.44	9.79	5.94	1.86	9.90	3.85	1.37	6.24
	0.24	0.18	0.41	0.24	0.22	0.40	0.19	0.17	0.32
US$2/day Poverty Line									
Headcount poverty rate	40.52	21.68	58.78	43.55	25.01	61.52	39.19	22.08	55.78
	0.71	0.96	0.88	0.72	1.03	0.87	0.71	1.00	0.89
Poverty gap	14.24	6.04	22.19	15.12	7.00	22.99	12.53	6.03	18.83
	0.30	0.33	0.44	0.31	0.36	0.44	0.28	0.34	0.41
Severity of Poverty	6.51	2.35	10.54	6.86	2.74	10.85	5.26	2.28	8.15
	0.18	0.16	0.28	0.18	0.19	0.28	0.15	0.16	0.24
Watts Index	19.62	7.81	31.05	20.72	9.10	31.99	16.64	7.72	25.28
	0.46	0.46	0.70	0.47	0.51	0.70	0.41	0.47	0.61
*0.5*Median Poverty Line*									
Headcount poverty rate	15.39	4.69	25.76	15.65	5.75	25.25	13.00	5.32	20.45
	0.51	0.49	0.82	0.53	0.57	0.83	0.50	0.56	0.78
Poverty gap	3.73	0.93	6.44	3.51	1.05	5.90	2.66	0.95	4.31
	0.16	0.12	0.27	0.15	0.14	0.25	0.13	0.12	0.22
Severity of Poverty	1.33	0.28	2.34	1.16	0.30	1.99	0.82	0.25	1.37
	0.07	0.05	0.13	0.06	0.05	0.11	0.05	0.04	0.10
Watts Index	4.70	1.12	8.17	4.33	1.26	7.31	3.22	1.11	5.27
	0.21	0.16	0.37	0.20	0.18	0.34	0.17	0.15	0.29
Official Poverty Line									
Headcount poverty rate	27.00	12.42	41.13	28.19	14.01	41.93	28.41	15.16	41.25
	0.64	0.80	0.90	0.66	0.85	0.90	0.66	0.89	0.91
Poverty gap	7.15	2.75	11.42	7.44	3.12	11.63	7.24	3.53	10.83
	0.21	0.22	0.34	0.22	0.25	0.35	0.22	0.26	0.33
Severity of Poverty	2.71	0.89	4.47	2.78	1.03	4.47	2.59	1.16	3.98
	0.11	0.10	0.18	0.11	0.11	0.18	0.10	0.11	0.17
Watts Index	9.21	3.38	14.85	9.51	3.86	14.99	9.14	4.34	13.79
	0.30	0.29	0.49	0.31	0.33	0.49	0.30	0.34	0.46

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Note: Since these numbers are estimated from the longitudinal data, they are slightly different from the estimates presented in Chapter 2 which used pseudo-panel data. The numbers in smaller font size are standard errors.

Figures 5.2 and 5.3 show the results. For both figures, the rows correspond to the estimates for each of the four sets of poverty lines used in the computations while the columns correspond to the different measures of poverty estimated at the national, urban and rural levels. The height of the bars corresponds to the magnitude of intertemporal poverty wherein the dark-shaded bars correspond to persistent poverty while the light-shaded bars correspond to transient poverty.

There are several interesting features that can be drawn from the estimates based on the JR procedure. First, most of the indicators show that poverty is mostly persistent in nature. For instance, about 96% of the total observed US$2/day poverty is persistent and only 4% can be attributed to the effect of transitory income shortfall. Interestingly, the relative importance of persistent poverty declines with the poverty line. For example, if US$1.25/day poverty line is used instead of US$2/day, the relative importance of headcount poverty persistence drops to 87%.

Table 5.2 Poverty Transition Matrix, US$1.25/Day Poverty Line

	Philippines		Urban		Rural	
	Poor	**Non-Poor**	**Poor**	**Non-Poor**	**Poor**	**Non-Poor**
2003	**2006**					
Poor	67.21	32.79	54.84	45.16	69.86	30.14
Non-Poor	8.51	91.49	4.00	96.00	14.33	85.67
2006	**2009**					
Poor	55.69	44.31	47.56	52.44	57.57	42.43
Non-Poor	5.79	94.21	3.30	96.70	9.02	90.98
2003	**2009**					
Poor	49.42	50.58	35.68	64.32	52.36	47.64
Non-Poor	7.78	92.22	4.50	95.50	12.00	88.00

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 5.3 Poverty Transition Matrix, US$2/Day Poverty Line

	Philippines		Urban		Rural	
	Poor	**Non-Poor**	**Poor**	**Non-Poor**	**Poor**	**Non-Poor**
2003	**2006**					
Poor	84.64	15.36	75.77	24.23	87.81	12.19
Non-Poor	15.56	84.44	10.96	89.04	24.02	75.98
2006	**2009**					
Poor	76.14	23.86	66.57	33.43	79.91	20.09
Non-Poor	10.69	89.31	7.24	92.76	17.20	82.80
2003	**2009**					
Poor	75.28	24.72	64.05	35.95	79.30	20.70
Non-Poor	14.61	85.39	10.47	89.53	22.24	77.76

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 5.4 Poverty Transition Matrix, Half of Median Poverty Line

	Philippines		Urban		Rural	
	Poor	**Non-Poor**	**Poor**	**Non-Poor**	**Poor**	**Non-Poor**
2003	**2006**					
Poor	61.61	38.39	51.35	48.65	63.42	36.58
Non-Poor	7.30	92.70	3.51	96.49	12.01	87.99

2006	**2009**					
Poor	55.58	44.42	52.26	47.74	56.32	43.68
Non-Poor	5.10	94.90	2.46	97.54	8.33	91.67
2003	**2009**					
Poor	47.41	52.59	35.46	64.54	49.52	50.48
Non-Poor	6.74	93.26	3.84	96.16	10.36	89.64

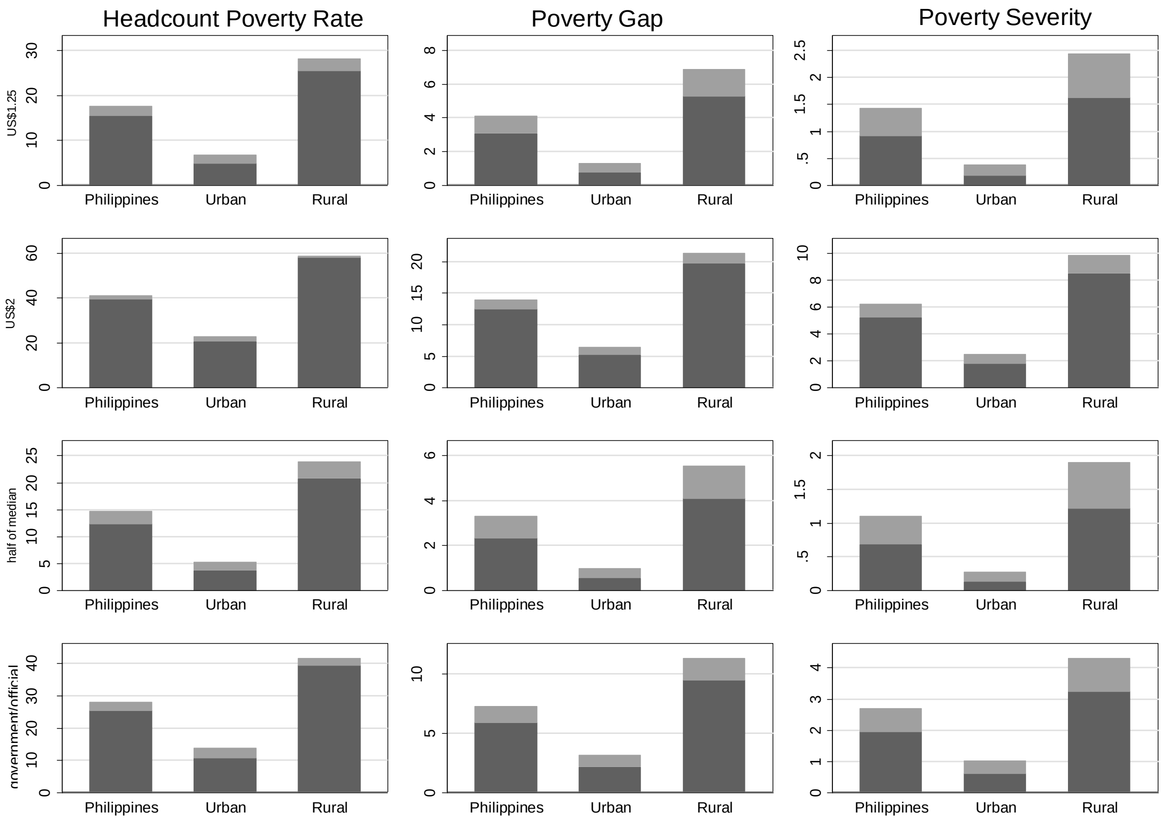
Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 5.5 Poverty Transition Matrix, Government Poverty Line

	Philippines		**Urban**		**Rural**	
	Poor	**Non-Poor**	**Poor**	**Non-Poor**	**Poor**	**Non-Poor**
2003	**2006**					
Poor	71.81	28.19	61.66	38.34	74.77	25.23
Non-Poor	12.06	87.94	7.25	92.75	18.99	81.01
2006	**2009**					
Poor	72.10	27.90	65.21	34.79	74.33	25.67
Non-Poor	11.26	88.74	7.00	93.00	17.36	82.64
2003	**2009**					
Poor	67.07	32.93	57.00	43.00	70.02	29.98
Non-Poor	14.11	85.89	9.22	90.78	21.15	78.85

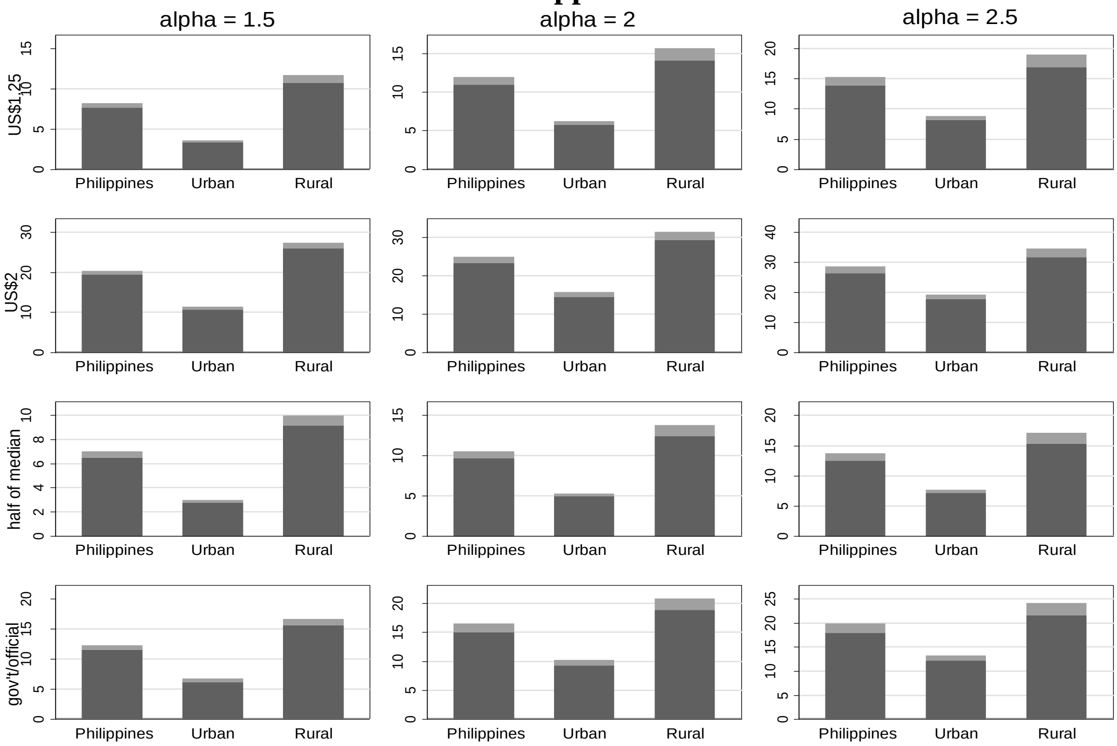
Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Figure 5.2 Intertemporal Poverty Estimates using the JR Approach



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009

Figure 5.3 Intertemporal Poverty Estimates using the DAG Approach



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

The share of transient poverty also increases when we shift from poverty incidence to poverty gap and poverty severity. In particular, about 10% to 29% of the poverty gap and 16% to 38% of the poverty severity can be linked with transient poverty. Second, transient poverty is more common in urban areas than in rural areas. In urban areas, transient poverty accounts for approximately 11% to 29% of its total headcount poverty rate while only 2% to 10% of the rural poverty can be attributed to transitory downturn in monetary fortunes.

As discussed in Chapter 1, the JR approach does not differentiate a household with a relatively stable income flow from a household with highly fluctuating income as long as their longitudinally-average incomes are equal. Hence, an interesting question to be asked is how will these poverty estimates be affected when we take into account people's risk aversion to unstable income flows? The DAG approach is used to investigate this issue. In the following analysis, I set the aversion parameter α = 1.5, 2 or 2.5, where higher values imply greater risk aversion. These values imply that households are not risk-neutral.[49] Figure 5.3 presents the poverty estimates. The rows identify the poverty lines used while the columns represent the intertemporal poverty estimates for different levels of risk aversion to income fluctuations at

[49] A value of 1 for the risk aversion parameter α would imply that all households are risk-neutral.

the national, urban and rural level. Again the height of the dark-shaded and light-shaded bars correspond to the magnitude of persistent and transient poverty, respectively. At $\alpha = 1.5$ and using US$2/day poverty line, the height of the light-shaded bar suggests that households would be willing to increase the average poverty gap by 1 percentage point just to remove the variability in the income shortfall observed from 2003 to 2009. If I divide the height of the light-shaded bar by the total height of the stacked bar, I find that the estimated share of transient poverty based on the DAG approach is roughly 5% to 7% of the total poverty when $\alpha= 1.5$ and increases to 8% to 9% when $\alpha= 2.5$. In other words, as households become more risk-averse, transient poverty becomes more common.

Poverty Estimates using the Spells Approach

Table 5.6 presents all possible poverty spells in years 2003, 2006 and 2009 with respect to different poverty lines. The results show that about 46% to 76% of the population never experienced poverty, 12% to 15% were poor for only one survey year, 9% to 13% were poor for two years and 6% to 28% were consistently poor for all three years. Following the conventional spells approach, these numbers may also be used to estimate persistent and transient poverty. If I define poverty persistence as being poor for at least two survey years, the estimates presented in Table 5.6 suggest that between 16% to 41% of the population were persistently poor. Despite the differences in the methodologies, it is interesting to note that the spells-based estimates of poverty persistence are roughly the same as the estimated proportion of population who were persistently poor based on the JR approach.[50] Both methodologies suggest that poverty is not just once-in-a-lifetime experience wherein a significant fraction of the population experience poverty for a long time period. However, a different story emerges when I compare the estimates of total poverty. Following the spells approach, total poverty would correspond to those who were poor for at least one time period. Given this definition, total poverty is estimated to be approximately 29% to 54% of the population. These numbers are significantly higher relative to the estimates of total poverty based on the components approach, which placed poverty at around 18% to 41%. Consequently, the relative importance of persistent and transient poverty also differ across these two estimation approaches. In particular, the results based on the conventional spells approach suggest that approximately 58% to 77% of the total (headcount) poverty observed is persistent, whereas the components

[50] The estimated proportion of population who are persistently poor based on the JR approach is 15% using the US$1.25 poverty line and 40% using the US$2 threshold.

Table 5.6 Population Share by Intertemporal Poverty Status

Poverty Status	$1.25 poverty line			$2 poverty line		
(2003, 2006, 2009)	Phils	Urban	Rural	Phils	Urban	Rural
P,P,P	7.75	1.91	13.4	28.33	12.33	43.84
	0.39	0.35	0.67	0.65	0.79	0.90
P,P,NP	4.55	1.67	7.33	5.97	4.1	7.78
	0.29	0.29	0.48	0.33	0.45	0.48
P,NP,P	1.29	0.42	2.14	2.18	1.56	2.78
	0.16	0.16	0.28	0.20	0.27	0.29
P,NP,NP	4.7	2.53	6.81	4.05	3.7	4.39
	0.29	0.37	0.44	0.27	0.42	0.34
NP,P,P	2.97	1.57	4.33	4.83	4.32	5.32
	0.25	0.31	0.40	0.33	0.53	0.41
NP,P,NP	3.98	2.17	5.74	4.42	4.26	4.58
	0.27	0.34	0.41	0.30	0.48	0.34
NP,NP,P	3.38	2.64	4.11	3.86	3.87	3.84
	0.28	0.42	0.38	0.30	0.48	0.36
NP,NP,NP	71.37	87.08	56.15	46.37	65.86	27.47
	0.65	0.81	0.91	0.73	1.11	0.79
	Half of median poverty line			**Gov't poverty line**		
	Phils	**Urban**	**Rural**	**Phils**	**Urban**	**Rural**
P,P,P	5.91	1.33	10.34	15.5	6.12	26.36
	0.35	0.28	0.61	0.54	0.60	0.83
P,P,NP	3.58	1.07	6	4.05	1.93	6.24
	0.26	0.23	0.45	0.27	0.30	0.43
P,NP,P	1.39	0.33	2.42	2.72	1.32	4.16
	0.16	0.13	0.28	0.23	0.26	0.37
P,NP,NP	4.52	1.95	7	5.2	3.68	6.83
	0.28	0.32	0.45	0.30	0.42	0.43
NP,P,P	2.8	1.67	3.88	5.02	3.48	6.68
	0.26	0.34	0.39	0.32	0.47	0.44
NP,P,NP	3.38	1.67	5.03	4.13	3.19	5.17
	0.25	0.31	0.39	0.27	0.39	0.37
NP,NP,P	2.91	1.99	3.81	5.69	5	6.52
	0.25	0.35	0.36	0.34	0.51	0.44
NP,NP,NP	75.53	89.98	61.52	61.08	80.29	44.03
	0.62	0.73	0.90	0.72	1.02	0.88

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Note: P - Poor, NP - Non-Poor. The numbers in smaller font size are standard errors.

approach suggests that persistent poverty account for 84% to 96% of total (headcount) poverty.[51]

As pointed out at the beginning of this chapter, the concepts of persistent and transient should not be used interchangeably because they are measuring different aspects of socio-economic disadvantage. Measuring persistent and transient poverty at the national-level is the first step to understand the dynamic feature of poverty in the country. Overall, the results presented in this section suggest that poverty in the Philippines can be considered to be mostly persistent in nature. Nevertheless, the magnitude of transient poverty is not negligible. The findings of the robustness checks point that the share of transient to total observed poverty tends to increase dramatically as I increase the poverty line and/or use a poverty index that is more sensitive to the illfare of the poorest of the poor.

5.4.2 Where are the Persistently and Transiently Poor?

This section revisits the spatial distribution of intertemporal poverty in the Philippines. Similarly to the previous section, estimates are presented for both the components and spells approaches. This allows us to evaluate the robustness of spatial poverty rankings across the methodologies considered in this study. Although this section does not provide more disaggregated estimates beyond the regional-level due to sample size restrictions, the analysis identifies proximate areas that could be potentially useful for the targeting of poverty-reduction programs.[52]

Components Approach

Figure 5.4 shows the spatial distribution of intertemporal headcount poverty while Figure 5.5 also presents the estimates for intertemporal poverty gap and poverty severity for the 17 geographic regions in the Philippines using the JR approach. The columns represent the estimated incidence, depth and severity of poverty while the row correspond to the different poverty lines used. One take on the results is that, when longitudinal average income data is used, it provides evidence that is consistent with an orthodox view that most of the persistently poor live in the regions with the lowest average per capita income. In particular, I find that

[51] Had I defined persistent poverty as those who experienced poverty for two consecutive survey years, the relative importance of persistent poverty would be approximately 50% to 73%.

[52] A more informative exercise is to provide estimates at the administrative level (e.g., provinces or municipalities). However, the small sample sizes may lead to high standard errors of intertemporal poverty estimates. In this context, there are several small area estimation techniques that can be used (Elbers, Lanjouw & Lanjouw 2003; Martinez 2013; Martinez, Lucio & Vilaruel 2014), etc. This is reserved for future research.

Regions 4B, 9, Caraga and ARMM have the highest prevalence of total poverty and poverty persistence. Not surprisingly, these regions have the lowest longitudinally-averaged income per capita (Appendix Table A5.3). On the other hand, NCR, the region with the highest longitudinally-averaged income, posted the lowest total poverty and poverty persistence rate. Other regions with low poverty persistence are also from the northern Philippines which include Regions 3 and 4A.

Focusing on the robustness of the results, I find that the regional ranking of poverty persistence is relatively uniform across varying measurement parameters. Nevertheless, there are slight changes in the rankings that are worth pointing out when measurement parameters are changed. For example, the magnitude of persistent poverty tends to be higher in Region 9 when lower poverty lines or poverty measures that are more sensitive to the ill fare of the poorest of the poor are used. The opposite happens for Caraga wherein poverty persistence decreases when either lower poverty lines or more inequality-sensitive measures are used.

A high level of transient poverty indicates how erratic a household income flow is over time. Understanding how erratic income flows create poverty cycles in certain areas is important to be able to prevent economic stagnation. Thus, like persistent poverty, it is also instructive to examine the regional distribution of transient poverty. Interestingly, a separate examination of transient poverty reveals a very different picture compared to what the estimates of poverty persistence portray. Both Figures 5.4 and 5.5 highlight that it is not necessarily the case that regions with the highest persistent poverty are also the same regions with the highest transient poverty. Furthermore, in contrast to poverty persistence wherein the regional ranking is quite robust under various measurement parameter specifications, the regional ranking with respect to transient poverty heavily depends on the poverty line and type of poverty measure used. For example, NCR ranks third among the regions with the highest proportion of households that are transiently poor with respect to the US$2 poverty line but it ranks bottom with respect to other measures of poverty persistence. On the other hand, ARMM posted the lowest transient poverty with respect to US$2 poverty threshold.[53]

When aversion to income fluctuations is taken into account by using the DAG approach the same regions with high and low persistent and transient poverty can be identified (Figure 5.6).

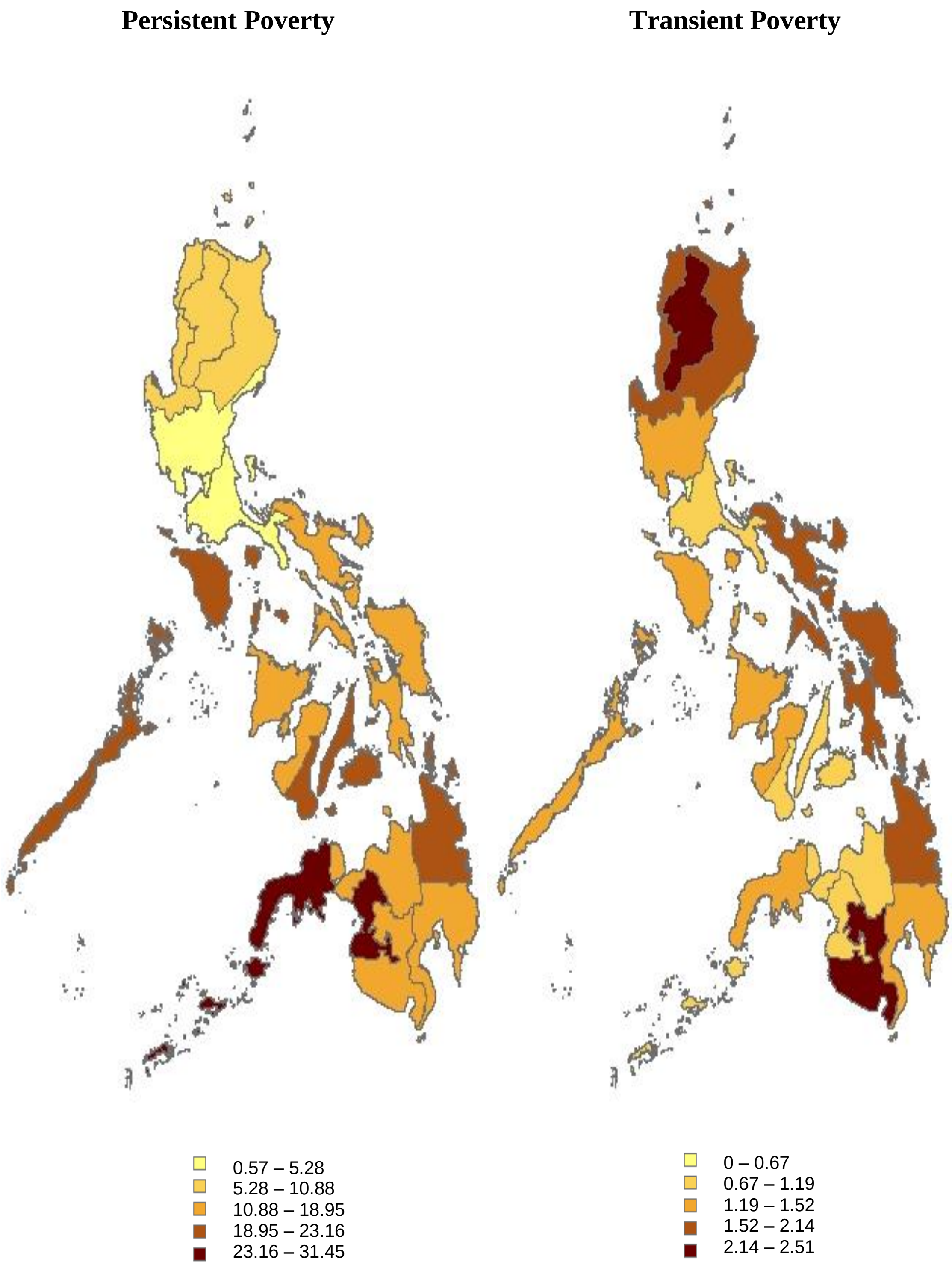
[53] As pointed out in Chapter 1, the JR approach does not ensure that the total poverty is always greater than or equal to poverty persistence. This happens in the case of Region 7 and ARMM wherein the computed US$2 transient poverty rates are negative. Appendix Table A5.3 provides adjusted estimates which ensure that all poverty estimates are non-negative.

Spells Approach

Figure 5.7 shows the estimates of selected indicators of intertemporal poverty following the spells approach. In particular, the first column presents the duration-adjusted poverty headcount ratio proposed by Foster (2009) while the second and third columns present selected indices from the class of intertemporal poverty measures proposed by GRC (2012). As explained in Section 1.4.1, the intertemporal poverty measures proposed by Foster (2009) and GRC (2012) address the limitations of conventional spells-based measures that narrowly focus on headcount poverty rate and are insensitive to poverty duration. It is clear from Figure 5.7 that Regions 7, 9, ARMM and Caraga have the highest intertemporal poverty estimates. In 7 out of 12 indicators, ARMM ranked first among the regions with the highest levels of poverty. For instance, roughly 55% to 90% of the household population in ARMM have experienced poverty for at least one episode from 2003 to 2009. Interestingly, except for the US$2/day poverty line, ARMM is not in the list of four regions with the highest average duration of poverty. Nevertheless, the average duration of poverty is still relatively high because a typical poor household in ARMM experienced poverty in two out of the three survey years. Like ARMM, Region 9 has widespread poverty that persists over the years. In fact, the estimates show that Region 9 posted the highest average poverty duration wherein households spend 2.1 to 2.5 (survey) years living with income less than the poverty line. In contrast, Regions 3, 4A and NCR have consistently shown the lowest intertemporal poverty levels.

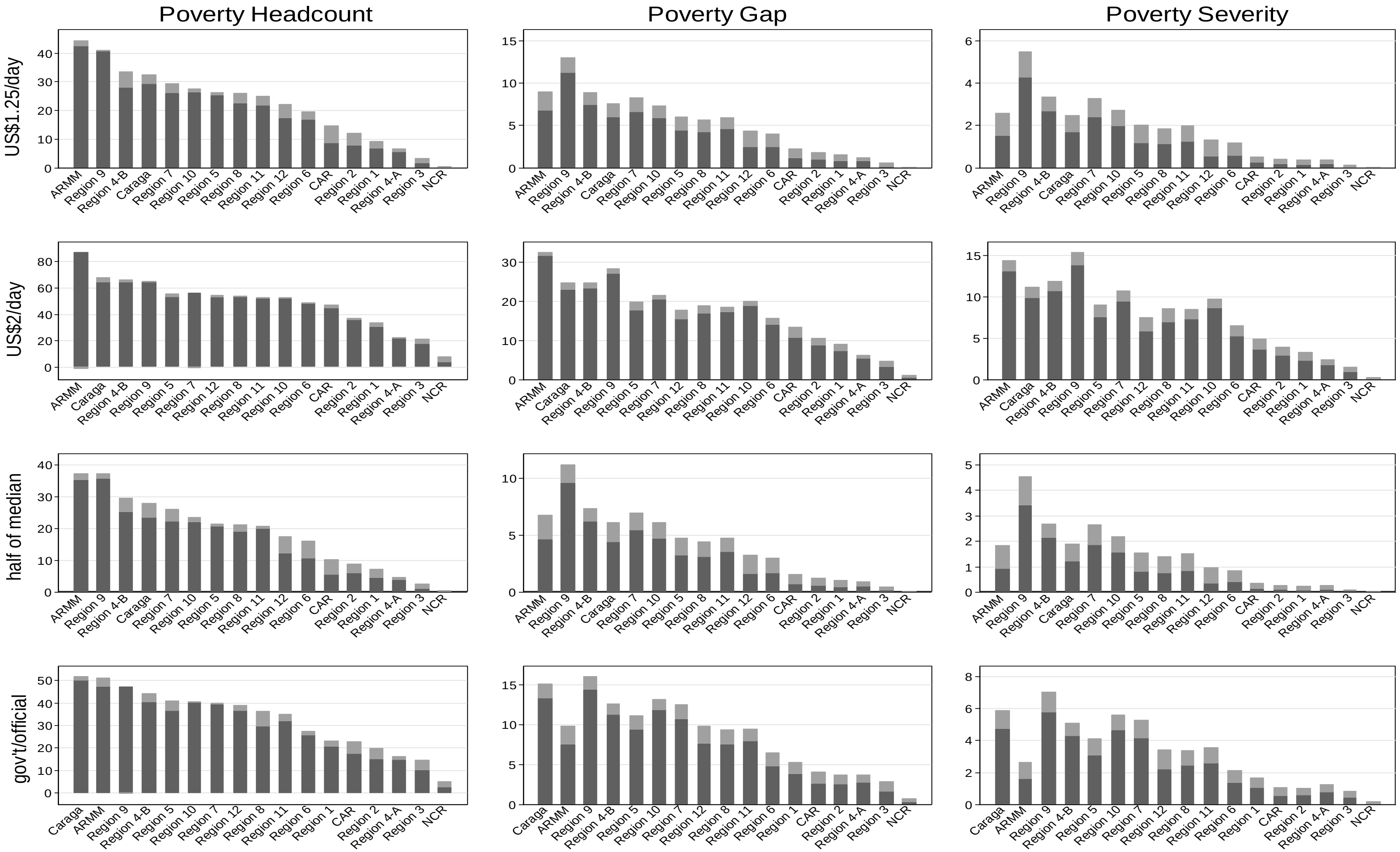
In summary, poverty in the Philippines has a remarkable spatial feature. In general, most of the regions with the highest levels of chronic or persistent poverty are in the southern part of the Philippines: Regions 7, 9, ARMM and Caraga. This is in sharp contrast with the regions that posted the lowest levels of poverty persistence which are all located up north, close to the country's centre of commerce. As I investigate the economic structure of each region, I find that the areas which heavily rely in the agriculture sector based on share of agricultural employment to total employment tend to have higher proportion of persistently poor households. This is consistent with the findings from a number of studies that have concluded poverty in the Philippines a predominantly rural and agricultural phenomenon (Schelzig 2005; Aldaba 2010). There are several substantial explanations for this. First, the structure of agriculture is predominantly small-scale and thus, those who are agriculture-dependent are unable to take advantage of economies of scale. Second, the Philippines has significant

Figure 5.4 Map of Persistent and Transient (Headcount) Poverty



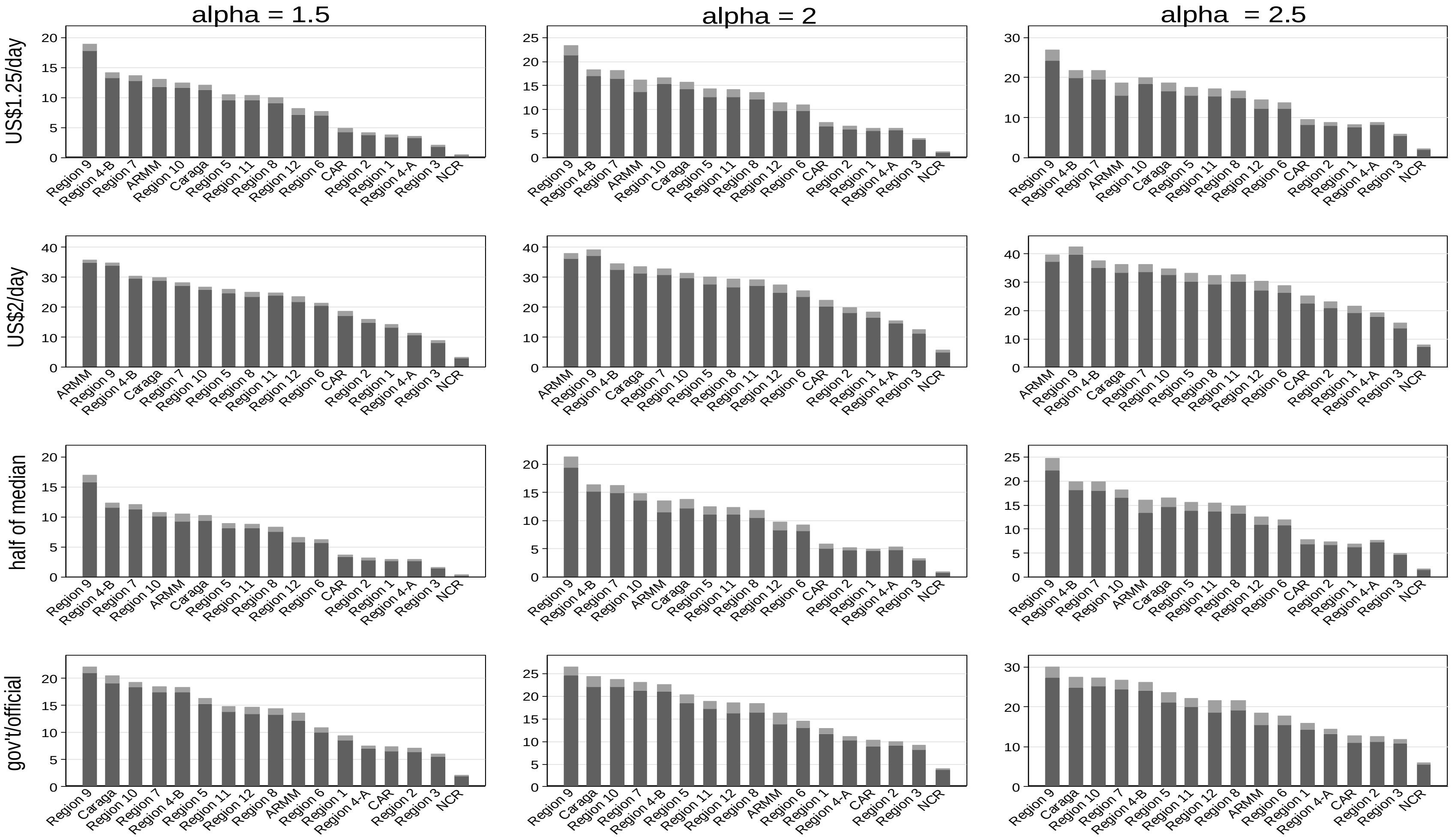
Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Figure 5.5 Regional Intertemporal Poverty Estimates (JR Approach)



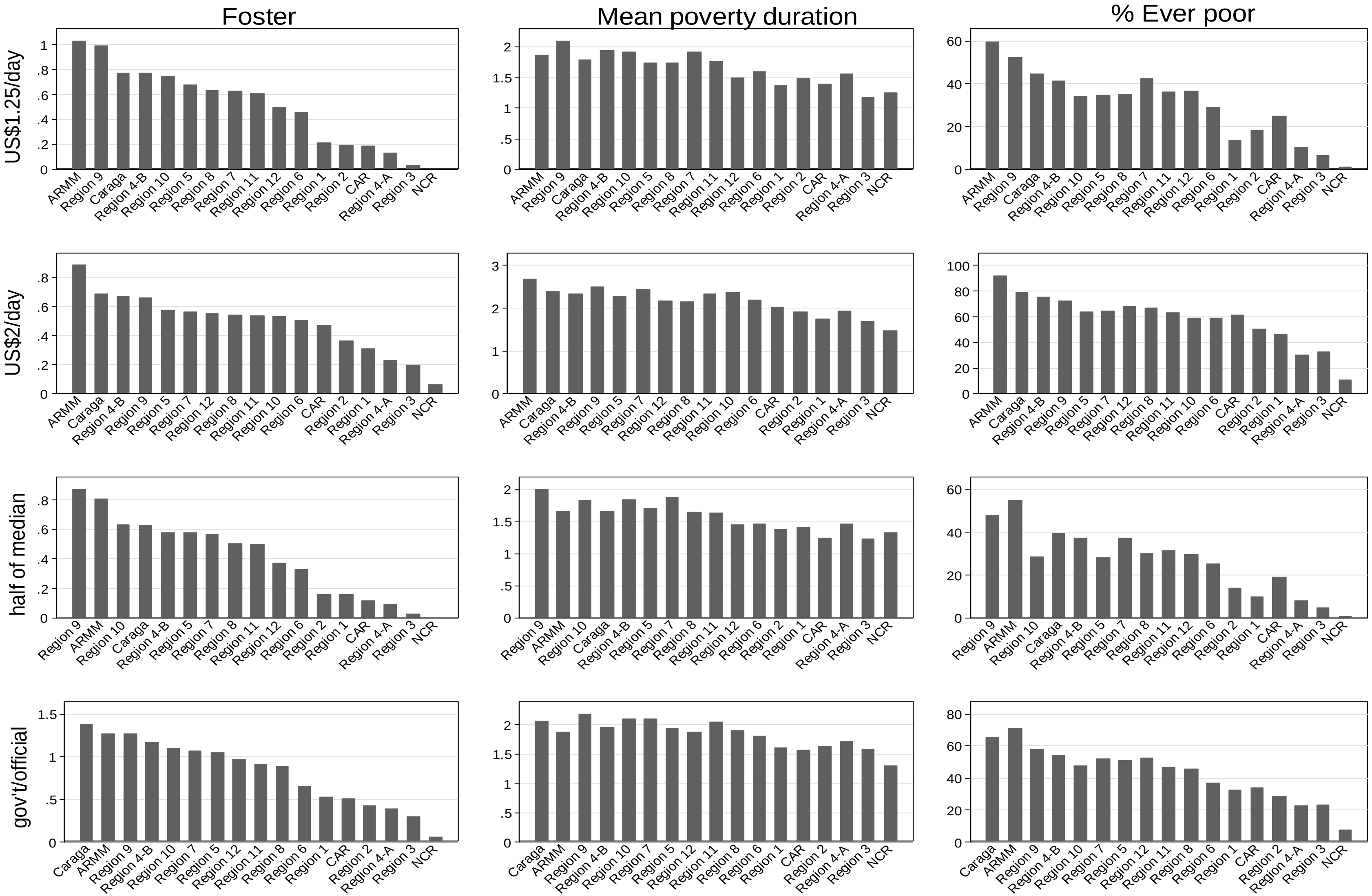
Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Figure 5.6 Regional Intertemporal Poverty Estimates (DAG Approach)



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Figure 5.7 Regional Intertemporal Poverty Estimates (Spells Approach)



Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

exposure to bad weather, as it sits in one of the most tropical cyclone-prone areas in the world that experience an average of ten typhoons every year (PAG-ASA 2014).[54] These weather disturbances often have debilitating effects as estimates suggest that a strong typhoon in the Philippines can destroy more than US$ 75 million (approximately 3 billion Philippine pesos using prevailing exchange rates) worth of agricultural crops (PAG-ASA 2014). Small scale agricultural workers are usually the most affected because their produce over several months can be wiped out easily by one typhoon. Third, the Philippines has weak institutions to support agricultural expansion or buffer risks present in the agricultural sector. Previous studies identify inadequate provision of socio-economic services such as lack of access to concrete or paved roads exacerbates the chronic poverty in remote agricultural areas (Schelzig 2005; Aldaba 2009). Weak property rights also contribute to why rural households are trapped in longer poverty episodes compared to their urban counterparts. While there have been several agrarian reforms that have been implemented in the Philippines since the 1970s which aim to improve the welfare of the low income households in rural areas who depend on access to land for their day-to-day living, existing systems (e.g., credit market) have not delivered the maximal economic opportunities envisaged by the reform (Balisacan 2002).

Although more urbanized regions like Regions 3, 4A and NCR show lower levels of persistent poverty, transient poverty is not a trivial problem in these areas. What are the causes of transient income downturn in urban areas? One is the lack of opportunities due to population strain. As the prospects of more economic opportunities usually attract the rural poor to migrate to urban centers, urban population starts growing rapidly. The scarce opportunities available for the growing population can lead to a highly unstable income flow. Second, it is also widely perceived that people living in urban areas are more exposed to health and safety risks due to makeshift housing, poor sanitation, fire hazards and crime (Housing and Urban Development Coordinating Council 2008; Aldaba 2009). In general, when socio-economic shocks erode the meagre assets accumulated by households, they can be pulled back into transient poverty.

Although the different intertemporal poverty estimation tools have produced roughly similar lists of regions with the highest and lowest levels of poverty persistence, the rankings are not perfectly robust across all approaches, especially with respect to transient poverty. While it may be true that the minimal differences in the regional rankings may not have a profound policy impact, policy research still needs to address the issue of the robustness of poverty estimates by using more comprehensive methods. In addition, the impact may be more severe if a similar computational exercise was undertaken at finer administrative levels where

[54] PAG-ASA, the Philippines's weather bureau, stands for Philippine Atmospheric, Geophysical and Astronomical Services.

resources are allocated on the basis of various indicators which includes poverty. However, due to sample size limitations, this study did not conduct a rigorous intertemporal poverty ranking of the provinces. This is reserved for future research.

5.4.3 Who are the Persistently and Transiently Poor?

The objective of this section is to draw our attention to the possible heterogeneity in the intertemporal poverty experience of Filipino households. Appendix Tables A5.1 and A5.2 provide a descriptive summary of the proportion of the population classified as persistently poor, transiently poor and non-poor, disaggregated by different household characteristics. The results show that the intertemporal poverty is higher in households whose heads are male, with low educational attainment and are working in the informal sector. In addition, those who are living in southern Philippines especially those who heavily rely on entrepreneurial activities and on agriculture sector have higher risk on experiencing more severe poverty status over time.

Table 5.7 summarizes the results of the statistical models that I estimated to measure the correlation of each factor with intertemporal poverty in the presence of other household characteristics using the components and spells approach and different poverty line specifications. In particular, it shows the regression coefficients of the multinomial logistic models for the probability of being classified as persistently poor, transiently poor and non-poor. These coefficients can be interpreted as multinomial log-odds, i.e., for a unit change in the explanatory variable, the logit of the propensity to be classified as persistently poor (or transiently poor) relative to being non-poor will change by an amount equivalent to the regression coefficient, holding all other explanatory variables constant.[55] As pointed out in Chapter 1, the explanatory variables are chosen based on standard human capital theories.

In general, the regression models presented in Table 5.7 confirm the importance of standard socio-demographic characteristics like sex, age and education in explaining a household's intertemporal poverty status. In particular, the results show that individuals living in female-headed households are at risk of spending more time in poverty than their counterparts living in male-headed households. Interestingly, this result deviates from the descriptive statistics provided in Appendix Tables A5.1 and A5.2 wherein I observe lower poverty rates for female-headed households. However, this does not imply that women in the country are not disadvantaged. In fact, controlling for a number of socio-demographic

[55] If we take the exponential of these regression coefficients, we will get the relative risk ratios.

characteristics seems to erode the advantage of female-headed households over male-headed households.[56] Hence, the model estimates suggest that after controlling for other factors, living in female-headed households in the country is still positively correlated with longer poverty spells. Thus, it is not surprising that the Philippine government still acknowledges women as one of the most vulnerable groups who must be provided with social protection against the risk of falling into a vicious cycle of poverty (NCRFW 2004). On the other hand, the age of the household head presents a typical concave relationship with income (Kearl & Pope 1983) and consequently, a convex relationship with the length of stay in poverty. In particular, during prime age years, individuals are in the process of climbing up the occupational ladder. With higher income accompanying this process, these people have less risk of falling into poverty. However, beyond a certain age threshold, individuals start to experience income deterioration. For instance, some of those who used to work in the formal sector could only rely mostly on pensions after retirement, representing a fraction of their previous income. With advancement in age, some of those who work in the informal sector have less employment opportunities because they are less capable of performing physical tasks that jobs in the informal sector entail. Furthermore, the estimated models reiterate the importance of education in minimizing the risk of falling into poverty. Better educated households, as proxied by educational attainment of the household head, face less risk of long poverty spells. In this context, higher educational attainment serves as a mechanism for expanding one's overall social mobility prospects. This is consistent with the human capital theory which suggests that the skills and knowledge imparted by higher educational attainment improves an individual's productivity, and in turn, his/her ability to mobilize resources (Tilak 2002). While educational attainment explains a significant portion of the differences in household income and poverty status, education remains a development puzzle in the country. For instance, compared to other countries with similar level of development, the Philippines has much higher gross enrolment rates in secondary and tertiary education (WDI 2014). Despite this advantage, significant pockets of

[56] The descriptive statistics confirm results from previous studies suggesting that Philippines is one of the few countries where female-headed households do not necessarily portray a vulnerable group (Chant 1997). Whereas female-headed households in many countries are usually characterized as a vulnerable group due to the presumed lack of ability of women to mobilize socio-economic resources for the family, female-headed households in the Philippines are more likely to be found in middle and high-income groups. Several reasons have been offered to explain this anomaly. First, the majority of these female heads are widows in their senior years who have had enough time to accumulate assets (Chant 1997). Second, female-headed households are more likely to have higher proportions of members who are already working. In fact, Ofstedal, Reidy & Knodel (2004) estimate that about 40% of total income of female-headed households come from the contributions of children and other family members compared to 25% for male-headed households. Third, female-headed households in the country are characterized by successful women who have higher educational attainment than an average male household head.

Table 5.7 Regression Coefficients of Multinomial Logistic Models for Intertemporal Poverty in the Philippines (Base = Non-poor)

Variable	Components Approach				Spells Approach			
	US$1.25		US$2		US$1.25		US$2	
	Persistent	Transient	Persistent	Transient	Persistent	Transient	Persistent	Transient
Main Island (base = NCR)								
Luzon	14.74	1.615**	1.761***	.7193**	1.738	1.835**	1.37***	.7893***
Visayas	15.94	2.246***	2.63***	.8773***	2.871**	2.439***	2.161***	.918***
Mindanao	16.18	2.438***	3.055***	1.192***	3.093**	2.643***	2.645***	1.15***
Urban	-.7792***	-.3362**	-.8372***	-.4097***	-.6535***	-.3525**	-.752***	-.4219***
Hhld head is Male	-.8212*	-0.02772	-0.3164	0.1372	-.7392*	0.01908	-0.3364	0.2069
Hhld head's Age	-.146***	-.07295***	-.06805**	1.29E-02	-.146***	-.0658**	-.04758*	0.008981
Hhld head's Age^2 (x 10000)	15.39***	7.989***	8.414***	0.1004	15.47***	7.21***	6.263**	0.5388
Marital Status of hhld head (base = Single)								
Married	-0.1719	-.7561*	0.1995	0.0541	-0.06679	-.854**	0.2322	-0.004984
Other	-0.9965	-.8357**	-0.5165	-0.03779	-0.8185	-.8883**	-0.4676	-0.02353
Hhld head's Educational Attainment (base = Primary education)								
Secondary education	-1.168***	-.6984***	-1.059***	-.3709***	-.9229***	-.7924***	-1.007***	-.314**
College education	-2.815**	-1.69***	-2.782***	-1.255***	-2.813**	-1.723***	-2.717***	-1.117***
Hhld type (base = Single family)								
Extended family	0.07459	0.115	-0.1549	0.1655	-0.07087	0.1817	-0.1142	0.163
Two or more non-related individuals	-11.13	-16.69	-13.45	0.7791	-9.873	-12.28	-12.91	0.8591
Proportion of hhld members who are young	3.247***	1.297***	3.364***	1.538***	2.72***	1.381***	3.119***	1.487***
Family size	.742***	.4392***	.8163***	.3285***	.7093***	.428***	.7315***	.3336***

Table 5.8 (con't) Regression Coefficients of Multinomial Logistic Models for Intertemporal Poverty in the Philippines (Base = Non-poor)

Variable	Components Approach				Spells Approach			
	US$1.25		US$2		US$1.25		US$2	
	Persistent	Transient	Persistent	Transient	Persistent	Transient	Persistent	Transient
Agricultural hhld	.8974***	.2856*	1.176***	.4413**	.8569***	.2588*	1.073***	.4618**
At least one hhld member is working abroad	-.7014**	-.3591*	-.7894***	-.2559*	-.8061***	-.2991*	-.7763***	-0.2092
Proportion of employed hhld members	0.4205	0.2748	.4709*	0.2968	.4735*	0.228	0.3439	.3691*
Proportion of employed members with permanent job	-0.07962	-0.1215	-0.08583	0.05797	-0.1474	-0.0843	-0.04303	0.03026
Proportion of employed members with formal job	-.402*	-0.1718	-.5577***	-.382**	-.4598*	-0.1229	-.4919***	-.3998**
Hhld owns land/house	-.4552**	-0.2301	-.3351*	-0.1405	-.4813**	-0.185	-.3067*	-0.1419
Type of toilet facility (base = water-sealed)								
Closed pit	.6018***	0.2427	.5974***	0.1466	.5389***	0.2467	.4783**	0.2026
Open pit / others	.2949*	0.1142	.628***	0.2503	.3215**	0.06999	.5258***	.3141*
Hhld had access to electricity	-1.188***	-.7223***	-1.18***	-.523***	-1.068***	-.7524***	-1.123***	-.4776**
Hhld had access to water faucet	-0.007578	-0.1731	-.4351***	-.3877***	-0.01936	-0.1857	-.4319***	-.3783***
Hhld owns refrigerator	-1.939***	-1.089***	-1.616***	-.8847***	-2.053***	-1.008***	-1.54***	-.8438***
Hhld owns information gadget	-.7699***	-.4366***	-1.051***	-.5772***	-.7733***	-.3914***	-1.066***	-.4502**
Hhld owns phone	-2.778***	-.7764***	-1.671***	-.847***	-2.251***	-.7423***	-1.523***	-.8375***
Hhld owns washing machine	-2.676***	-.9971***	-1.893***	-.8125***	-2.116***	-.9966***	-1.729***	-.7868***
Hhld owns transportation	-1.749**	-.716**	-1.603***	-.4255**	-1.014*	-.8483**	-1.191***	-.4947**

Table 5.9 (con't) Regression Coefficients of Multinomial Logistic Models for Intertemporal Poverty in the Philippines (Base = Non-poor)

Variable	Components Approach				Spells Approach			
	US$1.25		US$2		US$1.25		US$2	
	Persistent	Transient	Persistent	Transient	Persistent	Transient	Persistent	Transient
Change in family size	.3561***	.1942***	.3646***	.1605***	.3297***	.1928***	.3417***	.1523***
Hhld head's educational attainment deteriorated	0.4681	.4844*	.5828**	0.1836	0.2238	.6087**	.5648**	0.143
Hhld head's educational attainment improved	-.5328*	-.4706**	-.6961***	-0.2968	-.7037**	-.3785*	-.6523***	-0.2691
Hhld's main source of income shifted from non-agri to agri	.6844***	.3169*	.9244***	.4908**	.8224***	0.1815	.8916***	.4555*
Hhld's main source of income shifted from agri to non-agri	-0.1961	0.111	-.4627*	0.06591	-0.1116	0.08199	-.3925*	0.04958
Hhld shifted from land/house ownership to non-ownership	.5236**	0.2467	.354*	0.1604	.5041**	0.2397	.3573*	0.1283
Hhld shifted from land/house non-ownership to ownership	-0.1944	-0.1136	-0.04462	0.0284	-0.2016	-0.0989	0.0085	-0.0115
Change in the proportion of employed members	-0.2479	0.0131	-.5914**	-0.2664	-0.2002	0.008346	-.4976**	-0.2935
Intercept	-16.29	-2.146**	-2.41**	-2.172***	-2.915*	-2.553**	-1.936**	-2.513***

Source: Author's computations using data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Note: The dependent variable is based on household expenditure per capita.

poverty remain in the country. In fact, other Southeast Asian countries such as Indonesia and Thailand with almost the same levels of secondary and tertiary enrolment rates have significantly better poverty trends. This finding challenges the quality of the education system in the country and the extent to which it is possible to arrest poverty in the future. Thus, it is imperative for socio-economic planners to implement policies that will make the education system more responsive to the needs of the poor. To raise the country's quality of education and be at par with other countries in Southeast Asia, the Philippines shifted from a 10-year to 12-year basic education system starting 2014. This system, commonly referred as K-12, is widely adopted by both industrialized and developing countries (Magno 2011). The system aims to provide competitive basic education. However, whether it will contribute to poverty reduction or not, is a test of time. The result may also be indicative of the limited good jobs available in the labour market. Several studies show that the Philippines confronts a dual jobs challenge which entail expanding formal sector employment and at the same time, improving the quality of jobs in the informal economy (WB 2013). In addition, the impact of expanding non-traditional employment arrangements which accompany globalization on the working poor is an issue that has to be examined as well. This topic is further discussed in Chapter 8.

Household composition is also a significant explanatory factor in inferring one's length of stay in poverty. Larger households have higher risks of experiencing longer poverty spells. In particular, the odds of staying in poverty increases with the number of dependent children in the family. This is consistent with the mounting evidence suggesting that lower fertility is correlated with improved socio-economic outcomes. In particular, instead of allocating a portion of its available resources for more productive economic activities, households must reallocate its available resources for every additional member. For example, having more dependent children in the family limits the ability of women to engage in paid employment as they are usually expected to do childrearing (Adair et al. 2002). At the same time, having more children in the family could also have a negative impact on household savings. For instance, using data from the 2009 FIES, I estimate that the correlation between the number of children and household saving is -0.11 (p-value<0.0001). Since larger households have less savings, they are more vulnerable to unexpected income shocks arising from illness, unemployment, among other factors that lead to reduced income flows. Nevertheless, larger household sizes could also have a negative impact on the duration of poverty spell in the later stage of the household's life cycle. For instance, the estimated models suggest that the risk of staying in poverty decreases with the proportion of household members who are working. In this context, some argue that parents who were initially disadvantaged during their early childrearing years would fare better in the future because there will be more children to contribute in mobilizing resources for the household even after these children form their own families due to close family ties of Filipinos (Ongsotto & Ongsotto 2002). However, several arguments have been offered against this hypothesis. For instance, studies show that an additional child in the household reduces the probability of other children in the family being enrolled in school (Conley 2000) which in turn, may hinder these children from reaching their full economic potential in the future. In other words, while they may be able to contribute to income generation for the household, the income may be at sub-optimal levels.

The patterns of poverty dynamics in the country have a remarkable spatial feature. The results of the estimated models suggest that those who live in rural areas particularly in the southern part of the country have higher risks of staying in poverty.[57] On the other hand, individuals living in urban areas where most of the economic activities are centred, experience shorter poverty spells. Some even argue that those who experience longer-than-average poverty spells in urban areas may be partly considered as a spill-over effect of the socio-economic disadvantage in rural areas (Reyes 2002b; CEDAW 2009). As poor households migrate from rural to urban areas, many of them remain poor until they get good jobs. Thus, they inflate the number of urban poor. Hence, urban poverty reflects residual absorption of rural migrants (Mitra 1992). In general, the prominent spatial feature of the distribution of poverty is not unique in the Philippines. In many developing countries, significant pockets of poverty are clustered in specific areas (Bigman & Fofack 2000; Hennigner & Snel 2002). Factors like climate, geography, natural resources, access to urban centers and local political conditions and economic opportunities drive the significant spatial variations in the length of poverty spells (Ravallion & Wodon 1997). The model results also confirm that greater access to basic services such as electricity, clean water and sanitary toilet facilities is correlated with lower intertemporal income poverty. For instance, having access to electricity contributes positively to higher household savings since a unit cost of lighting with electricity is generally cheaper than using candles or oil lamp. In turn, households can then use the additional savings as a cushion against the risk of falling into poverty in the future. On the other hand, experts agree that access to clean water and sanitation facilities (e.g., sanitary toilets) has a multiplier effect on many socio-economic indicators particularly, movements into and out of poverty (WHO and UNICEF 2008). In particular, access to these facilities have a direct impact on health outcomes. Not surprisingly, those who lack access to clean water and sanitation facilities have

[57] Most of the poorest provinces are in Mindanao. In addition, the risk of persistent poverty is highest in Mindanao.

higher risks of contracting diseases like cholera, typhoid, infectious hepatitis and polio. Consequently, these health shocks may contribute to income depletion of affected households, pushing them towards poverty. On the other hand, the cost-savings incurred by households with access to electricity, clean water and sanitation facilities may contribute to a household's increased propensity to start-up income-generating (micro-) entrepreneurial activities. This result suggests the need for the government to facilitate universal access to basic services.

The estimated models also suggest that ownership of land and other productive (disposable) assets like television, radio, telephone, washing machine, among others is negatively correlated with the duration of income poverty spells. There are several reasons why these variables are significantly correlated with intertemporal income poverty. For instance, during periods of economic uncertainties, these assets may be sold to cushion the disruptions in income flows. Some of these assets may also be used to improve access to information that will enhance efficiency for planning their routine economic activities. For example, farmers who own television or radio may be warned about an impending weather disturbance earlier. More importantly, many of these assets could also be used to generate income. Furthermore, most of these variables could be considered as indicators of material deprivation and hence, it is difficult to infer the direction of their relationship with intertemporal poverty.

Variation in employment outcomes is one of the statistically significant correlates of intertemporal poverty. Labour serves as one of the few assets that low income individuals have access to. In this context, having more household members who are working would naturally decrease the risk of staying in poverty for extended periods of time. This is confirmed by the negative coefficient of the proportion of household members who are employed, on poverty status as discussed earlier. But beyond the number of members working for the family, the type of employment also matters. For instance, the estimated models suggest that households which rely mostly on wages, particularly in non-agricultural sectors, experience shorter poverty spells than those who rely on agricultural wage employment or earnings from self-employment. The level of productivity in the agriculture sector is one of the reasons why this is the case. In particular, low agricultural productivity contributes significantly to persistent poverty in many developing countries. In addition to low productivity, frequent income fluctuations arising from crop loss (due to weather disturbances) or sudden changes in food prices also contribute to longer poverty durations for those who rely on agricultural wage employment. Among agricultural workers, farmers and fishermen have the highest risk of more severe poverty spells (NSCB 2012). Like agricultural wage employment, self-employment is also correlated with longer poverty durations relative to those who rely on non-agricultural wage employment.

Although they do not comprise a homogeneous group, a significant bulk of the self-employed in many developing countries including the Philippines are working on own-account with significantly less income. Banerjee & Duflo (2007) argue that much of the self-employed in developing countries are running their business because "*they are still relatively poor and every little bit helps*" until they find a more stable wage job. In the case of the Philippines, this is confirmed by the study of Hasan & Jandoc (2010) who concluded that the majority of the self-employed in the country are not "capitalists in waiting." In this context, it is not surprising to note that transitions from either agricultural wage or self-employment into non-agricultural wage employment reduces the risk of long poverty spells. Similarly, employment in the formal sector decreases the risk of being trapped in longer episodes of poverty. Compared to an informal job, a typical job in the formal sector is associated with higher and more stable income flows. Formal jobs also offer wider social protection coverage. These features serve as a cushion for unexpected income shocks which in turn, decreases the risk of falling into poverty. Interestingly, the negative effect of formal employment is stronger in the US$2 poverty line-based model suggesting that having a formal job is not quite common among the poorest of the poor. Lastly, households where at least one member is working abroad tend to spend less time in poverty. The Philippines is one of the large-labour exporting countries and previous studies suggest that it contributes to improved macro and micro socio-economic outcomes for the country (Ang, Sugiyarto & Jha 2009). For instance, remittance from a migrant worker abroad eases liquidity constraint for many low income households. This allows households to restructure their economic activities away from traditional subsistence activities and towards more efficient economic ventures (Brown & Leeves 2008).[58] In addition, remittance from abroad has a positive impact on investment on productive assets which in turn, could lead to lower risks of falling into poverty. Similarly, domestic remittances also contribute positively to minimizing poverty durations. In fact, its impact on the length of poverty spells could be stronger than remittance from abroad because low income individuals are more likely to receive remittance from internal migration (Pernia 2008).

5.5. Summary

Reducing poverty is considered as one of the most important tasks of the developing world. Not surprisingly, poverty monitoring remains at the heart of the economic development

[58] Some argue that international remittance could also lead to negative outcomes on a household's welfare. For instance, Rodriguez & Tiongson (2001) find that households with migrant workers have lower labour force participation rates and shorter work hours. The authors attribute it to the propensity of the migrant's relatives to substitute income-generating activities for more leisure.

literature aiming to advance poverty reduction efforts. In the Philippines much effort is needed to be able to eradicate extreme poverty as according to recent estimates, about two out of five Filipinos are still living below US$2/day (WDI 2014). Compared to its other Southeast Asian neighbours, the country has shown lower growth-elasticity of poverty and performed dismally on other social economic indicators for many years. This has earned the country its title *Sick Man of Asia* (Ching 1993). Nevertheless, a more robust and stronger economic performance has been noted in recent years, prompting economic analysts to upgrade their growth forecasts for the Philippines.

The examination of household panel data in the Philippines reveals that despite faster economic growth over the past decade, poverty remains a prominent feature of its development landscape. This poverty has two forms: persistent and transient. For instance, while about 40% of the population were US$2/day-poor at any given (survey) year between 2003 and 2009, estimates suggest that about 30% were poor in all (survey) years examined while 60% experienced. Overall, this suggests a more dynamic poverty phenomenon in the country than what is conventionally perceived when examination is only based on trends in cross-sectional indicators of poverty. To be able to respond to the challenge of reconciling stronger economic growth with positive gains in poverty reduction, it is important to implement policies that can minimize both persistent and transient forms of poverty. However, this calls for a different mix of policies. This prompts the need to address the question: how long do the poor stay in poverty? Consistent with the findings of Reyes et al. (2011) and Bayudan-Dacuycuy & Lim (2013), the results presented in this chapter suggest that most poverty experiences of Filipino households were persistent. In other words, households tended to stay in poverty for extended periods of time. This pattern is in sharp contrast with the intertemporal poverty in industrialized countries wherein the share of persistent poverty would normally be much smaller compared with transient poverty. This implies that poverty reduction programs in developing countries like the Philippines should be aimed primarily at providing long-term human capital development. Nevertheless, the robustness analysis presented in this chapter revealed that the relative importance of persistent and transient poverty were sensitive to the type of poverty measure used and the poverty line specified. In particular, the relative importance of transient poverty increased dramatically as the poverty line decreased or as the poverty measure becomes more sensitive to the illfare of the poorest of the poor.

In conclusion, the results can be used to illuminate several important broad policy implications. First, an insignificant change in the cross-sectional estimates of poverty from 2003 to 2009 does not imply that all poor households were systematically excluded from reaping the benefits of the faster economic growth that transpired during this period. In particular, about 15% to 20% of the households classified as poor in an initial time period managed to escape poverty in the succeeding survey wave. Nevertheless, the risks of falling into poverty were also not trivial. For instance, about 10% to 15% of the initially non-poor households fell into poverty in the succeeding wave. In other words, transition from poverty to non-poverty does not necessarily imply a permanent escape from socio-economic dearth. To be able to understand poverty vulnerability in the Philippines better, future research may use the concept of fuzzy logic (Lemmi & Betti 2006) or construct poverty vulnerability lines such as those proposed by Dang and Lanjouw (2014). More importantly, the relevance of poverty vulnerability also means that existing social protection systems should be improved to minimize the adverse consequences of income shocks for both the poor and economically vulnerable. Second, for about 15% to 40% of the population, poverty has been a long episode of socio-economic deprivation. A more aggressive policy intervention is needed for these persistently poor households. One of the first steps might be to institutionalize an effective targeting system that will identify persistently poor households. Equally important is to ensure that intervention programs are accessible as many of these chronically poor households are likely situated in remote and hard-to-reach areas. Third, given that estimates could change depending on measurement parameters, programs that rely on poverty ranking should be examined rigorously. Overall, both persistent and transient poverty should be of concern for the country's socio-economic planners and there should be a balanced policy program that supplements long-term investment on the development of human capital of the persistently poor with provision of social safety nets that can stabilize income flows of the transiently poor.

Appendix Table A5.1 Intertemporal Poverty Headcount Rate using the Components Approach (%), by Household Characteristics

Hhld characteristics	US$1.25			US$2			half of median poverty line			government/official		
	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor
Rural	25.45	18.4	56.15	58	14.53	27.47	18.8	19.68	61.52	36.74	21.72	41.54
Urban	4.9	8.02	87.08	20.5	13.64	65.86	3.4	6.62	89.98	10.16	13.37	76.46
NCR	0	1.09	98.91	4.29	11.11	84.6	0	0.89	99.11	2.4	8.66	88.94
Luzon	9.03	10.77	80.2	30.7	16.31	52.99	6.37	9.55	84.07	17.79	17.08	65.13
Visayas	21.44	18.3	60.26	52.04	12.95	35.01	15.2	19.36	65.44	29.54	19.75	50.7
Mindanao	28.64	18.67	52.7	60.13	11.93	27.94	21.89	20.04	58.07	38.77	20.34	40.89
Female-headed hhld	5.86	8.33	85.81	20.17	12.52	67.31	3.78	8.39	87.83	10.29	13.77	75.94
Male-headed hhld	16.75	14.03	69.22	42.43	14.33	43.24	12.33	13.98	73.69	25.66	18.18	56.16
Single	2.97	11.54	85.49	15.9	13.87	70.23	2.61	7.48	89.91	5.92	14.89	79.18
Married	16.73	13.53	69.74	41.89	13.92	44.19	12.33	13.72	73.95	25.42	17.8	56.78
Widowed/Separated/ Others	6.55	11.75	81.71	25.19	15.44	59.37	4.01	10.58	85.4	12.89	16.58	70.53
Primary school	26.64	19.07	54.28	59.09	14.78	26.13	20.19	19.28	60.53	38.91	22.17	38.92
Secondary school	7.21	9.95	82.84	27.62	14.97	57.41	4.63	9.79	85.58	13.29	15.91	70.8
College	0.24	1.28	98.48	2.18	5.94	91.88	0	0.66	99.34	0.2	3.25	96.55
Family size ≤ 3	4.27	10.06	85.67	21.23	17.87	60.9	3.12	8.3	88.59	8.5	18.01	73.49
3 < Family size ≤ 5	9.27	11.22	79.5	31.45	14.01	54.54	6.12	11.17	82.71	15.78	15.62	68.61
5 < Family size ≤ 7	18.44	13.73	67.83	44.36	13.28	42.37	13.89	13.87	72.24	27.76	18.18	54.06
7 < Family size ≤ 9	28.29	19.59	52.12	60.96	13.24	25.81	21.6	19.12	59.28	40.77	22.24	36.99
Family size > 9	33.65	17.26	49.09	60.46	11.45	28.1	24.7	21.31	53.99	48.43	15.71	35.86
Hhld head's age ≤ 35	23.12	14.58	62.3	50.58	11.77	37.66	18.27	15.69	66.05	33.07	18.18	48.75
35 < Hhld head's age ≤ 44	17.59	13.41	69	44.43	13.82	41.75	12.09	14.16	73.74	26.98	18.1	54.92
Hhld head's age > 44	9.76	12.53	77.71	30.61	15.51	53.88	6.89	11.39	81.72	16.57	17.01	66.43
Non-agriculture hhld	7.06	10.39	82.55	26.37	14.85	58.79	4.68	9.23	86.09	13.49	15.74	70.77
Agriculture hhld	38.36	21.37	40.27	76.19	11.99	11.82	29.42	24.45	46.12	51.96	22.83	25.21
Main source of income: entrepreneurial income	18.49	14.17	67.34	42.65	14.11	43.24	13.95	14.43	71.62	26.37	18.08	55.55
Main source of income: Agricultural wage/salary	38.39	22.16	39.45	80.55	9.1	10.35	29	26.62	44.38	54.92	21.21	23.87
Main source of income: Non-agricultural wage/salary	7.15	10.53	82.32	27.89	15.05	57.06	4.56	9.27	86.17	14.38	16.36	69.26

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Appendix Table A5.2 Intertemporal Poverty Headcount Rate using the Spells Approach (%), by Household Characteristics

Hhld characteristics	US$1.25			US$2			half of median poverty line			government/official		
	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor
Rural	27.2	16.65	56.15	59.72	12.81	27.47	22.64	15.85	61.52	40.98	17.48	41.54
Urban	5.57	7.34	87.08	22.3	11.83	65.86	4.41	5.61	89.98	12.23	11.31	76.46
NCR	0.24	0.85	98.91	6.27	9.14	84.6	0.24	0.65	99.11	2.79	8.27	88.94
Luzon	9.78	10.02	80.2	32.43	14.57	52.99	7.89	8.04	84.07	21.08	13.79	65.13
Visayas	23.29	16.45	60.26	53.42	11.57	35.01	19.36	15.21	65.44	33.03	16.27	50.7
Mindanao	30.61	16.7	52.7	62.23	9.83	27.94	25.5	16.43	58.07	42.53	16.58	40.89
Female-headed hhld	6.46	7.73	85.81	22.11	10.58	67.31	4.61	7.56	87.83	11.87	12.19	75.94
Male-headed hhld	18.06	12.72	69.22	44.17	12.59	43.24	15.02	11.29	73.69	29.06	14.78	56.16
Single	3.74	10.78	85.49	17.47	12.3	70.23	3.74	6.35	89.91	6.84	13.97	79.18
Married	18	12.25	69.74	43.66	12.15	44.19	15.01	11.04	73.95	28.79	14.43	56.78
Widowed/Separated/ Others	7.42	10.87	81.71	26.91	13.71	59.37	4.88	9.72	85.4	14.84	14.63	70.53
Primary school	27.94	17.77	54.28	60.96	12.92	26.13	23.72	15.75	60.53	43.03	18.05	38.92
Secondary school	8.58	8.58	82.84	29.54	13.05	57.41	6.49	7.93	85.58	16.14	13.06	70.8
College	0.24	1.28	98.48	2.61	5.51	91.88	0	0.66	99.34	0.18	3.26	96.55
Family size ≤ 3	5.31	9.02	85.67	24.1	15	60.9	4.14	7.28	88.59	12.51	14	73.49
3 < Family size ≤ 5	10.28	10.22	79.5	33.46	12	54.54	8.07	9.23	82.71	18.42	12.97	68.61
5 < Family size ≤ 7	19.89	12.28	67.83	46.05	11.59	42.37	16.94	10.83	72.24	31.19	14.75	54.06
7 < Family size ≤ 9	29.27	18.62	52.12	61.7	12.5	25.81	25.51	15.21	59.28	44.35	18.66	36.99
Family size > 9	35.92	14.99	49.09	60.8	11.11	28.1	27.42	18.59	53.99	50.55	13.6	35.86
Hhld head's age ≤ 35	24.99	12.71	62.3	52.59	9.76	37.66	22.13	11.83	66.05	37.34	13.91	48.75
35 < Hhld head's age ≤ 44	18.51	12.49	69	46.3	11.95	41.75	15.02	11.24	73.74	29.86	15.22	54.92
Hhld head's age > 44	10.82	11.47	77.71	32.17	13.95	53.88	8.28	10	81.72	19.31	14.26	66.43
Non-agriculture hhld	7.86	9.59	82.55	28.27	12.95	58.79	6.08	7.83	86.09	16.27	12.96	70.77
Agriculture hhld	40.75	18.98	40.27	77.58	10.6	11.82	34.79	19.09	46.12	56.21	18.58	25.21
Main source of income: entrepreneurial income	19.71	12.95	67.34	44.26	12.5	43.24	16.12	12.26	71.62	29.32	15.13	55.55
Main source of income: Agricultural wage/salary	41.79	18.76	39.45	80.48	9.17	10.35	37.51	18.11	44.38	58.25	17.87	23.87
Main source of income: Non-agricultural wage/salary	7.94	9.74	82.32	30.19	12.75	57.06	6.14	7.69	86.17	17.77	12.97	69.26

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Appendix Table A5.3 Intertemporal Poverty Headcount Rate using the JR approach (%), by Region

Location	Permanent Income (US$)	US$1.25			US$2			half of median			government/official		
		Persistent	Transient	Total	Persistent	Transient	Total	Persistent	Transient	Total	Persistent	Transient	Total
NCR	2,244.39	0.00	0.44	0.44	3.10	4.61	7.72	0.00	0.38	0.38	1.75	3.11	4.86
CAR	1,092.29	7.10	7.64	14.74	38.11	8.65	46.76	4.56	5.66	10.22	13.77	9.04	22.81
Region 1	1,222.25	4.53	4.81	9.33	25.99	7.74	33.73	2.72	4.40	7.12	15.57	7.57	23.13
Region 2	1,243.33	6.43	5.58	12.01	30.22	6.85	37.07	3.93	4.87	8.80	11.76	7.86	19.62
Region 3	1,384.29	0.92	2.28	3.20	14.07	7.01	21.08	0.70	1.85	2.55	8.06	6.35	14.41
Region 4-A	1,554.14	4.18	2.45	6.63	17.99	4.60	22.59	2.46	2.16	4.62	10.90	5.15	16.05
Region 4-B	810.75	25.27	8.14	33.41	59.25	6.49	65.75	21.23	8.21	29.44	34.95	9.04	44.00
Region 5	1,091.79	19.68	6.50	26.18	48.06	7.26	55.32	14.64	6.66	21.29	31.08	9.73	40.81
Region 6	1,075.84	12.19	7.45	19.64	42.59	6.06	48.66	7.19	8.92	16.10	19.86	7.51	27.37
Region 7	965.06	22.41	6.80	29.21	51.46	3.53	54.98	18.53	7.39	25.92	33.08	6.80	39.89
Region 8	1,056.29	18.02	7.85	25.87	47.49	6.38	53.88	13.83	7.29	21.11	24.59	11.51	36.10
Region 9	935.81	35.01	5.98	40.99	60.59	4.31	64.90	30.17	7.03	37.20	40.15	6.72	46.87
Region 10	1,077.15	21.76	5.80	27.56	48.02	4.04	52.06	16.63	6.95	23.58	34.95	5.67	40.63
Region 11	1,011.30	18.54	6.54	25.08	47.17	5.28	52.45	14.84	5.85	20.69	28.10	6.78	34.89
Region 12	885.82	12.38	9.72	22.10	46.43	7.60	54.04	8.04	9.47	17.51	28.89	9.84	38.74
ARMM	553.51	34.22	10.12	44.34	82.60	2.47	85.08	24.51	12.77	37.28	36.87	14.19	51.06
Caraga	755.41	24.73	7.78	32.51	60.39	7.50	67.89	18.47	9.35	27.82	42.77	8.81	51.57

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009

Appendix Table A5.4 Standard Errors of Intertemporal Poverty Headcount Rate using the Components Approach (%), by Household Characteristics

Hhld characteristics	US$1.25			US$2			half of median poverty line			government/official		
	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor
Rural	0.83	0.70	0.91	0.88	0.60	0.79	0.76	0.72	0.90	0.90	0.73	0.88
Urban	0.54	0.65	0.81	0.96	0.81	1.11	0.46	0.59	0.73	0.76	0.80	1.02
NCR	0.00	0.56	0.56	1.23	1.86	2.13	0.00	0.52	0.52	0.85	1.70	1.86
Luzon	0.66	0.69	0.90	1.02	0.81	1.11	0.57	0.64	0.82	0.88	0.81	1.06
Visayas	1.32	1.22	1.54	1.56	1.02	1.48	1.17	1.24	1.51	1.46	1.25	1.56
Mindanao	1.24	1.01	1.32	1.28	0.78	1.18	1.15	1.04	1.31	1.31	1.02	1.29
Female-headed hhld	0.89	1.07	1.34	1.55	1.23	1.82	0.71	1.08	1.26	1.22	1.30	1.67
Male-headed hhld	0.58	0.53	0.72	0.77	0.55	0.78	0.52	0.52	0.68	0.69	0.59	0.77
Single	1.38	3.05	3.31	3.42	3.45	4.61	1.33	2.26	2.61	1.89	3.87	4.19
Married	0.59	0.52	0.72	0.77	0.54	0.78	0.52	0.52	0.68	0.69	0.59	0.78
Widowed/Separated/ Others	0.98	1.34	1.59	1.77	1.39	1.99	0.76	1.28	1.44	1.44	1.44	1.86
Primary school	0.95	0.82	1.05	1.03	0.74	0.93	0.87	0.80	1.03	1.04	0.85	1.02
Secondary school	0.56	0.65	0.82	0.98	0.78	1.09	0.46	0.65	0.77	0.75	0.80	1.00
College	0.24	0.52	0.57	0.65	1.23	1.37	0.00	0.35	0.35	0.20	0.87	0.89
Family size ≤ 3	0.63	0.97	1.12	1.25	1.23	1.54	0.54	0.90	1.02	0.87	1.25	1.42
3 < Family size ≤ 5	0.62	0.70	0.89	1.04	0.78	1.14	0.52	0.69	0.83	0.82	0.80	1.05
5 < Family size ≤ 7	1.04	0.89	1.26	1.36	0.95	1.39	0.93	0.88	1.19	1.21	1.02	1.37
7 < Family size ≤ 9	1.92	1.70	2.18	2.16	1.50	1.96	1.75	1.64	2.12	2.13	1.86	2.14
Family size > 9	3.21	2.54	3.45	3.40	2.29	3.12	2.93	2.73	3.42	3.44	2.48	3.34
Hhld head's age ≤ 35	1.27	1.01	1.45	1.51	0.96	1.48	1.17	1.04	1.41	1.42	1.11	1.51
35 < Hhld head's age ≤ 44	1.08	0.94	1.30	1.40	0.98	1.40	0.94	0.96	1.24	1.26	1.07	1.41
Hhld head's age > 44	0.58	0.67	0.83	0.92	0.73	1.01	0.50	0.63	0.76	0.75	0.76	0.96
Non-agriculture hhld	0.46	0.54	0.68	0.78	0.63	0.87	0.39	0.50	0.61	0.63	0.64	0.81
Agriculture hhld	1.27	1.02	1.22	1.04	0.76	0.80	1.22	1.08	1.25	1.26	1.02	1.05
Main source of income: entrepreneurial income	0.78	0.66	0.93	0.97	0.66	0.99	0.71	0.67	0.89	0.89	0.73	0.98
Main source of income: Agricultural wage/salary	2.35	1.94	2.29	1.81	1.26	1.42	2.23	2.09	2.34	2.34	1.87	1.95
Main source of income: Non-agricultural wage/salary	0.62	0.75	0.92	1.08	0.86	1.18	0.51	0.68	0.82	0.86	0.89	1.11

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Appendix Table A5.5 Standard Errors of Intertemporal Poverty Headcount Rate using the Spells Approach (%), by Household Characteristics

Hhld characteristics	US$1.25			US$2			half of median poverty line			government/official		
	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor	Persistently Poor	Transiently Poor	Non-Poor
Rural	0.84	0.67	0.91	0.87	0.57	0.79	0.80	0.66	0.90	0.91	0.67	0.88
Urban	0.56	0.63	0.81	0.99	0.77	1.11	0.50	0.56	0.73	0.82	0.74	1.02
NCR	0.24	0.50	0.56	1.48	1.69	2.13	0.24	0.46	0.52	1.04	1.61	1.86
Luzon	0.68	0.67	0.90	1.04	0.78	1.11	0.62	0.60	0.82	0.94	0.73	1.06
Visayas	1.35	1.18	1.54	1.55	0.97	1.48	1.27	1.14	1.51	1.49	1.18	1.56
Mindanao	1.26	0.96	1.32	1.27	0.73	1.18	1.20	0.96	1.31	1.31	0.95	1.29
Female-headed hhld	0.93	1.03	1.34	1.61	1.13	1.82	0.79	1.02	1.26	1.28	1.24	1.67
Male-headed hhld	0.60	0.51	0.72	0.77	0.52	0.78	0.56	0.48	0.68	0.71	0.54	0.77
Single	1.57	2.96	3.31	3.55	3.32	4.61	1.57	2.10	2.61	2.03	3.82	4.19
Married	0.60	0.50	0.72	0.78	0.52	0.78	0.56	0.48	0.68	0.71	0.54	0.78
Widowed/Separated/ Others	1.06	1.29	1.59	1.80	1.31	1.99	0.85	1.22	1.44	1.50	1.37	1.86
Primary school	0.96	0.80	1.05	1.03	0.71	0.93	0.91	0.74	1.03	1.05	0.79	1.02
Secondary school	0.61	0.61	0.82	1.00	0.73	1.09	0.53	0.60	0.77	0.82	0.74	1.00
College	0.24	0.52	0.57	0.71	1.20	1.37	0.00	0.35	0.35	0.18	0.87	0.89
Family size ≤ 3	0.69	0.93	1.12	1.32	1.15	1.54	0.61	0.86	1.02	1.06	1.13	1.42
3 < Family size ≤ 5	0.66	0.67	0.89	1.05	0.74	1.14	0.59	0.63	0.83	0.87	0.73	1.05
5 < Family size ≤ 7	1.07	0.85	1.26	1.38	0.88	1.39	1.00	0.79	1.19	1.26	0.93	1.37
7 < Family size ≤ 9	1.93	1.69	2.18	2.16	1.50	1.96	1.85	1.51	2.12	2.16	1.75	2.14
Family size > 9	3.27	2.37	3.45	3.39	2.25	3.12	3.02	2.61	3.42	3.45	2.29	3.34
Hhld head's age ≤ 35	1.30	0.95	1.45	1.51	0.88	1.48	1.25	0.93	1.41	1.45	0.99	1.51
35 < Hhld head's age ≤ 44	1.10	0.91	1.30	1.41	0.93	1.40	1.01	0.87	1.24	1.30	1.00	1.41
Hhld head's age > 44	0.60	0.65	0.83	0.94	0.71	1.01	0.54	0.59	0.76	0.80	0.70	0.96
Non-agriculture hhld	0.48	0.53	0.68	0.80	0.59	0.87	0.43	0.47	0.61	0.67	0.59	0.81
Agriculture hhld	1.28	0.96	1.22	1.02	0.73	0.80	1.25	0.98	1.25	1.24	0.94	1.05
Main source of income: entrepreneurial income	0.80	0.63	0.93	0.98	0.63	0.99	0.75	0.63	0.89	0.91	0.68	0.98
Main source of income: Agricultural wage/salary	2.37	1.82	2.29	1.84	1.34	1.42	2.34	1.82	2.34	2.31	1.78	1.95
Main source of income: Non-agricultural wage/salary	0.65	0.73	0.92	1.10	0.81	1.18	0.58	0.63	0.82	0.94	0.80	1.11

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Appendix Table A5.6 Standard Errors of Intertemporal Poverty Headcount Rate using the JR approach (%), by Region

Location	US$1.25			US$2			half of median			government/official		
	Persistent	Transient	Total	Persistent	Transient	Total	Persistent	Transient	Total	Persistent	Transient	Total
NCR	0.00	0.56	0.56	1.23	1.86	2.13	0.00	0.52	0.52	0.85	1.70	1.86
CAR	2.10	2.89	3.26	3.50	2.76	3.32	1.74	2.62	2.97	2.79	2.83	3.43
Region 1	1.65	1.86	2.33	2.60	2.16	2.68	1.38	1.82	2.18	2.37	2.10	2.69
Region 2	1.69	2.24	2.60	2.86	2.05	2.91	1.44	2.02	2.36	2.18	2.36	2.83
Region 3	0.66	1.31	1.44	1.90	1.82	2.32	0.50	1.19	1.28	1.44	1.80	2.13
Region 4-A	1.16	1.21	1.61	1.97	1.59	2.24	0.96	1.07	1.40	1.72	1.43	2.06
Region 4-B	3.34	2.77	3.49	3.20	2.27	2.66	3.15	2.90	3.51	3.51	2.73	3.33
Region 5	2.63	2.15	2.85	2.82	2.12	2.51	2.44	2.08	2.79	2.79	2.39	2.76
Region 6	1.93	1.92	2.39	2.47	1.76	2.34	1.52	2.05	2.32	2.15	2.00	2.47
Region 7	2.34	2.04	2.62	2.61	1.42	2.50	2.19	2.00	2.58	2.59	1.92	2.62
Region 8	2.65	2.50	3.06	3.05	2.19	2.83	2.41	2.40	2.98	2.77	2.80	3.03
Region 9	3.22	2.28	3.23	3.07	1.84	2.79	3.14	2.36	3.26	3.24	2.39	3.17
Region 10	2.94	2.14	3.13	3.11	1.64	3.01	2.71	2.31	3.09	3.13	1.98	3.10
Region 11	2.62	2.15	2.97	3.04	1.87	2.92	2.50	2.08	2.90	2.89	2.19	3.05
Region 12	2.47	2.66	3.04	3.01	2.11	2.72	2.04	2.63	2.95	2.97	2.56	2.95
ARMM	3.41	2.94	3.09	2.34	1.37	1.99	3.28	3.12	3.23	3.39	3.21	2.81
Caraga	3.23	2.64	3.40	3.21	2.45	2.63	3.00	2.74	3.39	3.41	2.67	3.08

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Chapter 6 Who are Income Mobile?

6.1 Introduction

Chapter 5 has discussed mobility among low income range people and found that poverty in the Philippines is mostly persistent in nature. This chapter extends the discussion by examining the mobility patterns of people from other income segments. Here, mobility is defined in terms of how fast income is growing. The discussion focuses on the relationship between income inequality and income mobility by identifying the characteristics of those who benefitted from economic growth through high positive income mobility and of those who were left out because they experienced negative income mobility. This is an important analytical exercise because as explained in the previous chapters, the high levels of inequality in the Philippines could imply that different population groups benefit from economic growth at different rates. In particular, I address the following questions:

(i) What are the characteristics of the income mobile households in the Philippines?

(ii) How do the income mobility outcomes of initially advantaged and initially disadvantaged households differ?

In answering the first question, I will identify who has benefited from economic development and who has been left out. I will also examine whether the initially disadvantaged groups caught-up with the initially advantaged ones through faster income growth rates. For the second research question, I will examine whether the impact of economic development on initially advantaged and initially disadvantaged households differ when the country's economy is expanding or contracting.

Investigating how the benefits of economic growth accrue to different groups is usually addressed by comparing the income growth rates of different segments of the population. Examining the growth incidence curves (GIC) provides a good starting point for this analytical exercise. We have learned earlier that a growth process is considered relatively pro-poor if it allows the poor to catch-up with the non-poor through faster income growth rates resulting in a downward sloping GIC. While several studies briefly examined this issue in the Philippines (e.g. Balisacan & Pernia, 2002; Pernia, 2003; Schelzig, 2005; Aldaba 2009), most used data from repeated cross-sectional surveys. Chapter 1 identified that the problem with working with cross-sectional surveys is that when individuals are ranked according to their income in each time period, the composition of a particular income quantile in the initial time period will not exactly match the composition of the same quantile in a subsequent time period because people move from one quantile to another over time. This process makes it difficult to infer whether the initially poor or initially non-poor experienced faster income growth rates (Grimm 2007). Another potential disadvantage of the GIC is that it implicitly ignores what happened in between the start and end of the observation period. The analyses in this chapter address the limitations of previous studies in several ways. First, I depart from the conventional approach of measuring income mobility using growth rates between initial and final-period incomes (Tabunda & Albert 2002; Reyes et al. 2011; Takahashi 2013) by incorporating the available information between the start and end of the observation periods. This allows me to distinguish people who experienced consistently positive or negative mobility from people who experienced unstable income flows, an issue that has not been explored in previous studies (Reyes et al. 2011; Takahashi 2013). Second, I go beyond the conventional approach of examining pro-poorness of growth by testing the convergence (vs. divergence) and symmetry (vs. asymmetry) of household income mobility following the approach of Fields et al. (2007). Similar to the concept of pro-poor growth, the concepts of convergence and symmetry refer to the effect that income mobility patterns over time have on the differences in income between the initially advantaged and initially disadvantaged people. From a policy perspective understanding these patterns would help us gauge the extent to which the high income inequality in the country is a reflection of inequitable distribution of socio-economic opportunities.

6.2 Different Patterns of Income Mobility

Variations in the effect of economic growth on people's living standards can be explained by differences in their socio-demographic characteristics, resource endowment, skills, risk aversion, effort and luck (Morrisson 2006; Marrero & Rodriguez 2013; Ros 2013). As pointed out earlier, there is more concern among policymakers when the observed inequality portrays inequality of opportunities rather than inequality of outcomes. Inequality of opportunities could lead to long episodes of segmentation between the advantaged and the disadvantaged groups and thus, can undermine the country's full economic potential (Braham, Rattansi & Skellington 1992; Pasha & Palanivel 2003) whereas if socio-economic opportunities are distributed equally, inequality of outcomes would only arise due to variation in efforts (Arrow, Bowles &

Durlauf 2004; Kenworthy 2004).[59] Hence, despite diversity being woven in the fabric of the socio-economic development process, there is much interest in understanding what causes socio-economic inequalities, especially in a developing country like the Philippines where rapid economic growth is accompanied by persistently high income inequality.

To determine the extent to which income inequality in the Philippines is characterized by inequality of opportunities, it is important to examine how the incomes of different population groups with varying levels of (initial) advantage change over time. In this context, the income mobility process can be generally classified as (i) convergent or divergent; and (ii) symmetric or asymmetric. Income mobility is said to be convergent when incomes of the initially disadvantaged are growing at least as fast as their initially advantaged counterparts and it is divergent when the initially disadvantaged group receives disproportionately less benefits from the observed mobility process (Shorrocks & van der Hoeven 2004; Grimm et al. 2007).

There are several factors that can contribute to convergent income mobility. For instance, if economic growth expands the access of initially disadvantaged to credit markets, then the additional capital can unleash the growth potential of the poor leading to faster income growth rates. Similarly, macro-level policies on government spending and progressive taxation may also contribute to faster income growth rates among the poor (Pintus 2008). Analogously, a divergent income mobility process could be attributed to capital market imperfection wherein the initially disadvantaged systematically confronts borrowing constraints which in turn, prevents them from reaping the benefits of economic growth (Galord 1996; Banerjee & Duflo 2003; Ravallion 2012). On the other hand, the movement of the additional capital created by growth could also be perfectly fluid in which case, a person's initial resources will not have a significant effect on his/her subsequent income growth. In general, convergent income mobility can be linked to the concept of pro-poor growth while divergent mobility can be associated with poverty traps and cumulative advantage.

Solely relying on a converging income mobility process cannot guarantee that the poor will have adequate resources such as financial capital, education and employment that would assure that they will never experience poverty again. In particular, even if the income mobility pattern is convergent (or divergent) for a specific time period, it is not always the case that the same pattern will persist over time. For instance, a convergent income mobility spell may be followed by a divergent income mobility spell, or vice-versa. Hence in addition to convergence,

[59] Kenworthy (2004) examined the hypothesis that economic growth is always accompanied by increasing inequality. He concluded that there is no necessary trade-off between equality and economic growth as long as an optimal balance of policy options are combined to create a fair economy.

it is also important to examine the symmetry of income mobility to be able to understand how people's income mobility prospects change over time. A mobility process is said to be symmetric when the group that experienced better (inferior) income mobility outcomes during a specific time period experiences inferior (better) mobility outcomes in the subsequent period. A good example of a symmetric income mobility process is when the rich benefits disproportionately more during episodes of economic growth but they also lose more during episodes of economic turmoil (Fields et al. 2007). It can be observed during financial markets-induced crises when the rich bear its negative impact more than the poor because of their higher exposure to credit markets.[60] Analogously, an income mobility process could also be considered symmetric when the poor benefits more during episodes of economic growth but they also lose more during periods of economic uncertainties probably because they have limited access to social safety nets that can cushion them from large income losses.

Testing whether income mobility is converging or diverging and whether it is symmetric or asymmetric will help us understand how the economic development processes in the Philippines allow the initially disadvantaged to catch up with the rich, or whether these processes systematically exclude them from reaping the benefits of economic growth.

6.3. Methods

6.3.1 Classifying Households According to Income Mobility Trajectories

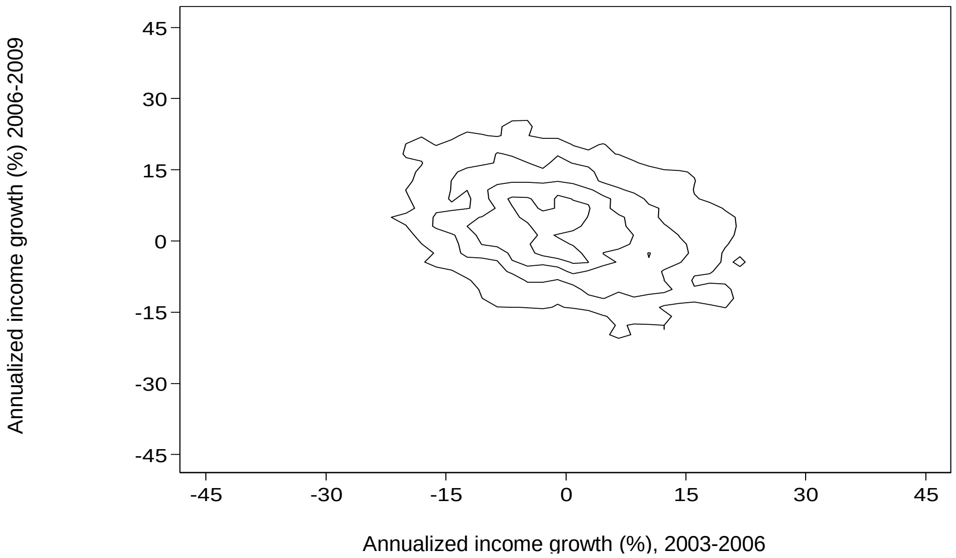
In this chapter, income mobility is measured in terms of changes in log per capita household consumption derived from the FIES. Convergence and symmetry of mobility are gauged in terms of how fast people's incomes are growing with respect to its initial levels. Instead of simply looking at growth rates from 2003 to 2009, I estimate the growth rates from 2003 to 2006 and 2006 to 2009, separately to unmask interesting features about the household income flows that may otherwise be hidden if I simply look at the income differences between 2003 and 2009. Compared to the approach used in Chapter 1, this analytical strategy further capitalizes on the longitudinal feature of the data. For instance, it is possible that some households that experienced high income growth rates between 2003 and 2009 also experienced very volatile income flows. As noted in Chapter 1, this is not necessarily a desirable outcome especially when households are averse to income fluctuations. Furthermore, it is possible that a high (low) income growth observed in 2006-2009 might offset a low (high) income growth observed in 2003-2006 which in turn may be mistakenly classified as

[60] Whether the rich or the poor suffer more during economic crises is a debatable issue. Some argue that the poor suffer more because the rich are more likely to be compensated by government bail outs (Halac & Schmukler 2004).

immobility if one simply relies on the income growth rate in 2003-2009. Estimating the growth rates for 2003-2006 and 2006-2009 separately also allows me to examine how income mobility changes over time and thus, test whether it is symmetric or asymmetric.

Figure 6.1 shows the top view of the density plot of the annualized growth rates between 2003 and 2006 in the x-axis and the annualized growth rates between 2006 and 2009 in the *y*-axis. The plot reveals a negative correlation between the two sets of growth rates, i.e., faster income growth between 2003 and 2006 tends to be followed by slower income growth between 2006 and 2009, and vice-versa. It also shows that the density peaks near the origin which means that a significant fraction of the households experienced consistently slow income growth from 2003 to 2009.

Figure 6.1 Joint Distribution of Income Trajectories, 2003-2006 and 2006-2009



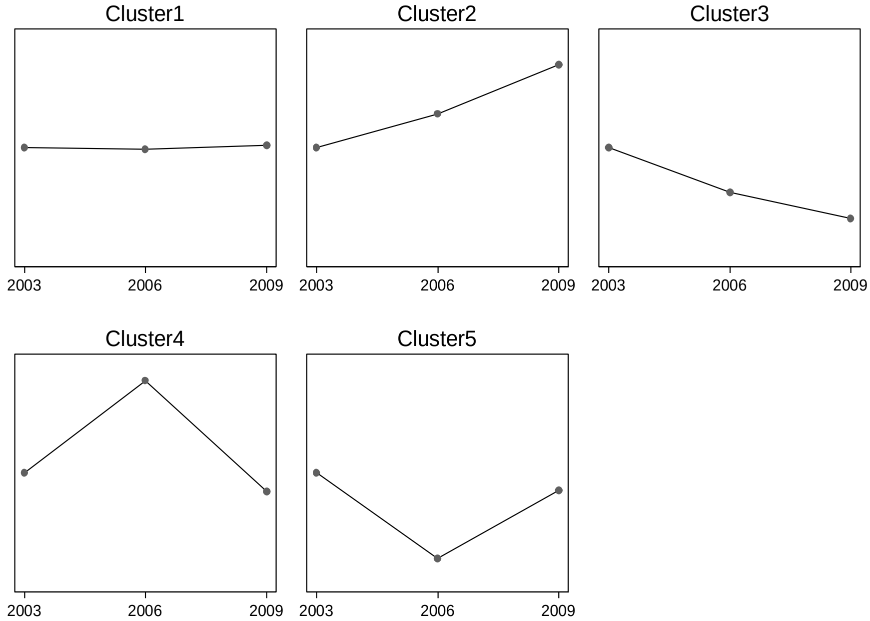
Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

I follow a heuristic approach in grouping households that have homogeneous income mobility trajectories. In particular, households that experienced slow to moderate income growth (at most +/- 5% per year) in both 2003-2006 and 2006-2009 periods are grouped in the first cluster.[61] Households that observed consistently positive or consistently negative growth rates, wherein at least one growth rate exceeds 5%, are classified under the second or third cluster, respectively. Lastly, households that experienced highly positive income growth (>5%) in 2003-2006 yet highly negative income growth (< -5%) in 2006-2009 are classified in the

[61] The median absolute income growth rate for 2003-2006 and 2006-2009 is about 9% per year.

fourth cluster while households that experienced highly negative growth (< -5%) in 2003-2006 followed by highly positive growth (> 5%) in 2006-2009 are classified in the fifth cluster. As illustrated in Figure 6.2, the first cluster corresponds to households with very modest income growth. The second and third clusters include households that experienced consistently upward and downward mobility, respectively. The last two clusters correspond to households that experienced high transitory income fluctuations. Section 6.3.4 provides the details about the empirical strategy on how these clusters are used to test convergence and symmetry of income mobility.

Figure 6.2 Different Types of Income Trajectories, 2003-2009



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

6.3.2 Measures of Socio-economic Advantage

Since the objective of this study is to examine the extent to which a household's initial level of socio-economic advantage predicts its subsequent income growth trajectory, it is essential to provide a measure of socio-economic advantage. To do this, I group the households using two methods. First, I use the quintiles of the observed income in 2003. In general, grouping households according to quantiles is a common approach in income distributional analysis (RC 2003). However, although this approach is useful for capturing how income is appropriated into different segments of the society, it is unable to capture polarization or the implicit clustering of individuals into groups (Chakravarty & Ambrosio 2010). While both income inequality and polarization are concerned of the variability of the income distribution, high income inequality does not always imply a "divided" or "polarized" society (Gochoco-

Bautista, Bautista, Maligalig & Sotocinal 2013).[62] Thus, in addition to examining inequality, it is also important to study polarization because a segmented society is usually prone to conflict due to skewed distribution of opportunities (Gasparini et al. 2008). To capture polarization, I follow the approach proposed by Liao (2006) which entails fitting latent cluster models on initial income in 2003.[63] Model-based clustering is one of the sophisticated statistical tools that has been increasingly used by researchers to stratify population units based on various characteristics of interest. Unlike conventional clustering methods, model-based clustering assumes that the underlying population is made up of different clusters, each following a different probability distribution (Stahl & Sallis 2012). In other words, the data is assumed to be a realization from a specific mixture probability density function and this reduces the clustering task into estimating the parameters of the assumed mixture distribution. One of the main advantages of using this approach in empirical application is that it allows researchers to find optimal clusters even with limited prior information about how the units are clustered in theory (Vermunt & Magidson 2002). Compared to conventional clustering methods, model-based clustering uses a less arbitrary approach in minimizing within-cluster and maximizing between cluster-variations (Vermunt & Magidson 2002; Liao 2006). Furthermore, unlike group membership according to quintiles, the choice of the optimal number of clusters in model-based clustering is less arbitrary because it is based on the values of the Bayesian Information Criterion computed from different candidate models.

In empirical studies, it is common to find initial incomes to be negatively correlated with subsequent income growth (Khor & Pencavel 2008). However, as pointed out in Chapter 1, income data from household surveys is usually subject to measurement errors (Fields et al. 2003, Forbes 2000, Khor & Pencavel 2008) and if left unaddressed, may lead to spurious correlation between income mobility and initial income. For instance, underestimated initial incomes may lead to mean reversion and the process would erroneously portray a convergent income mobility. To address this issue, I also consider the household's permanent income as an alternative monetary measure of advantage. For each household, I approximate permanent income by taking its longitudinal average income from 2003, 2006 and 2009.

[62] For example, for an n-individual society where one individual has Z units of income ($Z > n-1$) while each of the $n-1$ individuals has one unit of income only, the resulting inequality will be very high but polarization is low. Liao (2006) provided a more detailed discussion on how the notion of polarization can produce different trends of income variability than Gini-based measures of inequality.

[63] I used the Mclust package available in R in estimating latent cluster models.

6.3.3 Other Correlates of Income Mobility

In examining the impact of initial socio-economic advantage on income mobility, I control for the effect of gender, education, location as well as demographic and economic events. A demographic event is defined as changes in household composition while economic events refer to changes in income sources. Demographic events may affect income mobility systematically in several ways. First, it is a common assumption that individuals within a household pool their resources. Thus, income is expected to move in the same direction as the change in the number of household members who are engaged in paid employment. However, if income is fixed but the number of non-working members increases, then the need to allocate the pooled resources among more people might eventually manifest as negative income mobility. This is because these households are likely to have less savings. In turn, lower savings implies higher vulnerability to unexpected income shocks arising from illness, unemployment, among other factors that lead to reduced income flows. In general, the extent of negative effect of an additional non-working member depends on his/her age. An additional dependent child may limit the ability of women to engage in paid employment due to the amount of time needed for child rearing, leading to a reduced income flow for a significant period of time. On the other hand, the negative impact of an additional member could be less severe if the additional member is of working age because he/she has the potential to contribute to generation of additional income or provide unpaid work around the household should the need arise in the future. Moreover, a significant portion of incomes of households from developing countries is generated from earnings related to paid employment (Dicken 2011). However, income mobility can't be solely determined by the number of household members employed because each working member may be employed in different economic sectors which offer varying levels of income opportunities. In other words, the source of income is also an important factor that could explain one's income trajectories.

6.3.4 Statistical Models of Income Mobility

To examine the convergence and symmetry of the income mobility regime that transpired in the Philippines over the past decade, I estimate a multinomial logistic model wherein the dependent variable corresponds to the propensity to be classified in each of the five clusters and the independent variables correspond to the different indicators of socio-economic advantage, as shown in (6.1).

$$log\left(\frac{p^{cluster_j}}{p^{cluster_1}}\right) = \beta_j X_{i1}^{income} + \theta_j W_{i1}^{non-income} + \gamma_j Z_{i1}^{events} \qquad (6.1)$$

where $p^{cluster_j}$ denotes the probability of falling in cluster j = *2,.., 5*, while X_{i1}^{income} denotes a household's initial monetary advantage, $W_{i1}^{non-income}$ denotes a household's initial non-monetary advantage, Z_{i1}^{events} corresponds to the various demographic and economic events. To account for the potential varying impact when income is measured in terms of actual observed income or permanent income, two variants of (6.1) are estimated:

$$log\left(\frac{p^{cluster_j}}{p^{cluster_1}}\right) = \beta_j X_{i2003}^{income} + \theta_j W_{i2003} + \gamma_j Z_{i1}^{events} \qquad (6.2)$$

$$log\left(\frac{p^{cluster_j}}{p^{cluster_1}}\right) = \beta_j X_{iave}^{income} + \theta_j X_{i2003} + \gamma_j Z_{i1}^{events} \qquad (6.3)$$

In the context of the hypotheses about income mobility described in the previous section, the signs and the magnitude of the estimates for β_j and θ_j after controlling for Z_{i1}^{events}can be used to determine whether income mobility is converging or diverging and whether it is symmetric or asymmetric. Recall that the first cluster corresponds to nil income growth throughout the observation period while the second and third cluster correspond to consistently positive and consistently negative growth rates, respectively. The fourth and fifth clusters correspond to a steep change in the income growth trajectories. Since convergence refers to the initially disadvantaged group catching up with the initially advantaged group, then I can argue that the income mobility in the Philippines is convergent throughout the past decade if the value of either β_2 or θ_2 is higher for the initially disadvantaged households than the initially advantaged group. The mobility process can also be considered convergent if the value of either β_3 or θ_3 is lower for the initially disadvantaged households than the initially advantaged group. In other words, convergence occurs when the initially disadvantaged experience higher growth than the initially advantaged, or the initially disadvantaged experience less decline in growth than the initially advantaged. On the other hand, income mobility is said to be symmetric if the values of either β_4, θ_4, β_5 or θ_5 are significantly different between the initially advantaged and disadvantaged groups.

6.4 Empirical Results

6.4.1 Trends in Income Inequality and Polarization

From the Lorenz curves derived from the distribution of income for each survey wave and the distribution of the longitudinally-averaged income, we can see that over the past decade, both cross-sectional and long-run inequality barely moved (Figure 6.3).[64] More recent studies also show that the country's observed inequality has been accompanied by high levels of polarization or stratification of individuals into different income segments (Gochoco-Bautista et al. 2013). The results presented in Table 6.1 confirm this finding. The numbers under the column labelled as "*Total*" correspond to the estimated value of the Gini coefficient for each of the survey year while the numbers under columns labelled as "*%within*" and "*%between*" correspond to the percentage share of the variability of incomes within and between segments that were formed using latent cluster analysis to the total value of the Gini coefficient, respectively. Here, I find that at least 70% of the observed cross-sectional inequality and about 80% of long-run inequality can be attributed to polarization.

Which income source contributes significantly to the observed inequality? To answer this question, I adopt the method proposed by Shorrocks (1982) which entails doing the following steps. Suppose a household's (total) income is denoted by Y_i and Y_{ik} refers to the income from the k^{th} income source. Thus,

$$Y_i = \sum_k Y_{ik} \tag{6.4}$$

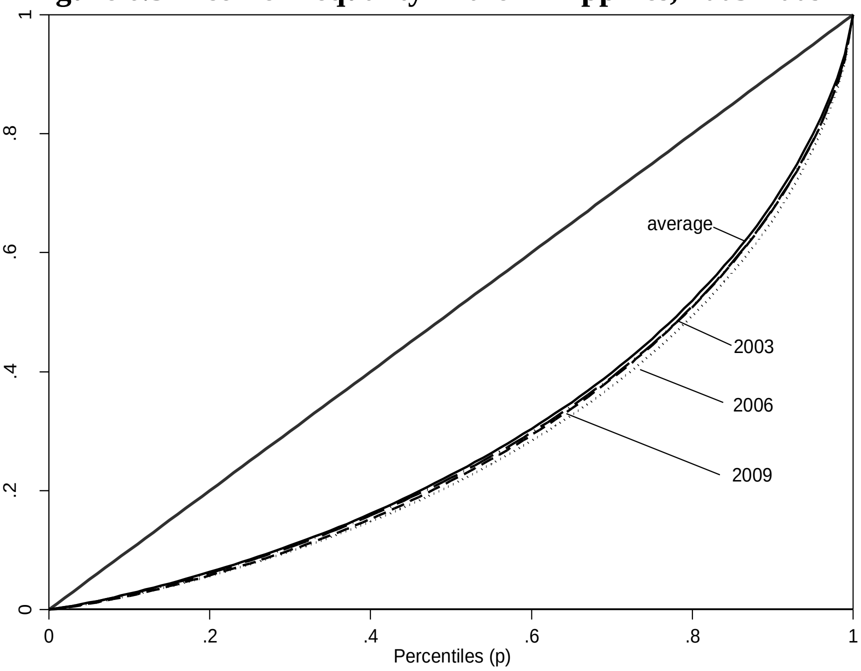
Shorrocks denotes by s_k the *relative factor inequality weight* or the proportion of income inequality that can be attributed to the k^{th} income source. Technically, Shorrocks showed that s_k is equal to the covariance between the total income and the income from k^{th} source divided by the variance of the total income, i.e.,

$$s_k = \frac{Cov(Y,Y_k)}{\sigma_Y^2} \text{ such that } \sum_k s_k = 1 \tag{6.5}$$

Table 6.2 presents the estimates of the factor inequality weight s_k (multiplied by 100%) for each income component. The results suggest that variations in employment income account for approximately 85% of the total inequality. Interestingly, the contribution of variations in income from self-employment or entrepreneurial income to total inequality seems to be increasing over the years. This pattern is probably driven by the impact of the global financial crisis (GFC) which started in 2008. As jobs were lost during the GFC, a significant fraction of household earnings derived from wage employment shifted to entrepreneurial or self-employment (Yap, Reyes and Cuenca, 2009). I turn to this issue in Chapter 8.

[64] The value of the Gini coefficient is equal to the area below the line of perfect equality and above the Lorenz curve wherein higher values suggest higher inequality.

Figure 6.3 Income Inequality in the Philippines, 2003-2009



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

6.4.2 Income Mobility and Inequality

In this section, I examine how initial advantage affects income mobility prospects. If advantage is gauged in terms of income, the GIC is a good graphical tool for examining pro-poorness of growth. As discussed in Chapter 1, there are two ways of deriving GICs. The first approach entails comparing the income of a household with a certain income rank based on the distribution of initial period incomes with another household with the same income rank based on the distribution of final period incomes. The resulting curve is the conventional GIC. The alternative approach is to derive the IGIC by computing the income growth rates of the same respondents and plotting these growth rates with the quantiles of the initial income. The solid lines in Figure 6.4 represent the IGICs while the broken lines represent the conventional GICs. Since the slopes for the IGICs are more negative than the slope of the conventional GICs, it implies that the development process has worked to the advantage of the initially poor more than what we can perceive based on conventional GICs. This is consistent with the result of the simple simulation experiment using pseudo-panel data presented in Chapter 2 which suggests that IGIC is likely to portray a more (relative) pro-poor growth than the conventional GIC.

Table 6.1 Decomposition of Inequality by Income Clusters

Location	2003			2006			2009			Permanent Income		
	Total	%within	%bet	Total	%within	%bet	Total	%within	%bet	Total	%within	%bet
Philippines	42.84	30.00	70.00	44.28	15.68	84.32	42.15	28.96	71.04	41.14	15.96	84.04
Urban	39.26	38.62	61.38	42.18	43.89	56.11	40.38	27.89	72.11	38.43	28.73	71.27
Rural	39.28	28.47	71.53	38.8	27.09	72.91	37.43	27.36	72.64	36.28	27.68	72.32
NCR	37.12	38.95	61.05	42.78	39.81	60.19	38.65	46.6	52.4	36.93	33.37	66.63
Luzon	39.66	28.47	71.53	40.66	28.34	71.66	38.63	28.53	71.47	37.55	27.94	72.06
Visayas	41.73	37.14	62.86	42.98	38.68	61.32	42.40	26.04	73.96	40.36	26.01	73.99
Mindanao	41.96	27.25	72.75	42.02	26.01	73.79	41.70	27.45	72.55	39.89	27.02	72.98

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 6.2 Decomposition of Inequality by Income Source

Income Source	2003	2006	2009	Permanent Income
Wage income	48.45	40.04	29.28	41.88
Entrepreneurial income	38.56	43.39	62.97	45.63
Asset income	7.34	5.43	3.31	5.87
Income from transfers	0.44	1.88	0.92	1.07
Remittance income	4.39	8.15	2.93	4.86
Other income	0.82	1.10	0.59	0.68
Total	100.00	100.00	100.00	100.00

Source: Author’s computations using household income per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

One of the main limitations of using IGIC is that it examines only two income vectors at a time. As explained earlier, this can be problematic if one wants to differentiate households that have experienced volatile income flows from households that have experienced more stable income changes. Table 6.3 summarizes how different levels of income growth rates are distributed in each time period. If short-distance move is defined as absolute income growth rate of less than 5%, it would account for less than one-third of the total observed mobility in 2003-2006 as well as in 2006-2009. On the other hand, medium-distance moves or absolute income growth rates between 5% to 20% account for more than half of the observed mobility while long-distance moves or absolute income growth rates exceeding 20% contribute to about 13% of the total observed mobility in 2003-2006 and 2006-2009. Interestingly, the distribution of growth rates in 2003-2009 is less varied wherein about half of the observed mobility is characterized by short-distance moves, 48% are medium-distance moves and only 2% are long-distance moves. A possible reason for this is that the 2003-2006 growth rates offset the 2006-2009 growth rates. Table 6.4 provides evidence for this hypothesis by showing that there is a non-negligible number of households that experienced consistently positive or consistently negative growth rates. Overall, positive and negative changes in household income are both common throughout the observation period suggesting that the development process has created both “winners” and “losers”.

6.4.3 Testing Convergence, Divergence and Symmetry of Income Mobility

Using Income as a Measure of Advantage

Tables 6.5 and 6.6 show the distribution of income trajectories from 2003 to 2009, by income quintile and income cluster. When initial income in 2003 is used, the latent cluster analysis produced two clusters which I labelled as “Poor” and “Non-poor” in Table 6.5 and when longitudinally-averaged income is used, the method produced three clusters which I labelled as “Poor”, “Middle” and “Rich” in Table 6.6. If initial (monetary) advantage was independent of income mobility, the expected value in each cell should be approximately the same as the overall distribution of income trajectories depicted in Table 6.4. However, the results are characterized by mixed patterns. For instance, if households are grouped according to actual income in 2003, I find that the middle 60% households were more likely to be classified under the first cluster than the poorest 20% and richest 20% households. In terms of the groups formed by latent clustering method, I find that the poor are significantly more likely to fall in the second cluster while the non-poor are significantly more likely to fall in the third

Table 6.3 Distribution of Income Growth Rates (%)

annualized growth (g)	2003-2006	2006-2009	2003-2009
-20% ≥ g	7.07	5.56	0.55
-20% < g ≤ -10%	16.21	11.39	7.36
-10% < g ≤ -5%	14.12	10.43	13.72
-5% < g ≤ 5%	29.7	31.88	50.52
5% < g ≤ 10%	12.42	14.86	17.09
10% < g ≤ 20%	13.94	17.99	9.97
20% < g	6.55	7.9	0.79
Total	100	100	100

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 6.4 Distribution of Income Trajectories (%)

Type of income trajectory	%Population
Cluster 1: slow to moderate growth	10.64
Cluster 2: generally positive income growth	30.84
Cluster 3: generally negative income growth	24.48
Cluster 4: high positive growth in 2003-2006, high negative growth in 2006-2009	14.11
Cluster 5: high negative growth in 2003-2006, high positive growth in 2006-2009	19.93
Total	100

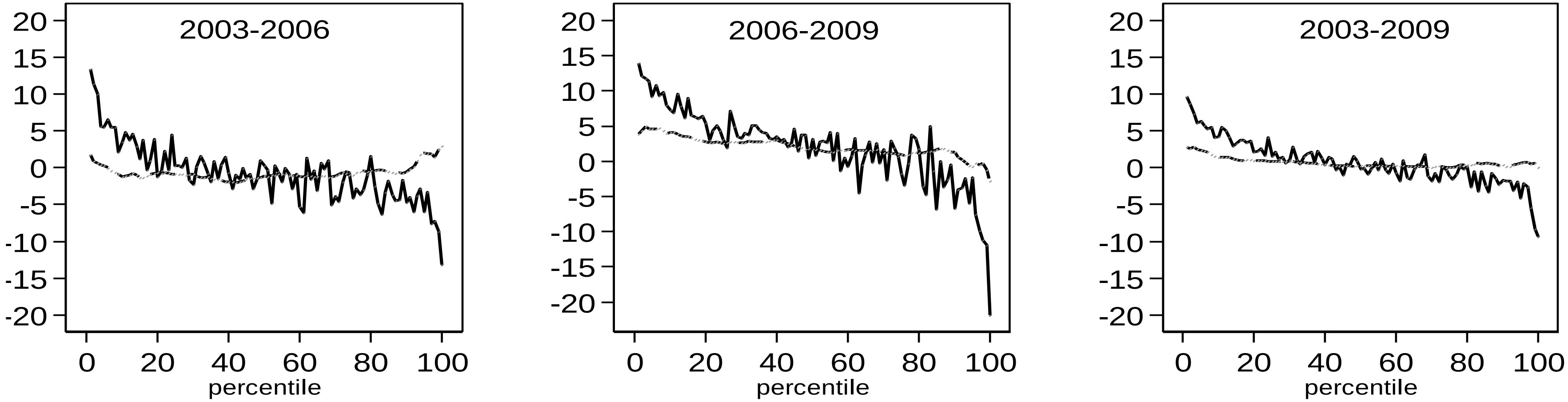
Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 6.5 Distribution of Income Trajectories (%), by Segments of Initial Income

Group	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Total%
(Initial) quintile 1	9.75	54.38	9.16	11.40	15.31	100
(Initial) quintile 2	12.94	33.39	18.88	13.74	21.05	100
(Initial) quintile 3	11.24	26.57	28.43	14.23	19.54	100
(Initial) quintile 4	11.34	24.33	29.31	14.07	20.95	100
(Initial) quintile 5	8.17	16.01	36.01	17.03	22.79	100
Poor cluster	11.34	39.02	18.23	12.99	18.41	100
Non-poor cluster	9.72	20.27	32.55	15.56	21.90	100
All	10.64	30.84	24.48	14.11	19.93	100

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Figure 6.4 Anonymous and Non-Anonymous Growth Incidence Curves, 2003-2009



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

group. On the other hand, when households are grouped according to longitudinally-averaged income, it is the poorest 20% households who were most likely to be classified under the first cluster.

Regardless whether households are grouped according to initial income in 2003, longitudinally-averaged income or income quintile or clusters formed from latent cluster analysis, the results suggest that the poorest group is more likely to be classified under the second cluster than the rest of the population. In other words, the poorest (on various definitions) experienced the best income mobility outcomes. On the other hand, I find mixed patterns when looking at households that experienced consistently negative income growth rates. In particular, when households are grouped according to initial income, the propensity to be classified under the third cluster increases as one moves up the income ladder. However, when households are grouped according to longitudinally-averaged income, middle income households had the highest risk of experiencing consistently downward mobility. Lastly, I find that the richest households based on initial income in 2003 were more likely to be classified under the fourth and fifth clusters. However, when longitudinally-averaged income is used, the rich households were more likely to be classified under the fourth cluster but the poor households were more likely to be classified under the fifth cluster.

In terms of the income mobility patterns, the results provide empirical support for (unconditional) convergence of mobility when households are grouped according to either initial income in 2003 or longitudinally-averaged income, because poor households have the highest probability to be in the generally positive income growth cluster while the non-poor have the highest probability to be in the generally negative income growth cluster. In addition, the results also provide evidence for (unconditional) symmetry of mobility when households are grouped according to longitudinally-averaged income because this suggest that the rich households were more likely to be in the high positive growth in 2003-2006 and high negative growth in 2006-2009 cluster while the poor households were more likely to be in the high negative growth in 2003-2006 and high positive growth in 2006-2009.

Table 6.6 Distribution of Income Trajectories (%), by Segments of Permanent Income

Group	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Total %
(Ave.) quintile 1	12.50	37.83	19.55	7.64	22.48	100
(Ave.) quintile 2	11.01	30.68	25.81	12.15	20.35	100
(Ave.) quintile 3	10.66	29.02	27.37	13.23	19.71	100
(Ave.) quintile 4	10.82	29.56	25.98	16.02	17.63	100
(Ave.) quintile 5	8.11	26.58	24.22	21.80	19.29	100
(Ave.) Poor cluster	11.58	34.81	22.52	9.58	21.50	100
(Ave.) Middle income cluster	10.99	28.80	26.88	14.10	19.23	100
(Ave.) Rich cluster	9.12	27.80	24.65	19.82	18.62	100
All	10.64	30.84	24.48	14.11	19.93	100

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Table 6.7 Distribution of Income Mobility by Household Characteristics (%)

Group (based on 2003 data)	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Total %
Female-headed hhld	7.21	30.92	26.33	17.23	18.31	100
Male-headed hhld	11.15	30.83	24.20	13.65	20.17	100
Marital status of hhld head: Single	4.19	21.59	32.26	26.07	15.88	100
Married	11.23	31.23	24.10	13.44	20.01	100
Widowed/Separated/Others	7.05	29.32	26.21	17.46	19.96	100
Educational attainment of hhld head:						
Primary education	10.88	32.01	23.11	12.68	21.33	100
Secondary education	10.59	29.62	26.22	14.75	18.81	100
Tertiary education	9.66	31.29	22.29	18.07	18.69	100
Family size: 1 to 3	7.77	18.71	38.79	15.44	19.30	100
4 to 5	12.29	25.96	25.79	15.22	20.75	100
6 to 7	10.47	35.47	20.73	13.67	19.66	100
8 to 9	10.56	40.00	17.21	12.59	19.63	100
10 or more	8.87	45.85	16.61	10.03	18.64	100
Rural	10.13	34.60	22.00	12.90	20.38	100
Urban	11.16	26.97	27.03	15.37	19.47	100
NCR	8.16	21.27	28.28	18.50	23.79	100
Luzon	11.08	29.61	25.94	14.65	18.72	100
Visayas	10.14	35.32	22.27	12.59	19.68	100
Mindanao	11.25	33.01	22.04	12.66	21.03	100
Main source of income:						
Non-Agriculture	10.48	28.89	26.28	15.19	19.16	100
Agriculture	11.07	36.27	19.48	11.11	22.07	100
All	10.64	30.84	24.48	14.11	19.93	100

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Socio-demographic variables

I use geographic location, household head's sex, educational attainment, marital status, household size and main source of income as control variables. As pointed in Chapter 1, these variables are correlates of socio-economic well-being used in the existing literature. Table 6.7 shows the distribution of the types of income trajectories for each group (based on 2003 data). Here, I find that single, female-headed households experienced more volatile income flows than their married, male counterparts. The results also suggest that households with highly educated heads were more likely to experience very high income growth rates in 2003-2006 but they also had the highest risk to incur high income losses in 2006-2009. In contrast, households headed by primary educated individuals were more likely to experience high income losses in 2003-2006 and high income gains in 2006-2009. Significant variations in income mobility outcomes are also apparent when households are grouped according to household size. In particular, households with more members were more likely to experience consecutive episodes of upward mobility while smaller-sized households were more likely to experience consecutive episodes of downward mobility. Furthermore, I also find that rural agricultural households, especially those from Visayas and Mindanao had better income mobility outcomes. Overall, the results suggest that initially disadvantaged households especially with respect to family size, geographic location and employment sector experienced faster income growth rates than advantaged households.

6.4.4 Estimated Statistical Models

In the previous section, I find evidence that income mobility outcomes differ in terms of the marginal distribution of income status and other socio-demographic characteristics. This section measures the statistical significance of each of these factors in explaining mobility in the presence of other factors. Furthermore, it also examines the significance of demographic and economic events in explaining the variations in income mobility.

Table 6.8 shows the coefficients of the multinomial logistic models based on (6.3) and (6.4) for the monetary indicators. The full regression results are provided in Appendix Table A6.1. The coefficients are interpreted as follows. For instance, based on the first entry in Table 6.8, the multinomial logit for households from the second quintile relative to those in the poorest quintile is 1.1 unit lower for being in the cluster of households that experienced consistently upward mobility (cluster 2) relative to the cluster that experienced nil income mobility (cluster 1). The other numbers can be interpreted analogously. Since the coefficients for cluster 2 decrease as the income quintiles increase and the coefficients for cluster 3 increase as the income quintiles increase, we can conclude that the poorest 20% households had the highest (logged) odds to experience consistently upward mobility (cluster 2), followed by the middle income households and lastly by the richest 20% households. On the other hand, the richest quintile had the highest odds of experiencing consecutive episodes of downward mobility (cluster 3), followed by the middle-income households and lastly by the poorest quintile. These results support the finding described in the previous sections that households from the poorest quintile had experienced generally better income mobility outcomes than households from the richest quintile. Notably, the differences in the odds to experience either consistently upward or consistently downward mobility became less pronounced when longitudinally-averaged income was used as the measure of advantage rather than initial income. Furthermore, the data based on the longitudinally-averaged income also suggest that the richest two quintiles had the highest odds of experiencing the most volatile income movements (clusters 4 and 5).

Appendix Table A6.1 also shows the impact of the control variables. When both income and socio-demographic variables are included in the model, the only significant patterns are that higher educational attainment (of the household head) and lower dependency ratio were positively correlated with the propensity to experience better income trajectories. Furthermore, after adding the different indicators of demographic and economic events in the models, I find that an additional non-working age family member is correlated with inferior income mobility outcome while an increase in the number of employed members improves a household's income mobility prospects. Overall, the results of the estimated models suggest that while initial advantage is a significant determinant of a household's income trajectory, it only explains a small fraction of the variations in the income mobility outcomes. Changes in household composition and employment outcomes provide additional information in predicting a household's income trajectory.

In summary, the empirical investigation presented in this chapter leads to mixed findings. First, if advantage is measured in terms of initial income (in 2003), I find that the households from the richest quintile had the lowest propensity to experience slow to moderate income changes and were most likely to experience consistently downward mobility throughout the observation period. Furthermore, initially advantaged households had the highest propensity to experience consistently upward mobility. Second, if advantage is measured in terms of longitudinally-averaged income, I still find that the richest quintile tend to be the least immobile and were most likely to experience the most erratic income fluctuations. In particular, the richest quintile had the highest propensity to experience very high income growth rates in 2003-2006, a period when average income was decreasing and very high income losses in 2006-2009, a period when average income was increasing. In addition, the poorest quintile had the lowest propensity to experience consistently downward mobility. Nevertheless, although the results suggest that advantage is a significant determinant of income mobility, I also find that demographic changes (e.g., changes in household composition) and economic events (e.g., employment transitions) are also important determinants of mobility.

6.5 Summary and Discussion

How does income segmentation affect income mobility? Does economic growth allow initially disadvantaged people to catch up through faster income growth or are they left out because of the cumulative effect of advantage over time? These are the questions that I tried to address in this paper. The results provided in the last two sections show that income advantage is an important correlate of subsequent income trajectories. In particular, initial income has a negative correlation on income growth rates such that households starting with lower initial income were more likely to experience higher income growth rates than those who had higher initial income. However, this result needs to be interpreted with care because it is possible that those who were either below or above their permanent income in 2003 only regressed towards their longitudinally-averaged income in the subsequent years. In other words, the consistently significant negative relationship between initial income and income growth rates may simply be an artefact of the regression to the mean phenomenon as previous studies suggest that initial income's explanatory power can be a mix of genuine income dynamics and measurement errors (Fields et al. 2003). To examine the robustness of the findings, I also considered using the longitudinally-averaged income instead of initial income as a measure of advantage. After doing this, I still find that the lower income households experienced (slightly) better income mobility outcomes. However, their edge over higher income households was much smaller when longitudinally-averaged income was used. Although these patterns portray convergence, it can be argued that part of this convergence can be attributed to temporal income fluctuations. Furthermore, the results also point to symmetry of mobility based on initial incomes and longitudinally-averaged incomes. In particular, the data shows that based on initial income, the richest households had the greatest propensity to experience the highest income losses during economic contraction in 2003-2006 and highest income gains during economic expansion in

Table 6.8 Regression Coefficients of Multinomial Logistic Models
(Reference category: Cluster 1 (slow to moderate growth))

<table>
<tr><th rowspan="2">Income Segment</th><th colspan="4">Initial income in 2003</th><th colspan="4">Permanent income</th></tr>
<tr><th>cluster 2</th><th>cluster 3</th><th>cluster 4</th><th>cluster 5</th><th>cluster 2</th><th>cluster 3</th><th>cluster 4</th><th>cluster 5</th></tr>
<tr><td>Cluster
(base: 1st quintile)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>2nd quintile</td><td>-1.077***</td><td>.8009***</td><td>-.4979***</td><td>.3609**</td><td>-0.0101</td><td>.4144***</td><td>.536***</td><td>0.2296</td></tr>
<tr><td>3rd quintile</td><td>-1.434***</td><td>1.573***</td><td>-.6894***</td><td>.6826***</td><td>0.1281</td><td>.4823***</td><td>.633***</td><td>0.264</td></tr>
<tr><td>4th quintile</td><td>-1.79***</td><td>1.849***</td><td>-.8973***</td><td>.9757***</td><td>0.2813</td><td>.4459**</td><td>.9259***</td><td>.4173**</td></tr>
<tr><td>5th quintile</td><td>-2.233***</td><td>2.604***</td><td>-.7946***</td><td>1.677***</td><td>.4677**</td><td>.6626***</td><td>1.536***</td><td>.899***</td></tr>
<tr><td>Cluster
(base: Poor cluster)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Middle income cluster</td><td rowspan="2">-0.7121*</td><td rowspan="2">0.8753***</td><td rowspan="2">-0.259*</td><td rowspan="2">0.6719***</td><td>0.0901</td><td>0.1671</td><td>0.3166**</td><td>0.1171</td></tr>
<tr><td>Rich cluster</td><td>.3053*</td><td>0.1537</td><td>0.7754***</td><td>0.4317**</td></tr>
</table>

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

2006-2009. In contrast, based on longitudinally-averaged income, the data suggest that the richest quintile had the highest probability of observing very high income growth rates even if the rest of the population experienced decreasing incomes in 2003-2006 and incurred income losses when the rest of the population observed positive income growth in 2006-2009.

In terms of policy implications, the result that income trajectories of the poor, middle income and rich households are statistically different, reiterates that the impact of economic development is not uniform. Thus, policies should be tailor-fitted according to the diverse circumstances confronting different population groups. Similar to the findings presented in the previous chapters, I find evidence to suggest that low income households are more likely to experience better income mobility outcomes than the rest of the population even after controlling for temporary income fluctuations. Nevertheless, the finding that significant fraction of low income households experienced income losses during the observation period suggests that existing poverty reduction programs could be improved further. This re-echoes what I have argued in Chapter 5 that to speed up the poverty reduction, it is important that intervention programs should be responsive to the long-term human capital development needs of the chronically poor and social protection needs of the transiently poor.

Like the poor, the significant gains experienced by some middle income households were offset by the losses incurred by others. This contributed to the slow income growth of middle income households. If such trend continues, this may push the country to a middle income trap like many countries in Latin America (Jankowska, Nagengast & Perea 2012). If the middle income households remain stagnant, it will be difficult for the Philippines to really take-off because a strong middle class is usually the engine for growth. To minimize this danger, one of the steps that the government can take is to create more jobs of better quality not only for college graduates but also for non-college graduates which comprise a significant fraction of the middle class. Although this is easier said than done as job creation often requires strengthening the competitiveness of local firms in the global production chain which usually comes at the expense of quality of employment, this feat is not impossible as seen in the experiences of other Asian countries like Singapore and South Korea which have improved the quality of jobs held by workers without college degrees (Li 2002). Economists reckon that the first step is to build a strong manufacturing sector because without a strong manufacturing sector, non-college graduates are often left to take low paying jobs in the services sector which can hardly sustain upward mobility in the long-run (Usui 2011, 2012). However, this may also require upgrading the skills of workers in the traditional manufacturing sector so that they will remain competitive in the labour market as the country transitions from traditional to modern manufacturing. For higher income households, this study finds that they experienced the most erratic income fluctuations. Although higher income households may be better-off in handling income fluctuations because they suffer less from liquidity constraints than lower income households, it is important that policies should still aim to minimize these volatilities. One way to address this issue is to facilitate a socio-economic climate conducive for business as majority of high income households rely on income from entrepreneurial activities. A WB study shows that the business regulations in the country are among the most complicated and costliest in Southeast Asia (WB 2013). This should prompt policymakers to review how the existing rules and regulations in doing business in the country can be simplified.

Interestingly, my findings that demographic and economic events are significant correlates of income trajectories resonate some of the advances in the literature of socio-economic stratification. Traditionally, sociologists and economists have been interested in understanding the patterns of social segmentation due to income, social class, gender or educational level and how these factors shape a person's socio-economic prospects. Lately, the research focus has shifted to the importance of life course events as predictors of income trajectories (Vandecasteele 2010). This calls for the need to collect more relevant data on life course events to be able to assess their structuring effect on a person's socio-economic well-being.

Appendix Table A6.1 Regression Coefficients of Multinomial Logistic Models for Income Growth Trajectories in the Philippines

Variable	Initial Income in 2003				Permanent Income			
	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Male-headed hhld	-0.2998	-0.2744	0.0235	-0.1082	-0.2951	-0.2558	0.0189	-0.0911
Hhld head's age	0.0247	0.0092	0.0190	-0.0032	0.0110	0.0205	0.0050	0.0010
Hhld head's age squared	-0.0003	0.0000	-0.0001	0.0000	-0.0001	-0.0001	0.0000	0.0000
Marital status of hhld head (base = Married)								
Single	-0.0722	-0.2082	-0.1912	-0.1505	-0.2944	-0.0685	-0.3789	-0.0867
Separated/widowed/others	0.1257	-0.1301	0.1157	0.2155	-0.0780	-0.0317	-0.0624	0.2591
Hhld head's educational attainment								
Primary education	.4796***	-.321**	.3327**	-.2492**	0.0618	-0.0326	-0.0229	-0.1224
Tertiary education	.9064***	-.9734***	0.3552	-.5875**	0.0462	-.4324*	-0.3180	-0.3676
Region (base = NCR)								
Luzon	-0.0324	0.0056	-0.1405	-0.2897	0.1175	-0.0822	-0.0413	-0.3216
Visayas	0.0737	0.1643	-0.2562	-0.0160	.4972**	-0.0741	0.0587	-0.1204
Mindanao	-0.1536	0.0964	-0.3340	-0.1249	0.2978	-0.1606	0.0193	-0.2248
Urban	-0.0728	-.3324***	-0.0768	-.4153***	-.326***	-0.1309	-.2855**	-.3209***
Hhld type (base = Single Family)								
Extended family	0.1876	0.1757	0.0754	-0.0360	0.0606	.266*	-0.0348	0.0052
Two or more non-related individuals	13.0900	12.2300	12.6800	12.8000	13.8700	13.6700	13.5300	14.0900
Proportion of hhld members who are young	-1.301***	.8153**	-1.555***	0.4440	-0.3063	0.1972	-.7377*	0.2106
Family size	-.05809*	0.0442	-.08264**	0.0524	0.0474	-0.0329	0.0098	0.0202

Appendix Table A6.1 Regression Coefficients of Multinomial Logistic Models for Income Growth Trajectories in the Philippines

Variable	Initial Income in 2003				Permanent Income			
	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Main source of income is Agriculture	-.2153*	0.0700	-.3374**	0.1834	0.1230	-0.1632	-0.0355	0.0800
Hhld head is employed	-0.0443	-0.0753	-0.5284	0.0957	-0.1522	-0.0175	-0.5917	0.1653
At least one hhld member is working abroad	.356***	-0.2200	0.1607	-0.0786	0.0283	-0.0046	-0.1129	0.0149
Hhld income quintile (base = 1st quintile)								
2nd quintile	-1.077***	.8009***	-.4979***	.3609**	-0.0101	.4144***	.536***	0.2296
3rd quintile	-1.434***	1.573***	-.6894***	.6826***	0.1281	.4823***	.633***	0.2640
4th quintile	-1.79***	1.849***	-.8973***	.9757***	0.2813	.4459**	.9259***	.4173**
5th quintile	-2.233***	2.604***	-.7946***	1.677***	.4677**	.6626***	1.536***	.899***
Proportion of hhld members who are employed	0.1016	0.3492	.415*	.4722**	0.1962	0.2934	.4838**	.4457*
Proportion of employed hhld members with permanent job	0.0151	-0.0474	0.0371	-0.0656	-0.0429	-0.0074	-0.0180	-0.0452
Proportion of employed hhld members with formal job	0.0417	0.1503	.363**	-0.0411	-0.1728	.2905*	0.1765	0.0157
Proportion of employed hhld members with multiple jobs	-.3544**	-0.1265	-0.2858	-0.1841	-.2788*	-0.1751	-0.2310	-0.2169

Appendix Table A6.1 (con't) Regression Coefficients of Multinomial Logistic Models for Income Growth Trajectories in the Philippines

Variable	Initial Income in 2003				Permanent Income			
	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Hhld head's sex changed (2003-2006)	0.2852	0.0852	.6397**	0.3313	0.2402	0.0693	.588**	0.3163
Hhld head's sex changed (2006-2009)	-.3587*	-0.0628	-.5687**	-.4354*	-0.3414	-0.0884	-.5462**	-.4567**
Hhld head's marital status changed (2003-2006)	-0.1066	0.1113	-0.2411	-0.2356	-0.0630	0.1322	-0.2136	-0.2133
Hhld head's marital status changed (2006-2009)	0.1633	-0.1201	0.2943	0.2741	0.1831	-0.1087	0.3007	0.2919
Hhld head's educational attainment improved (2003-2009)	0.2655	-.4082**	0.1668	-0.0437	0.0396	-0.2846	-0.0335	-0.0076
Hhld head's educational attainment deteriorated (2003-2009)	-0.0638	0.3076	0.0452	0.2497	0.1301	0.1560	0.1987	0.1793
Change in family size (2003-2006)	-.2441***	.2704***	-.2545***	.1894***	-.2154***	.2552***	-.2144***	.1886***
Change in family size (2006-2009)	-.2515***	.2358***	.2061***	-.2308***	-.2393***	.2334***	.2238***	-.2245***
Change in proportion of young members (2003-2006)	-0.1521	0.1559	-1.073**	0.5103	0.0853	0.1086	-.8799**	0.4970
Change in proportion of young members (2006-2009)	-1.004***	.8568**	0.2630	-0.0610	-.7299**	.6831*	0.5123	-0.1159
Change in proportion of employed members (2003-2006)	0.3623	-.7166**	-0.2402	-0.1501	0.4545	-.7677**	-0.1960	-0.1707
Change in proportion of employed members (2006-2009)	0.1369	-.9959***	-.7275***	0.2938	0.1748	-.9815***	-.7338***	0.3062
Main source of income changed (2003-2006)	0.0245	0.2347	0.2020	0.1158	0.1130	0.1874	.2823*	0.1058
Main source of income changed (2006-2009)	0.1641	0.2315	0.0937	.4979***	0.2184	0.1659	0.1622	.4776***
Constant	2.375***	-1.0700	1.2440	-0.0516	0.7808	0.0758	-0.1508	0.3540

Source: Author's computations using data from the longitudinal subsample of FIES 2003, 2006 and 2009.
Note: The dependent variable is based on household expenditure per capita. The results based on the latent cluster analysis are qualitatively similar. To save space, I don't present the results here.

Chapter 7 What Drives Income Distribution Dynamics in the Philippines?

7.1 Introduction

The previous two chapters examined the dynamics of poverty and inequality by taking into account the mobility of incomes. A good understanding of how much various factors affect poverty and inequality is important for strategic planning and policy making as it allows socio-economic planners devise policy interventions that could help economic growth achieve maximum impact on reducing socio-economic deprivation. For instance, if one finds that changes in employment income drive upward mobility, labour market policies that promote growth in sectors where most of the poor are should become the focus. On the other hand, if economic shocks drive downward mobility, policymakers should strengthen social safety nets. In the Philippines, several studies have attempted to identify why poverty and inequality remain high despite faster economic growth (e.g., Balisacan & Hill 2003; Schelzig 2005; ADB 2007; Aldaba 2009) by identifying factors that correlate with these two phenomena. In the previous chapters, I have also implicitly focused on correlations between mobility and various socio-economic variables. However, solely relying on correlations make it hard to gauge the extent to which perturbations in different factors would affect the distribution of household income. For example, although many of the existing studies in the recent years suggest that sub-optimal employment outcomes highly correlate with higher poverty (ILO 2009; ADB 2011b), they are silent about how much of the observed changes in poverty levels can actually be attributed to the changes in employment outcomes. The main objective of this chapter is to contribute to the existing literature in identifying proximate determinants of poverty and inequality dynamics in the Philippines. Using a general Shapley (1953)-based accounting method proposed by Shorrocks (2013), the analysis presented in this chapter departs from the conventional correlation-based approaches by carrying out a series of counterfactual simulations to decompose the changes in poverty and inequality into the contribution of changes in various income correlates. While there are also limitations in the decomposition approach proposed by Shorrocks (2013), the result of such an accounting tool is easier to interpret and facilitates a more straightforward ranking of the relative importance of each factor in driving poverty and inequality because the estimated contributions sum up to the observed changes in poverty and inequality compared to the conventional correlation-based approaches. This exercise may be considered as a head start to better understand how to prioritize policy intervention programs to induce better household income distribution outcomes in the country.

In identifying the factors that have contributed to the observed household income distribution dynamics, I examine the extent to which changes in poverty and inequality depend on the changes in people's socio-economic capital or to changes in the economic returns to these capital. Simply put, a socio-economic capital (SEC) can be viewed as an economic tool that a person can use to extract the available wealth in the society to be able to improve his/her well-being. The type of education, employment and assets held are examples of SECs.[65] In general, each SEC is valued differently. For example, having a college education does not necessarily have the same impact on a person's well-being as having a small parcel of land. I refer to this value as socio-economic returns (SER). In addition to employment, many studies have highlighted the importance of having higher skill set through better educational qualification in promoting upward mobility (Greenstone et al. 2013, Morgan et al. 2006). Some studies, particularly in the Philippines, have also stressed the limited access to basic social services and productive assets as underlying cause of poverty and inequality (Balisacan 2007). However, how changes in the returns to various forms of capital contribute to the evolution of household income distribution in the Philippines remains an empirical issue. For instance, as the supply of a specific form of socio-economic capital increases, it is tempting to expect for its corresponding economic returns to decline assuming that the demand for such capital remains fixed. This potential trade-off between capital and economic returns and the fact that either demand or supply of socio-economic capital hardly remains constant relative to the other make it less straightforward to infer how poverty and inequality would change over time. It may lead to either poverty reduction if low income households are acquiring additional capital faster than economic returns are dropping or increasing poverty if economic returns are deteriorating faster than the rate at which low income households are acquiring additional capital. Alternatively, poverty reduction will be much faster or lower than expected if both socio-economic capital and returns to capital are simultaneously increasing or decreasing, respectively. Counterfactual analysis allows me to investigate which of these scenarios hold in the Philippines. In particular, I address the following questions:

(i) Are changes in households' socio-economic capital and/or changes in returns to capital important in explaining the evolution of poverty and inequality in the Philippines?

[65] In other sociological literature, education is considered as an endowment while employment is considered as a type of functioning (i.e., capacity to translate an endowment to resources that can be used directly to improve one's well-being). In this study, I considered both education and employment as different types of socio-economic capital to account for the fact that people have different capacities to make endowments function towards improving one's living standards.

(ii) What are the socio-economic factors that have contributed significantly to changes in poverty and inequality in the Philippines over the past decade?

Like in other chapters, I use the longitudinal subsample data from the FIES-LFS to answer these questions. Throughout the study, estimates are presented at the national and (broad) regional levels.

7.2 Concepts and Methods

7.2.1 Drivers of Income Distribution Dynamics

Following the convention used in the previous chapters, I use the (log) household expenditure per capita as the main measure of well-being and I refer to this as income. To be able to measure the contribution of changes in SECs and changes in SERs to the observed trends in poverty and inequality, equation (7.1) decomposes (log) per capita income as a stochastic function of several correlates of a household's well-being that are typically used in the existing literature (Canlas et al. 2009).

$$Y_{it}^{pce} = \beta_t^{location} X_{it}^{location} + \beta_t^{hhldcomp} X_{it}^{hhldcomp} + \beta_t^{employ} X_{it}^{employ} + \beta_t^{svcs} X_{it}^{svcs} + \beta_t^{assets} X_{it}^{assets} + \varepsilon_{it} \quad (7.1)$$

Similar to how I categorized the proximate determinants of poverty dynamics in Chapter 5, the SECs are broadly grouped into (i) (geographic) location, (ii) education, (iii) employment, (iv) access to (basic) services and (v) physical assets.[66] Although all of these SECs are important, identifying which of them have the most significant impact on household income distribution outcomes will enable policymakers prioritize intervention programs. In a developing country like the Philippines, setting policy priorities and channelling the limited resources available to areas where interventions could have optimal impact is critical.

How does the relationship between SEC and SER affect household income distribution outcomes? It is worth pointing out that simply increasing households' capital levels would not necessarily guarantee better living standards (King, Montenegro, & Orazem 2012; Schultz 1975). For instance, if the labour force had higher stockpile of skills, it is not absolutely consequential that this would result in upward economic mobility across the board unless the demand for better-skilled workers also increases. A higher supply of skilled workers with a fixed demand for such type of labour would likely result in lower SERs. The same can be said about the other types of SECs. In this simple example, (absolute) poverty would increase if

[66] As mentioned earlier, there are other forms of socio-economic capital (e.g., health, social networks, etc.) that can influence the household income distribution based on the existing literature but they are not included here due to data limitations.

SER falls faster than the rate at which SEC is increasing for low income households and it would decrease if SEC increases faster than the rate at which SER is falling. On the other hand, inequality would increase when SEC is increasing disproportionately faster in high income households or SER is decreasing disproportionately faster in low income households. The following section outlines the methodology for estimating the contribution of each of these factors on income distribution dynamics, separately.

7.2.2 Estimating the Contribution of SECs and SERs to the Evolution of the Income Distribution

Since the pioneering work of Oaxaca (1973) and Blinder (1973) who proposed methods for decomposing group differences in income into various components, substantial progress has been made in terms of understanding what contributes to income distributional variations across space and over time. The main idea behind the Oaxaca-Blinder method is to decompose income differentials (between groups) into factors that are attributable to differences in SECs and variations in the SERs. To illustrate the approach, assume the income of individual *i* from the g^{th} group, denoted by $Y_i^{(g)}$, is a function of his/her SEC $X_i^{(g)}$, SER $\beta^{(g)}$, and an unobserved error term $\varepsilon_i^{(g)}$as shown in Equation 7.2.[67] For simplicity, suppose we have two groups, *g = 0, 1*. The main objective of the Oaxaca-Blinder decomposition method is to explain the difference in group averages denoted by $\bar{Y}^{(1)} - \bar{Y}^{(0)}$. This is done by constructing income for one group, denoted by $\bar{Y}^{(c)}$, by assuming that it has the same income structure (i.e., same SER) as the other group as shown in Equation 7.3. Equation 7.4 shows that the difference $\bar{Y}^{(1)} - \bar{Y}^{(0)}$ can be arithmetically expressed as a sum of two components where the first term corresponds to the gap in the average SEC in each group while the second term corresponds to the variation in the SER.

$$Y_i^{(g)} = \beta^{(g)} X_i^{(g)} + \varepsilon_i^{(g)} \rightarrow \bar{Y}^{(0)} = \hat{\beta}^{(0)} X_i^{(0)} \text{and } \bar{Y}^{(1)} = \hat{\beta}^{(1)} X_i^{(1)} \qquad (7.2)$$

$$\bar{Y}^{(c)} = \hat{\beta}^{(1)} X_i^{(0)} \qquad (7.3)$$

$$\begin{aligned} \bar{Y}^{(1)} - \bar{Y}^{(0)} &= (\bar{Y}^{(1)} - \bar{Y}^{(c)}) + (\bar{Y}^{(c)} - \bar{Y}^{(0)}) \\ &= \left(\hat{\beta}^{(1)} X_i^{(1)} - \hat{\beta}^{(1)} X_i^{(0)}\right) + (\hat{\beta}^{(1)} X_i^{(0)} - \hat{\beta}^{(0)} X_i^{(0)}) \\ &= \hat{\beta}^{(1)}\left(\bar{X}^{(1)} - \bar{X}^{(0)}\right) + (\hat{\beta}^{(1)} - \hat{\beta}^{(0)})\bar{X}^{(0)} \end{aligned} \qquad (7.4)$$

[67] Here, income is expressed in the natural logarithmic form.

Since its inception, the Oaxaca-Blinder decomposition technique has been used extensively to estimate the separate contributions of group differences in outcomes of interest with respect to observable characteristics like sex, education, race, and location. Nevertheless, although the method was originally proposed to explain income discrimination between two groups for a fixed time period, the procedure can also be applied to explain temporal changes in average income of the same group. In general, the Oaxaca-Blinder decomposition method is very straightforward to apply as it only entails estimation of the coefficients of a linear regression model and the sample means of the underlying independent variables. However, the approach has two main shortcomings. First, it is limited to explaining differences in average income while differences in other parts of the income distribution are left unexplained. Second, the decomposition depends on the choice of a reference group. For example, when estimating separate wage regressions for five geographic locations, the results where the first geographic location is left-out would not necessarily be the same when the last geographic location were left-out. This portrays an identification problem wherein the results depend on an arbitrarily chosen reference group (Jones & Kelly 1984; Oaxaca & Ramson 1999). Over the years, several alternative decomposition methodologies have been proposed to address these limitations. To save space, I do not discuss them here but see Bourguignon, Ferreira & Lustig (2004) and Bourguignon & Ferreira (2008). More recently, Shorrocks (2013) provide a unified framework for different decomposition methods aiming to assess the contribution of a set of factors which together account for the observed value of some aggregate statistic.

This study adopts the procedure proposed by Shorrocks (2013) also known as the Shapley-Shorrocks (SS) approach using the Stata implementation developed by Azevedo, Nguyen & Sanfelice (ANS) (2012).[68] To illustrate the procedure, suppose we treat households as the unit of analysis and assume that there are two time periods. For notation purposes, I express (log) income Y_{it} as a function of C components where each component is denoted by F_{it}^{c}, $c = 1, 2, \ldots, C$; $t = 0, 1$ (7.5) and the term $M(Y_t)$ is used to denote a specific characteristic feature of the household income distribution. The main interest is to decompose the change in the characteristic feature of the income distribution between time 0 and time 1, $M(Y_1) - M(Y_0)$, into the contribution of changes F_{i1}^{c} - F_{i0}^{c}. As argued by ANS (2012), this can be done by simulating the income distribution by changing each F_{it}^{c} one at a time. The step-by-step procedure is outlined below.

[68] The Stata routine is called ADECOMP.

$$Y_{it} = f(F_{it}^{1}, F_{it}^{2}, \ldots., F_{it}^{C-1}, F_{it}^{C}) \tag{7.5}$$
$$M(Y_{it}) = \emptyset(f\left(F_{it}^{1}, F_{it}^{2}, \ldots., F_{it}^{C-1}, F_{it}^{C}\right)) \tag{7.6}$$

Shapley-Shorrocks' Algorithm for
Estimating the Contribution of F^{c} on $M_1(Y_1) - M_0(Y_0)$

Step #1: Using the formula provided below, compute the counterfactual income distributions at the initial time period and the corresponding parameter of interest $M(Y_0)^{(c)}$ for each factor F^{c}.

$$M(Y_0)^{(0)} = \emptyset\left(f\left(F_{i0}^{1}, F_{i0}^{2}, \ldots., F_{i0}^{C-1}, F_{i0}^{C}\right)\right) = M(Y_0)$$
$$M(Y_0)^{(1)} = \emptyset(f\left(F_{i1}^{1}, F_{i0}^{2}, \ldots, F_{i0}^{C-1}, F_{i0}^{C}\right))$$
$$M(Y_0)^{(2)} = \emptyset(f\left(F_{i1}^{1}, F_{i1}^{2}, \ldots, F_{i0}^{C-1}, F_{i0}^{C}\right))$$
$$\vdots$$
$$M(Y_0)^{(C-1)} = \emptyset(f\left(F_{i1}^{1}, F_{i1}^{2}, \ldots, F_{i1}^{C-1}, F_{i0}^{C}\right))$$
$$M(Y_0)^{(C)} = \emptyset(f\left(F_{i1}^{1}, F_{i1}^{2}, \ldots, F_{i1}^{C-1}, F_{i1}^{C}\right) = M(Y_1)$$

Step #2: Compute the contribution of F^{c} by subtracting $M_1(Y)^{(c-1)}$ from $M_1(Y)^{(c)}$.

$$Contribution(F_{i1}^{c} - F_{i0}^{c}) = M(Y_0)^{(c)} - M(Y_0)^{(c-1)} \tag{7.7}$$
$$\%Contribution(F_{i1}^{c} - F_{i0}^{c}) = \frac{M(Y_0)^{(c)} - M(Y_0)^{(c-1)}}{M(Y_1) - M(Y_0)} \tag{7.8}$$

Step #3: Repeat Steps #1 and #2 for all possible orderings of F^{c}'s and then take the average of (7.7) and (7.8).

At this point, important remarks are in order. First, like the Oaxaca-Blinder decomposition method, the procedure outlined in the first two steps is path-dependent. Suppose the income measure Y_{it} is expressed as a function of F_{it}^{c}'s and the characteristic feature of the income distribution is some function *M()* of Y_{it}, the idea behind the SS algorithm is to construct a counterfactual distribution of income by changing the values of the F_{it}^{c} from the observed value at the initial time period to the observed value at the succeeding time period, one at a time. In the example above, I started chronologically from F_{it}^{1} to F_{it}^{C}. Thus, the values of (7.7) and (7.8) depend on this specific ordering of the factors. However, had I started from F_{it}^{C} to F_{it}^{1} or followed any other ordering, the results would have been different. To address this issue, the third step entails computing the contribution of each factor across all possible permutations or "paths" and using the average to estimate the factor's contribution on $M_1(Y_1) - M_0(Y_0)$.

Second, the approach entails estimating the contribution of one factor at a time by holding the values of all other factors constant. Hence, the decomposition methodology does not reflect economic equilibrium because it employs a simplistic assumption that each factor can be changed one at a time while the rest can be held fixed (Azevedo et al. 2013). Nevertheless, the potential interactions between factors are partially taken into account by estimating the contribution of a specific factor as the difference between the cumulative counterfactuals.

Third, unlike the Oaxaca-Blinder method and other conventional decomposition tools which are mostly based on the means, the SS algorithm flexibly accommodates quantiles, variance and any other characteristic features of an income distribution. Although the methodology can be used to explain the temporal differences in various forms of $M(Y_t)$, this study defines $M_t(Y_t)$ in terms of poverty and inequality only, in particular, I focus on US$2 poverty gap and Gini coefficient (i.e., $\emptyset(f) = \cdots$).[69]

Fourth, to be able to construct counterfactual income distributions, the SS algorithm requires panel data. If repeated cross-sectional data is available, the algorithm can be modified by making additional assumptions as outlined in Azevedo et al. (2013).

To estimate the contribution of the changes in SEC and SER to poverty and inequality dynamics using the SS algorithm, each of the X_{it}^c (SEC) and the parameter β_t^c (SER) as well as the error term ε_{it} can be considered as one of the F_{it}^c's. Note that each SEC could have multiple indicators, for example, access to services can be measured in terms of access to either electricity, clean water or sanitary toilet, estimation of (7.7) and (7.8) could be very computationally-intensive due to the iterative nature of the SS algorithm if each indicator is treated as a separate F_{it}^c. To address this issue, I reduce the dimension of (7.1) by constructing an index for each SEC by following the approach outlined in UN (2005) and estimating a regression model (of income) and using the corresponding coefficients as weights for the index. In particular, I regress (log) income on the various indicators of SECs. Since I am interested to measure the impact of changes in SEC levels to poverty and inequality dynamics, I do not want the changes in the SEC indices to be artificially contaminated by the changes in the weights of the component indicators. Thus, I use the data from the initial survey year only to derive the weights for each component indicator. These weights are then multiplied to the value of each component indicator for the initial survey year and the succeeding time periods. The resulting indices are then used as inputs for the SS algorithm. Although the indicators included in the construction of the SEC indices in this study are similar to the ones commonly used in the existing literature (Montgomery et al. 2000; Aldaba 2009), these were chosen on an ad-hoc basis, subject to data availability and the results of descriptive analysis. In general, Montgomery et al. (2000) argued that in the empirical literature, indicators are usually chosen

[69] Results for other poverty and inequality indices are provided in Appendix Tables A7.2 and A7.3.

on an ad-hoc basis due to lack of "best practice" approach of selecting indicators that can proxy living standards comprehensively.

Furthermore, I treat the model residuals as a separate component that gauges the level of socio-economic shocks. In general, while variations in household incomes across space and over time can be mostly explained by differences in stock of socio-economic capital and economic returns, incomes could also fluctuate significantly due to unexpected shocks. As pointed out in the previous chapters, a quick review of the Philippines's economic history would reveal that socio-economic shocks (e.g., environmental disasters, financial crisis, etc.) have been prominent features of the country's development landscape (Bayudan-Dacuycuy & Lim 2013) but not much has been said about the magnitude of impact of these shocks on poverty and inequality dynamics using a longitudinal perspective in the country. By treating the model residuals as an approximate measure of shock, I can explicitly gauge how much of the changes in poverty and inequality observed in the past decade are attributable to shocks in household incomes, after accounting for the changes in SECs and SERs.[70]

7.2.3 Constructing Indices of Socio-Economic Capital

In constructing the SEC indices (i.e., *Location*, *Education*, *Employment*, *Services* and *Assets*), I derive the weights by estimating several regression models with the (log) income as the dependent variable and the various indicators of SEC that are available from the survey as independent variables. On the basis of preliminary analyses, I drop indicators that are not statistically significant and have counterintuitive signs of model coefficients to be able to come-up with sound and parsimonious SEC indices. The final SEC index *Location* consists of four dummy variables: (i) whether the household is living in urban area, (ii) whether the household is living in the National Capital Region (NCR), (iii) whether the household is living in Luzon and (iv) whether the household is living in Visayas. The index *Education* has three sub-component indicators: (i) proportion of working-age household members with primary education, (ii) proportion of working-age household members with secondary education, and (iii) proportion of working-age household members with post-secondary education. Similarly, the index Employment consists of three indicators: (i) proportion of working-age household members who are employed, (ii) proportion of employed household members working in the non-agriculture sector, (iii) proportion of employed household members with formal

[70] Here, since the model residuals are used to approximate shocks, these also contain household-specific effects and other factors that were not controlled in the model.

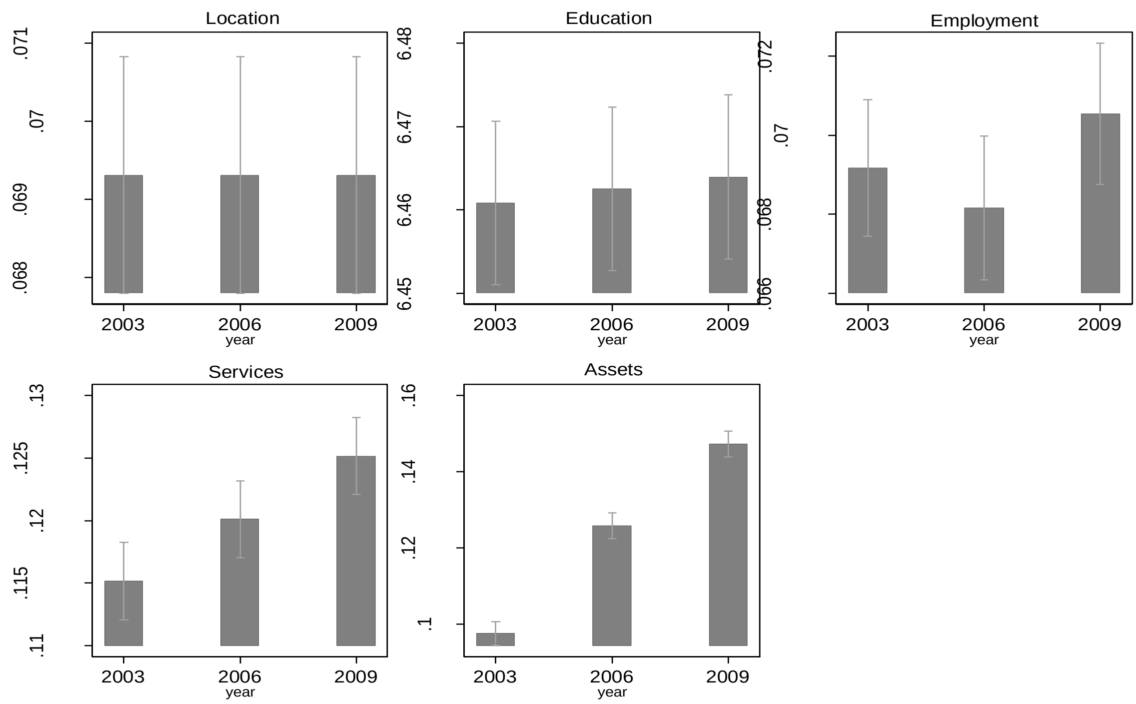
employment.[71] The index *Services* has four dummy variables: (i) whether household has electricity at home, (ii) whether household has water faucet at home, (iii) whether household has a sealed-toilet facility and (iv) whether household has closed-pit toilet facility. Lastly, the index *Assets* consists of four dummy variables: (i) whether household owns house/lot, (ii) whether household owns a refrigerator, (iii) whether household owns a phone and (iv) whether households owns a car.[72] Overall, although the resulting indices are not comprehensive, they provide a good starting point for a more nuanced understanding of how changes in SEC levels interplay with the changes in SER in driving household income distribution dynamics.

7.3 Results

7.3.1 Drivers of Household Income Distribution Dynamics in the Philippines

The objective of this section is to examine whether the observed changes in poverty and inequality can be attributed to changes in households' SECs or changes in the SERs. As pointed out earlier, the household income distribution dynamics is potentially shaped by how much the pace at which SECs and SERs are changing differ from each other.

Figure 7.1 Temporal Changes in the Levels of Socio-Economic Capital



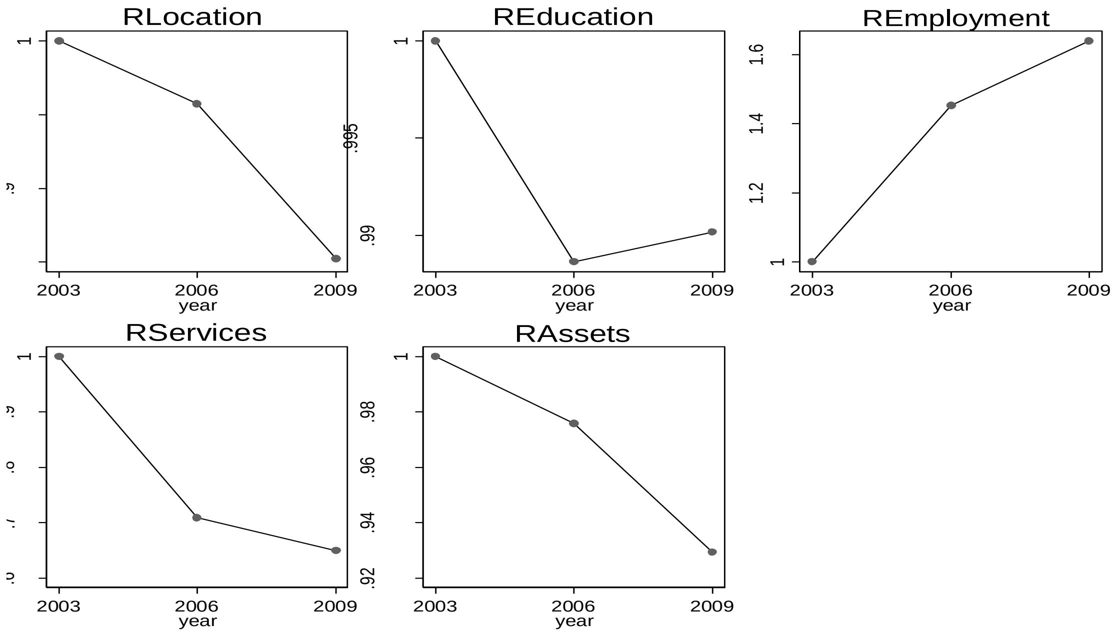
Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

[71] Here, formal employment refers to jobs held by government employees, professionals and wage workers employed in private businesses. Further details are provided in Chapter 8.

[72] As pointed out in Chapter 5, the variables that make up the Assets and Services indices could be considered as proxy measures of material deprivation. Since they could be endogenous with income poverty, I avoid inferring causal relationships in most of the succeeding discussions.

Figure 7.1 summarizes the evolution of the distribution of each SEC index over time. The bars correspond to the mean levels of each SEC while the bands correspond to 95% confidence intervals. In the case of *Location*, the distribution does not change because I am using data from households that did not move residential location throughout the observation period. On the other hand, I observe no changes in *Education* and *Employment.* This is consistent with the findings from previous studies which have attributed the low growth elasticity of poverty to its lack of enabling capacity to expand economic opportunities for the poor (Aldaba 2009). In contrast, significant improvements can be observed in *Services* from 2003 to 2009 and in *Assets* across all survey years.

Figure 7.2 Temporal Changes in the Socio-Economic Returns to Capital



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

To estimate the SERs, I regress (log) per capita income on the SEC indices for each survey year. The coefficients of the SECs are used as estimates of the SERs. Figure 7.2 shows how these SERs have changed over the past decade. Except for *REducation* and *REmployment,* the results provide empirical support to the hypothesis that improved SEC levels usually lead to lower SERs. In the case of *REducation*, there is a slight downward trend but the changes are not as remarkable as that of other SERs. Interestingly, I find that the *REmployment* have uniformly increased over the past ten years.

The estimated contribution of the changes in SECs and SERs to poverty and inequality dynamics are presented in Figure 7.3.[73] The bars represent how much each factor has contributed to the increase/decrease in poverty and inequality. Positive values indicate inflationary impact while negative values indicate deflationary impact on our income distributional measures. The number on top of each bar indicates the total change in poverty or inequality observed during the period under consideration.

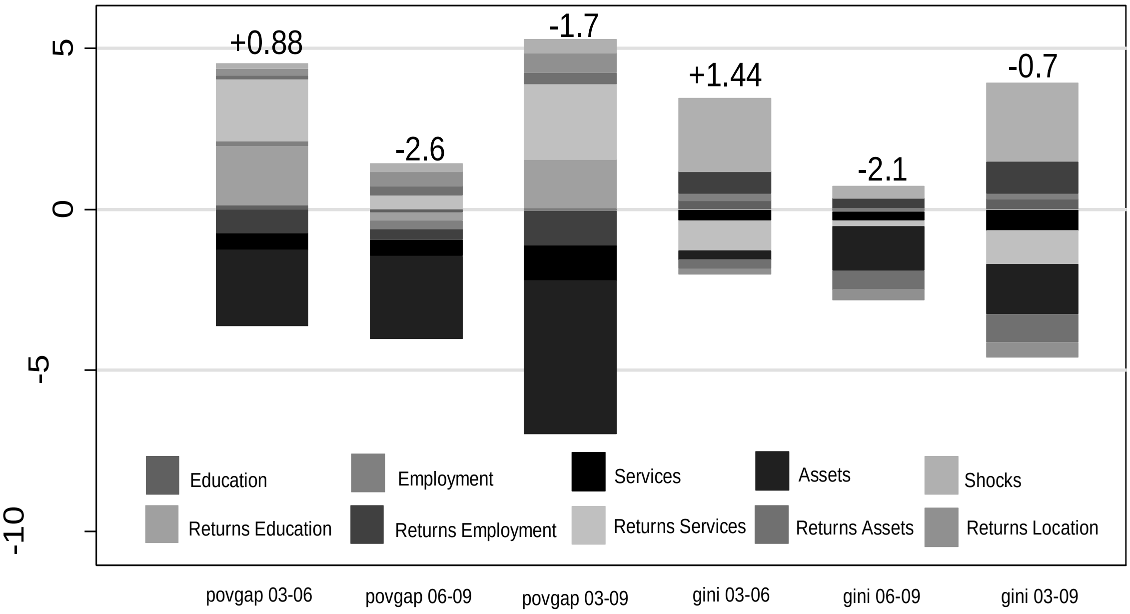
Between 2003 and 2006, the results of the counterfactual simulations based on the SS algorithm suggest that the SEC levels in terms of *Education*, *Employment* and *Services* had minimal inflationary effect on the overall poverty gap. In particular, the observed changes in *Education*, *Employment* and *Services* would have increased the overall poverty gap by 0.1, 0.4 and 0.5 percentage points, respectively, if all other factors remained constant. On the other hand, the observed changes in *Assets* had negative effect on poverty from 2003 to 2006. In particular, the changes in *Assets* would have coincided with reduction in poverty gap by 2.4 percentage points if all other factors were held fixed. In terms of the changes in SERs, I find that the changes in *REducation* and *RServices* between *2003 and 2006* had strong correlation with increase in poverty. In particular, the observed changes in *REducation* and *RServices* would have coincided with an increase in the overall poverty gap of 3.7 and 2.4 percentage points, respectively, if the values of all other components were held constant during this period. Similarly, the changes in *RLocation* and *RAssets* had increasing, albeit slightly weaker, correlation on poverty gap. In contrast, the changes in *REmployment* had a strong correlation with poverty reduction, contributing to a 3.6 percentage point reduction in poverty gap between 2003 and 2006, *ceteris paribus*.

On the other hand, the increase in the Gini coefficient from 42.8 in 2003 to 44.3 in 2006 can be mostly attributed to changes in *SEmployment.* Changes in *Education* and *Employment* also contributed positively to higher inequality during this period. However, this was largely offset by the inequality-reducing impact of changes in *Services*, *Assets*, *RLocation*, *REducation*, *RServices* and *RAssets*.

From 2006 to 2009, the US$2 poverty gap dropped from 16.3 to 13.6. The poverty-inflationary impact of the changes in *RLocation*, *REmployment*, *RServices* and *RAssets* have been largely offset by the changes in SECs, particularly *Assets* and *Employment* which together have contributed to a 3.0 percentage point reduction in US$2 poverty gap while the reduction in inequality during this period could be mostly attributed to the changes in *Assets*.

[73] The estimates are provided in Appendix Tables A7.2 and A7.3.

Figure 7.3 Estimates Contribution of Different Factors on Poverty and Inequality



Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

In summary, the results suggest that the changes in poverty gap between 2003 and 2009 coincided mostly with changes in returns to education, returns to access to basic services, returns to employment and levels of asset ownership. The last two factors are positively correlated with poverty reduction while the first two factors are positively correlated with increase in poverty. Interestingly, this has occurred at the backdrop of trivial changes in human capital (i.e., education and employment). While the results of these study have not established causal relationship with poverty and inequality, the findings seem to depart from the conventional wisdom that the underlying cause of the country's poverty and inequality in the 1980s and 1990s is the limited access to basic social services and productive assets (Balisacan 2007). Instead, the results may be indicative of the need to improve human capital outcomes. For instance, given the way how *Employment* index has been constructed, the finding that it did not contribute significantly to poverty reduction suggests that the poor did not experience improvements in their chance to be employed in the non-agriculture and formal sectors. This portrays a labour market segmentation wherein the poor workers continuously experience difficulty in moving to formal, non-agriculture sectors. Since more productive sectors require higher levels of skills, the stagnant education levels, which can be used to proxy skills, could probably explain why a significant fraction of poor workers were unable to move away from less productive sectors. Nevertheless, the finding that those who successfully transitioned to formal and non-agriculture jobs have experienced improved living standards due to higher economic returns of working in these sectors highlight the importance of improving employment outcomes for tackling poverty in the Philippines.

The results also confirm that the contribution of changes in the SECs and SERs to poverty and inequality generally offset one another. This usually happens when the demand for a specific type of SEC is fixed. To explicitly show this, I summed up the contribution of SEC and SER for the five correlates of well-being considered in this study and present the results in Table 7.1. Here, I find that assets and employment outcomes have contributed to lower poverty gap, leading to a 4.2 and 3.6 percentage point reduction, respectively. However, this gain has been partially offset by education and services outcomes. In terms of inequality, both SECs and SERs have generally contributed to a reduction in inequality. Assets and services outcomes have the highest poverty-reducing impact while employment outcomes have contributed to increasing inequality.

Table 7.1 Trade-off between Socio-Economic Capital and Socio-Economic Returns, 2003-2009

Factor	Poverty Gap (%)			Gini (%)		
	SEC	SER	Total Contribution	SEC	SER	Total Contribution
Location	0.00	0.74	0.74	0.00	-0.57	-0.57
Education	0.00	3.34	3.34	0.30	-0.07	0.23
Employment	0.00	-3.57	-3.58	0.22	1.92	2.14
Services	-1.02	2.69	1.68	-0.59	-1.21	-1.80
Assets	-4.65	0.50	-4.15	-1.48	-1.31	-2.80
Total Contribution	-5.67	3.70	-1.97	-1.55	-1.24	-2.80

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

In addition to SECs and SERs, I also disentangle the contribution of socio-economic shocks on the observed changes in poverty and inequality. This computational exercise is important because previous studies suggest that household income is subject to different forms of socio-economic risks. For instance, Dercon & Krishnan (2002) noted that income from employment may be heavily affected by ill-health or financial crisis-induced unemployment. Income transfers may be reduced due to uncertain access to public goods. Income reduction and value of assets, especially in the agriculture sector, may deteriorate due to war, theft, uncertainty in land tenure or environmental shocks like earthquakes or typhoons. While the impact of these shocks is usually transient, it can also have long-term effects on a household's future economic prospects (Albert, Elloso & Ramos 2009). Worryingly, socio-economic shocks may push poor and economically vulnerable households to further risk-induced poverty traps. In the Philippines, there are several sources of socio-economic shocks. Environmental hazards are good example. On average, about 20 tropical cyclones hit the country every year (PAG-ASA 2014) and these cost about 0.8% of GDP in damages (Oxford Economics 2013). Other sources of shocks that are commonly experienced by Filipino households are brought by illness, accident, unemployment, and economic crises (Albert et al. 2009).

7.3.2 Robustness Checks

Regional Estimates

In this section, I briefly examine the regional variations in terms of the contribution of SECs, SERs and socio-economic shocks to poverty and inequality dynamics over the past decade. As pointed out in the earlier chapters, the Philippines consists of three major island groups, Luzon, Visayas and Mindanao (Figure 3.1 in page 84). Although NCR is within Luzon, I separate the two in our analysis because NCR differs significantly from the rest of Luzon in terms of average income levels.

The results of the counterfactual simulations by region are presented in Appendix A7.3. Although the list of major contributing factors to the observed poverty and inequality dynamics is similar across regions, there are some spatial differences that are worth pointing out. First, the changes observed in SECs and SERs have significantly bigger impact on poverty in poorer regions of Visayas and Mindanao while socio-economic shocks played a more pronounced role in driving the changes in poverty and inequality in NCR and Luzon. Second, for low income households in Visayas and Mindanao, the level of SECs improved much faster than the rate at which its corresponding SERs declined, thus contributing to reduction in poverty gap. The same can be said for Luzon although the offsetting effect between its SEC and SER was stronger, leading to lower reduction in poverty gap. In contrast, poverty gap in NCR slightly increased between 2003 and 2009 and this can be explained by SERs declining faster than the rate at which SECs of low income households increased.

Other Measures of Poverty and Inequality

To examine the robustness of the results to the type of poverty and inequality indicators used, I also estimate the contribution of the changes in SECs, SERs and economic shocks to household income distribution dynamics using the proportion of population with income below US$2 a day (headcount poverty rate) and the average squared income shortfall (poverty severity) as alternative measures for poverty and the Theil coefficient as an alternative measure for inequality. The estimates are presented in the appendix. The results based on poverty gap and Gini coefficient are mostly similar with the results for poverty severity and Theil coefficient, respectively. However, there are some remarkable differences when one looks at US$2 headcount poverty rates. In particular, the impact of economic shocks are more pronounced when US$2 headcount poverty rates are used instead of poverty gap. For example, it has been mentioned earlier that the economic shocks had minimal deflationary effect on poverty gap between 2003 and 2006. However, when poverty headcount is used, I find that socio-economic shocks had a significant inflationary impact, contributing to a 2.2 percentage point increase in poverty gap between 2003 and 2006. This is equivalent to a +73% contribution to the observed increase in poverty headcount during this period, compared to its –3.9% contribution to the observed increase in poverty gap. A possible reason for this is that many of those who fell into poverty due to economic shocks between 2003 and 2006 were households that had incomes that were just a little lower than the poverty line. In such case, headcount poverty is more sensitive to capture these changes than poverty gap. On the other hand, the impact of socio-economic shocks on poverty between 2006 and 2009 is consistent, regardless of the poverty measure used. In terms of the qualitative results about income inequality, I did not find significant differences when inequality is measured using Theil index instead of the Gini coefficient.

7.3.3 Potential Limitations of the Accounting Exercise[74]

The decomposition approach adopted in this study is not a perfect tool for analysing determinants of income mobility. For instance, it falls short in capturing general equilibrium effects that can affect income distribution dynamics. A good example is a policy initiative that raises average wages. If higher wages also increase the prices of basic commodities up to the point that the purchasing power of people is where it was before the policy was implemented, it will be hard for such a decomposition exercise to capture this process. Another potential limitation of this study is that the measurement of socio-economic capital and returns to capital falls short in capturing the exact economic meaning of these concepts. If the statistical models suffer from severe omitted variable bias, then it will be difficult to assume that the model coefficients capture the socio-economic returns to capital. Taking into account all these limitations, adequate caution should be taken from inferring causal relationships from the

[74] I thank the external referees who reviewed this thesis for pointing out the issues of the decomposition approach adopted in this chapter.

results presented in this chapter. At best, it can be considered as a modest advance in probing beyond correlations.

7.4 Summary and Discussion

To be able to devise policies and intervention programs that could address poverty and inequality effectively, socio-economic planners need to understand the factors that shaped the household income distribution in the country. In this chapter, I use counterfactual simulations as an accounting tool to approximate the contribution of various factors to changes in poverty and inequality over the past decade and in turn, direct us to priorities for policy. I classify the hypothesized correlates into three broad factors: socio-economic capital, socio-economic returns to capital and socio-economic shocks. Analysis of the survey data suggests that while the correlates of income poverty and inequality are diverse, there is empirical evidence that the higher levels of ownership of assets and higher economic returns to formal, non-agricultural employment are correlated to lower income poverty while much work needs to be done so that income poverty reduction would coincide with education, employment and access to basic services. The results also re-echo the findings in the previous chapters about the existence of strong offsetting forces that lead to small changes in poverty and inequality at the aggregate-level over the past decade. In particular, I find that while the levels of socio-economic capital increased in some cases, the corresponding economic returns also declined at approximately the same pace. This departs from conventional wisdom that only portrays income poverty and inequality as a simple lack of socio-economic capital of those who are at bottom of the social pyramid because the changes in the various forms of capital held by Filipino households interact with the changes in its corresponding economic returns in driving the household income distribution.

The results of this chapter point to the need to ensure that the welfare-improving effect, i.e., the changes in SERs, do not work to the disadvantage of the poor is probably as important as providing access to SECs. There are several ways to do this. In terms of human capital, it is important that socio-economic planners provide enabling opportunities for the poor to get access to skills needed in higher-productivity sectors for the country's poverty reduction to speed up (ADB 2012b). At the same time that workers are stockpiling skills, it is also important that economic growth would be used to create high quality jobs continuously so that the economic returns to formal and non-agricultural employment will not deteriorate as the supply of high skilled workers increases. This is discussed further in the next chapter. On the other hand, the finding that the returns to basic services dropped faster than the rate at which access to basic services increased, contributing to higher income poverty, could be indicative of higher cost that low income households have to pay to access basic services due to the hike in electricity tariffs and expanded value added tax in utilities which started in 2006. Thus, to strengthen the correlation of increased access to basic services with poverty reduction, it is important to minimize the cost needed to provide such services. This can be done by investing more on infrastructure that can make the delivery of such services more efficient. However, although there are signs of improvement, the availability of key infrastructure in the country compares unfavourably with that in many of its Southeast Asian neighbours at present (ADB 2007, WB 2014).[75] Nevertheless, given the high economic growth and higher liquidity in the financial market nowadays, the government can respond to this problem by initiating more infrastructure investment and providing a socio-economic environment that will attract non-government players to play more actively in this role. In terms of access to assets, I find that access to assets increased much faster than the rate at which the returns to asset ownership dropped which in turn, contributed to lower poverty and inequality. For policy-makers, the challenge is to provide an economic environment that will sustain this trend by ensuring that access to productive assets is equitable and knowledge on how to use these assets for income-generation is easily accessible to everyone.

By using the residuals from the estimated models as proxy to socio-economic shocks, this chapter has also briefly examined the impact of shocks to poverty and inequality. At the national-level, the results suggest that shocks have smaller impact on poverty gap relative to the contribution of the changes in SECs and SERs between 2003 and 2006. In contrast, the impact of shocks on the change in poverty gap between 2006 and 2009 is comparable with the impact of changes in other factors, particularly the changes in returns to access to basic services and returns to asset ownership. In addition, socio-economic shocks have also contributed to increasing inequality. To some extent, this could mean that the shocks experienced by Filipino households over the past decade had debilitating impact for the poor. To minimize the adverse impact of economic shocks on poor and vulnerable households, social safety nets should be put in place. Often, this is the responsibility of the government. However, some studies suggest that the efforts of the government fall short in this respect. For instance, an ADB report surmised that despite the country being used to environmental disasters, the relief provided during such episodes remains inadequate (ADB 2007). Some studies also suggest that the weak

[75] According to the 2013-2014 Global Competitiveness Index compiled by World Economic Forum, the Philippines is ranked 96th out of 148 countries based on the Infrastructure pillar. Its Southeast Asian neighbours rank higher: Malaysia (29th), Thailand (47th) and Indonesia (61st) (WB 2014).

impact of the social protection programs in poverty reduction can be partially explained by the low coverage and limitations in targeting appropriate recipients (ADB 2007, Bird and Hill 2009, Reyes et al. 2011). When formal social safety nets are not working effectively, low income households would often turn to informal risk sharing networks where funds are raised through gifts and loans among members (Fafchamps & Lund 2003). However, informal risk-sharing is not always optimal for the poor (Fafchamps & Gubert 2007). In particular, although some loans made through this channel are usually subjected to zero interest rates or do not have to be repaid fully, others expect much higher payments leading the poor to further debts (Platteau 1997). In addition, members of a risk-sharing network may have a hard time raising funds if all of them are experiencing income shocks (Landmann, Vollan & Frolich 2012). Furthermore, the funds raised through this channel may only cover a fraction of the income shocks (Townsend 1994). Thus, it is important that policymakers examine the effectiveness of both formal and informal social safety nets that exist today. Nevertheless, this topic warrants further investigation using more sophisticated statistical tools to be able to better understand the different short and long-run effects of shocks as it is highly probable that the different socio-economic capital partially absorb the shocks with different timings.

There are also some limitations in this study. First, as the socio-economic correlates of poverty and inequality that were used here could be considered as measures of material deprivation. Although I used counterfactual simulations to measure their contribution to changes in poverty and inequality, it is still difficult to conclude causal relationships. Second, I might be more appropriate to examine the impact of changes in socio-economic returns to capital using longer observation period.

Nevertheless, the findings of this chapter are sufficient to highlight that the problem on poverty and inequality cannot be addressed by simply increasing the levels of socio-economic capital of the people living at the bottom of the social hierarchy. Without any intervention, the benefits of higher levels of socio-economic capital may just be washed out by lower economic returns. Thus, socio-economic planners should devise policies that would ensure that economic growth translates to improvement in socio-economic capital and creation of more opportunities where this capital can be used more productively. Throughout this process, the importance of providing access to social safety nets should not be taken for granted. In particular, although the results suggest that economic shocks between 2003 and 2006 did not contribute significantly to the observed changes in poverty gap, it drove US$2 headcount poverty rate to increase. Between 2006 and 2009, shocks contributed to higher poverty, regardless of the poverty index being used. In addition, economic shocks also contributed to higher income inequality for all periods. Given that the Philippines has a wide range of social safety nets in place (Ortiz 2001; Bird & Hill 2009; Reyes et al. 2011), the finding that income shocks have pushed (headcount) poverty and inequality up, should prompt socio-economic planners to re-evaluate the effectiveness of existing social protection programs. If left unaddressed, socio-economic shocks may deter the country's economic development.

Appendix Table A7.1 Descriptive Statistics of Variables Included in SEC Indices

SEC Indicators		2003		2006		2009	
		Mean / Proportion	**Standard Deviation**	**Mean / Proportion**	**Standard Deviation**	**Mean / Proportion**	**Standard Deviation**
LOCATION	Urban	0.49	0.5	0.49	0.5	0.49	0.5
	NCR	0.09	0.29	0.09	0.29	0.09	0.29
	Luzon	0.46	0.5	0.46	0.5	0.46	0.5
	Visayas	0.22	0.41	0.22	0.41	0.22	0.41
	(Mindanao)	0.23	0.42	0.23	0.42	0.23	0.42
EDUCATION	(Proportion of working age hhld members who have at most primary education)	0.36	0.37	0.35	0.36	0.32	0.35
	Proportion of working age hhld members who have at most secondary education	0.41	0.35	0.42	0.33	0.43	0.32
	Proportion of working age hhld members who have postsecondary education	0.23	0.32	0.24	0.32	0.25	0.32
EMPLOYMENT	Proportion of employed hhld members working in the non-agriculture sector	0.65	0.43	0.65	0.47	0.69	0.44
	Proportion of employed hhld members with formal employment arrangement	0.27	0.37	0.28	0.37	0.32	0.39
	Proportion of employed hhld members with permanent jobs	0.69	0.4	0.73	0.39	0.74	0.37

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Appendix Table A7.1 (con't) Descriptive Statistics of Variables Included in SEC Indices

SEC Indicators		2003		2006		2009	
		Mean / Proportion	**Standard Deviation**	**Mean / Proportion**	**Standard Deviation**	**Mean / Proportion**	**Standard Deviation**
BASIC SERVICES	Has access to electricity at home	0.78	0.41	0.83	0.38	0.87	0.34
	Has access to water faucet at home	0.44	0.5	0.44	0.5	0.49	0.5
	Has access to water-sealed toilet facility at home	0.72	0.45	0.75	0.43	0.81	0.4
	Has access to closed pit toilet facility at home	0.1	0.29	0.08	0.28	0.06	0.24
ASSETS	Owns a house/lot	0.72	0.45	0.76	0.42	0.75	0.43
	Owns a refrigerator	0.37	0.48	0.4	0.49	0.4	0.49
	Owns a phone	0.31	0.46	0.54	0.5	0.71	0.45
	Owns a car	0.12	0.33	0.18	0.39	0.25	0.43

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Appendix Table A7.2 Estimated Contribution of Different Factors on Changes in Poverty and Inequality in the Philippines

Factor	2003-2006					2006-2009					2003-2009				
	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil
Location	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Economic returns to location	0.90	0.38	0.19	-0.29	-0.54	0.84	0.39	0.19	-0.29	-0.53	1.81	0.74	0.37	-0.57	-0.96
Education	0.04	0.10	0.09	0.27	0.29	-0.26	-0.12	-0.06	0.02	-0.14	-0.19	0.00	0.03	0.30	0.21
Economic returns to education	6.95	3.71	2.16	-0.08	-0.14	-0.49	-0.27	-0.15	0.01	0.01	6.54	3.34	1.88	-0.07	-0.12
Type of employment	0.23	0.40	0.30	0.40	0.39	-1.15	-0.50	-0.28	-0.25	-0.51	-0.52	0.00	0.06	0.22	-0.02
Economic returns to type of employment	-7.68	-3.61	-1.91	2.02	3.89	0.13	0.07	0.03	-0.04	-0.07	-8.11	-3.57	-1.85	1.92	3.54
Access to services	-0.69	-0.47	-0.28	-0.29	-0.71	-0.77	-0.45	-0.26	-0.25	-0.38	-1.64	-1.02	-0.58	-0.59	-1.10
Economic returns to access to services	5.82	2.44	1.24	-1.16	-1.94	0.52	0.25	0.13	-0.10	-0.16	6.60	2.69	1.33	-1.21	-1.95
Assets held	-5.55	-2.31	-1.12	-0.23	-0.19	-4.45	-2.46	-1.34	-1.34	-2.66	-10.03	-4.65	-2.38	-1.48	-2.80
Economic returns to assets	0.80	0.27	0.12	-0.90	-1.53	0.56	0.22	0.10	-0.45	-0.74	1.47	0.50	0.22	-1.31	-2.13
Unobserved factors	2.21	-0.03	-0.42	1.71	2.18	0.71	0.29	0.04	0.56	1.96	2.75	0.26	-0.33	2.11	3.83
Total change	3.03	0.88	0.35	1.44	1.69	-4.36	-2.59	-1.60	-2.13	-3.20	-1.32	-1.71	-1.24	-0.68	-1.51

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Appendix Table A7.3 Estimated Contribution of Different Factors on Changes in Poverty and Inequality, by Region

National Capital Region

Factor	2003-2006					2006-2009					2003-2009				
	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil
Location	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Economic returns to location	1.61	0.32	0.10	0.00	0.00	1.37	0.38	0.12	0.00	0.00	2.44	0.59	0.19	0.00	0.00
Education	0.40	-0.06	-0.03	-0.22	-0.34	-0.15	0.02	0.00	0.08	-0.43	0.39	0.06	0.00	-0.01	-0.61
Economic returns to education	4.34	0.93	0.29	-0.07	-0.09	-0.42	-0.08	-0.02	0.00	0.01	3.41	0.80	0.26	-0.06	-0.08
Type of employment	0.08	0.04	0.00	-0.17	-0.38	-1.05	-0.16	-0.03	-0.78	-1.57	-0.52	-0.13	-0.04	-0.39	-0.79
Economic returns to type of employment	-5.16	-1.19	-0.36	1.63	2.20	0.09	0.03	0.01	-0.03	-0.04	-5.39	-1.10	-0.34	1.44	1.74
Access to services	-0.08	-0.01	0.01	-0.02	-0.11	-0.51	-0.14	-0.06	-0.18	-0.26	-0.49	-0.15	-0.05	-0.19	-0.34
Economic returns to access to services	4.39	0.93	0.29	-0.25	-0.33	0.47	0.11	0.03	-0.02	-0.02	4.25	0.99	0.32	-0.22	-0.26
Assets held	-1.35	-0.44	-0.15	-0.30	-1.14	-4.30	-0.67	-0.17	-1.40	-2.27	-4.21	-0.92	-0.29	-1.38	-2.80
Economic returns to assets	0.55	0.10	0.03	-0.71	-1.00	0.25	0.07	0.02	-0.34	-0.47	0.80	0.15	0.05	-1.00	-1.34
Unobserved factors	0.84	0.05	-0.03	5.77	10.56	-1.00	-0.05	0.01	-1.48	-3.60	-0.29	-0.15	-0.06	3.34	5.19
Total change	5.64	0.66	0.15	5.66	9.36	-5.25	-0.50	-0.10	-4.13	-8.64	0.39	0.15	0.05	1.53	0.71

Luzon

Factor	2003-2006					2006-2009					2003-2009				
	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil
Location	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Economic returns to location	1.20	0.53	0.27	-0.10	-0.15	1.18	0.53	0.27	-0.11	-0.19	2.57	1.04	0.51	-0.21	-0.30
Education	0.12	0.13	0.09	0.29	0.21	-0.30	-0.09	-0.04	0.07	0.00	-0.13	0.03	0.04	0.34	0.15
Economic returns to education	7.36	3.25	1.67	-0.07	-0.13	-0.53	-0.23	-0.12	0.01	0.01	6.83	2.90	1.46	-0.07	-0.12
Type of employment	0.21	0.30	0.20	0.37	0.40	-1.36	-0.48	-0.22	-0.12	-0.33	-0.77	-0.06	0.02	0.17	-0.18
Economic returns to type of employment	-7.94	-3.21	-1.55	1.77	3.66	0.13	0.06	0.03	-0.03	-0.06	-8.55	-3.22	-1.51	1.70	3.25
Access to services	-0.67	-0.31	-0.17	-0.22	-0.73	-0.78	-0.44	-0.25	-0.24	-0.36	-1.65	-0.89	-0.48	-0.54	-1.11
Economic returns to access to services	6.24	2.28	1.04	-0.94	-1.48	0.51	0.23	0.11	-0.08	-0.12	7.03	2.53	1.15	-0.97	-1.47
Assets held	-6.24	-2.28	-1.02	-0.22	1.03	-4.48	-2.03	-0.99	-1.10	-1.94	-10.94	-4.24	-1.95	-1.41	-1.50
Economic returns to assets	0.79	0.25	0.10	-0.87	-1.32	0.58	0.20	0.08	-0.43	-0.65	1.52	0.44	0.18	-1.28	-1.82
Unobserved factors	1.85	0.15	-0.09	0.99	-2.67	1.18	0.43	0.10	0.02	0.06	3.12	0.73	0.09	1.22	-1.68
Total change	2.92	1.09	0.56	1.00	-1.18	-3.88	-1.82	-1.03	-2.03	-3.58	-0.96	-0.73	-0.48	-1.03	-4.76

Appendix Table A7.3 (con't) Estimated Contribution of Different Factors on Changes in Poverty and Inequality, by Region

Visayas

Factor	2003-2006					2006-2009					2003-2009				
	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil
Location	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Economic returns to location	0.64	0.33	0.19	-0.13	-0.17	0.57	0.34	0.19	-0.13	-0.20	1.32	0.67	0.37	-0.25	-0.37
Education	-0.12	0.15	0.15	0.60	0.78	-0.30	-0.20	-0.11	0.12	0.07	-0.36	-0.01	0.03	0.68	1.01
Economic returns to education	7.32	4.52	2.80	-0.08	-0.13	-0.49	-0.33	-0.20	0.01	0.01	7.38	4.14	2.43	-0.07	-0.13
Type of employment	0.01	0.50	0.40	0.68	0.62	-0.86	-0.67	-0.39	-0.37	-0.68	-0.41	-0.06	0.04	0.35	-0.09
Economic returns to type of employment	-8.69	-4.56	-2.56	2.14	3.60	0.14	0.08	0.04	-0.04	-0.07	-9.05	-4.58	-2.48	1.99	3.41
Access to services	-0.87	-0.68	-0.43	-0.53	-0.88	-0.97	-0.59	-0.33	-0.29	-0.42	-2.09	-1.39	-0.81	-0.86	-1.32
Economic returns to access to services	5.90	2.86	1.54	-1.39	-2.10	0.57	0.30	0.16	-0.11	-0.17	7.04	3.21	1.67	-1.42	-2.14
Assets held	-5.45	-2.50	-1.32	0.64	0.07	-4.31	-3.11	-1.80	-1.36	-2.12	-10.23	-5.61	-3.03	-0.53	-1.58
Economic returns to assets	0.84	0.30	0.14	-0.97	-1.61	0.62	0.26	0.12	-0.50	-0.82	1.49	0.60	0.28	-1.42	-2.37
Unobserved factors	2.12	0.01	-0.35	0.29	2.86	1.49	0.05	-0.29	2.09	5.56	3.06	0.10	-0.55	2.20	7.78
Total change	1.70	0.94	0.56	1.25	3.06	-3.55	-3.87	-2.61	-0.59	1.15	-1.85	-2.93	-2.05	0.66	4.21

Mindanao

Factor	2003-2006					2006-2009					2003-2009				
	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil	FGT(0)	FGT(1)	FGT(2)	Gini	Theil
Location	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Economic returns to location	0.24	0.13	0.07	-0.14	-0.20	0.21	0.13	0.07	-0.13	-0.21	0.47	0.25	0.14	-0.27	-0.43
Education	-0.11	0.05	0.09	0.56	0.82	-0.17	-0.18	-0.10	-0.12	-0.21	-0.40	-0.09	0.01	0.45	0.62
Economic returns to education	6.82	5.03	3.32	-0.08	-0.13	-0.45	-0.37	-0.24	0.01	0.01	6.45	4.54	2.88	-0.08	-0.12
Type of employment	0.53	0.64	0.51	0.59	0.61	-1.05	-0.50	-0.38	-0.07	0.69	-0.12	0.21	0.20	0.49	1.06
Economic returns to type of employment	-7.24	-4.50	-2.68	2.48	3.58	0.15	0.08	0.05	-0.05	-0.08	-7.44	-4.35	-2.55	2.35	3.80
Access to services	-0.81	-0.78	-0.50	-0.40	-0.62	-0.69	-0.45	-0.30	-0.23	-0.38	-1.67	-1.28	-0.79	-0.62	-1.01
Economic returns to access to services	5.48	3.00	1.75	-1.66	-2.37	0.54	0.31	0.18	-0.15	-0.21	6.26	3.24	1.82	-1.76	-2.54
Assets held	-5.98	-2.96	-1.55	0.20	-0.69	-4.59	-3.46	-2.11	-1.05	-2.51	-10.41	-6.11	-3.52	-0.92	-3.18
Economic returns to assets	0.90	0.35	0.17	-1.04	-1.58	0.61	0.30	0.15	-0.53	-0.78	1.61	0.66	0.33	-1.51	-2.37
Unobserved factors	3.62	-0.49	-1.34	-0.46	0.75	-0.29	0.36	0.27	2.01	8.64	2.96	-0.39	-1.07	1.62	9.34
Total change	3.44	0.48	-0.16	0.06	0.19	-5.73	-3.78	-2.40	-0.31	4.98	-2.28	-3.30	-2.56	-0.25	5.16

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006 and 2009.

Chapter 8 Multiple Jobholding and Socio-Economic Mobility in the Philippines

8.1 Introduction

The results presented in the previous chapters have highlighted the importance of employment in inducing income mobility in the Philippines. Ideally, labour being one of the few assets available to everyone, should be a vehicle for upward mobility, especially for the poor. However, when a country's labour market is highly segmented, the poorest of the poor may be trapped in long episodes of low productivity and precarious employment. In other words, being employed is not a sure ticket out of poverty. This is particularly true in developing countries whose labour markets largely operate outside the periphery of government regulation. In addition to this informal economy, non-standard employment arrangements are also increasing as globalization takes a stronghold on labour markets. Worryingly, sparse data suggest that workers with non-standard jobs are also prone to sub-optimal social protection coverage and work under precarious conditions (Addabbo & Solinas 2012; Ebisui 2012). Nevertheless, non-standard jobs can also have potential benefits. For instance, structured and predictable flexibility associated with non-standard employment may enable workers to outline better work patterns that are more compatible with their other personal responsibilities. This dualistic nature and lack of a universally-accepted definition of non-standard employment makes it difficult to infer whether its emergence helps in promoting upward economic mobility or contributes to increasing labour market segmentation.[76] In general, while policymakers need to better understand non-standard employment arrangements to be able to expand social mobility prospects for workers relying on such kinds of jobs, the literature is limited especially in developing countries (Ruyter et al. 2009).

The Philippines provides a relevant case study for examining the relationship between non-standard employment and socio-economic mobility. We have seen from the previous chapters that despite high economic growth, significant improvement in the overall income distribution remains elusive as reflected in the slow pace of poverty reduction and persistently high income inequalities. At the same time, labour market trends suggest that this occurs at the backdrop of stagnant job creation. The country has one of the highest unemployment rates in South East Asia (about 7.0% in 2012).[77] On the other hand, more than half of its employed population relies on jobs outside the formal economy (ILO 2012). If many of these jobs have non-standard employment arrangements, then the emergence of non-standard jobs provides opportunities to participate in economic activities for

[76] "Standard and non-standard employment arrangement" terms can hardly be characterized with a precise legal meaning and have no universally-accepted definition. However, some literature recognizes the following characteristics of standard employment: 1) indefinite or permanent; 2) full-time; and to some extent, 3) done at the employer's workplace. Given these, the literature identifies three main sources of non-standard employment: casualization, informalization, and externalization.

[77] The latest unemployment rates in other Southeast Asian countries are as follows: Indonesia (6.6%, 2011), Malaysia (3.0%, 2012), Singapore (2.8%, 2012), Vietnam (1.8%, 2012), Lao PDR (1.4%, 2005), Thailand (0.7%, 2012) and Cambodia (0.2%, 2008) (WDI 2014).

workers who would have been unemployed otherwise. Nevertheless, it is still important to examine the quality of employment of non-standard workers in the Philippines. For instance, if non-standard jobs are systematically characterized by inferior working conditions, this may offset the job creation benefits of non-standard employment in the long-run. For this study, I examine the case of multiple job holding or pluriactivity as a form of non-standard employment. Owing to its conceptual simplicity, the incidence of multiple job holding is a simple but valid indicator of the prevalence of non-standard employment (Riddell & St-Hilaire 2002).[78] Moreover, I distinguish constrained from non-constrained pluriactivity to be consistent with the perceived dualistic nature of non-standard employment.

Although labour force data suggest that a significant fraction of the Philippines's employed population are relying on multiple jobs, about 14.3% in 2009, the characteristics and working conditions of multiple job holders have not been examined extensively in the existing literature. Using the merged FIES-LFS, this chapter seeks to answer the following questions:

(i) What are the characteristics of multiple job holders? How do they differ from single job holders?

(ii) Does multiple job holding improve a person's socio-economic mobility prospects?

8.2. Theoretical Model for Multiple Jobholding and Income Mobility

8.2.1 Determinants of Multiple Jobholding

In general, evidence is mixed about whether multiple jobholding constitutes a temporary phenomenon or a more permanent feature of the labour market, particularly in industrialized countries (Wu, Baimbridge & Zhu 2009; Panos, Pouliakas & Zangelidis 2011; Casacuberta & Gandelman 2012). Traditionally, multiple job holding is seen as a temporary strategy to address sub-optimal levels of utility derived from one's primary job (Perlman 1966; Shisko & Rostker 1976; Krishnan 1990) or as a hedge against the risk of unemployment (Bell, Hart & Wright 1997). In other words, workers engage in multiple jobs to avoid experiencing downward economic mobility. However, recent evidence from industrialized countries suggests that multiple job holding can also be used to develop further expertise and acquire new skills, which in turn, may lead to better occupational outcomes (Panos et al. 2011). This type of labour supply behaviour can be part of a worker's portfolio of long-term strategies for career growth. Whether this also applies in developing countries is unclear as this multiple job holding has not been studied extensively outside industrialized countries.[79]

[78] Technically, multiple job holding can be a combination of standard and non-standard employment (i.e., office employee with a full-time day job and another part-time night job). Aside from multiple job holding, other indicators of non-standard employment include part-time, self-, and short-tenure employment (Riddell & St-Hilaire 2002; De Bruin & Dupuis 2004).

[79] Theisen (2009) argues that studies on developing countries' labour markets usually start under the presumption that multiple job holding is not a norm. This probably contributes to the dearth of studies examining this type of labour supply behaviour in developing countries.

Multiple job holding potentially has both negative and positive aspects for workers. It may provide additional income particularly useful for emergency purposes (Danzer 2011) and give additional satisfaction especially when the second job is related to one's personal interests (Renna & Oaxaca 2006). It may also increase one's productivity as it provides opportunities to acquire new skills and develop expertise (Panos et al. 2011). Hence, pecuniary and non-pecuniary factors may drive people to engage in multiple jobs. However, multiple job-holding has also some potential disadvantages for workers. A second job may lessen one's productivity by diverting a worker's focus to a multitude of tasks. Having multiple jobs may also mean less time for finding more productive employment prospects. Moreover, this type of labour supply behaviour may have adverse consequences for one's health and family relationships if having multiple jobs mean working longer hours (Alam, Biswas and Hassan 2009). Thus, even though multiple job holding has a potential to provide more economic opportunities and to strengthen labour force, it may also increase workers' vulnerability to socio-economic uncertainties.

The perceived positive and negative impacts of multiple job holding gave rise to a number of theoretical models about the determinants of multiple job holding. Such theoretical models include: *hours constraint model, target income model, main job insecurity model,* and *heterogeneous job portfolio model*. The *hours constraint model* by Shisko & Rostker (1976), Bell et al. (1997), Conway & Kimmel (1998) and Wu et al. (2009) provides a springboard to understand the other approaches.

According to the hours constraint model, workers usually aim to maximize their "utility" or the level of satisfaction from consuming goods, services, or leisure. Consider an average worker with a well-behaved utility function denoted by:

$$Utility = f(C, L) \tag{8.1}$$

where C is a composite consumption good and L is (time spent for) leisure. The value of consumption is usually subject to a budget constraint equivalent to an individual's wage and non-wage income. This can be represented as:

$$C = W + NW \tag{8.2}$$

where W corresponds to wage income and NW to non-wage income. The income from work is subject to hours constraint, i.e., the number of hours available to any worker is finite,

$$\begin{aligned} W &= (T - L)*w \\ &= h*w \end{aligned} \tag{8.3}$$

where T is the worker's hours constraint, h is the number of hours spent for work and w is the hourly income rate. Graphically, this can be represented by indifference curves and budget constraints. An indifference curve is the combination of income and leisure which an individual would accept to maintain a given level of utility while a budget constraint is the combination of goods and services that the worker can avail given his/her income budget. Note that the slope of the budget constraint is equal to the income rate.

We can distinguish between two types of pluriactivity: constrained and non-constrained (Averett 2010). In constrained pluriactivity, the quality of the second job is usually inferior to the quality of the main job because under this scenario, a worker is willing to take any additional job to make ends meet. In contrast, in non-constrained pluriactivity, the quality of the second job can be at par or better relative to the primary job.[80] Figure 8.1 illustrates these concepts under the hours-constraint model. In particular, the figure illustrates three levels of utility that can be attained by a worker, depending on employment circumstances (Averett 2010). In this example, I_3 denotes the highest level of utility that can be attained by a worker with an (hourly) income rate w_1 who spends $h_1 + h_2$ hours for employment. In the left side of Figure 8.1, the curve I_1 denotes the lowest level of utility that the same worker can attain if he/she only spends h_1 hours for employment. This happens when the main job prevents him/her from working for $H = h_1 + h_2$ hours. However, the left side of the figure also suggests that this worker can still attain a higher level of utility denoted by I_2 if he/she is willing to take on a second job even if it offers a lower (hourly) income rate. This represents constrained pluriactivity in the sense that this pluriactive worker will earn less compared to a single job holder with basically the same qualification (and thus the same wage rate w_1) who also works for H_1+H_2 hours. Under the hours constraint model, an inferior second job is one with a lower hourly wage rate than the primary job. By contrast, the right side of Figure 8.1 represents non-constrained pluriactivity wherein the wage rate offered in the second job is higher. In other words, a multiple job holder will earn more relative to his counterpart with only one job. This may happen when the job quality (in this case, income-related dimensions) of the secondary employment exceeds the quality of the primary job. The case of a university professor or researchers engaged in part-time outside consultancy projects or workers accepting a part-time employment as a second job while waiting for a full-time employment opportunity to open up are some instances when this could happen.

In addition to the hours-constraint model, there are several other models identifying the factors that drive workers into pluriactivity. For example, the target income model suggests that workers will allocate work on different jobs to meet a specific income goal assuming that jobs offer different pecuniary and non-pecuniary benefits (Lundborg 1995; Wu et al. 2009). This perspective is supported by the findings of Krishnan (1990) who concluded that the propensity to take on multiple jobs

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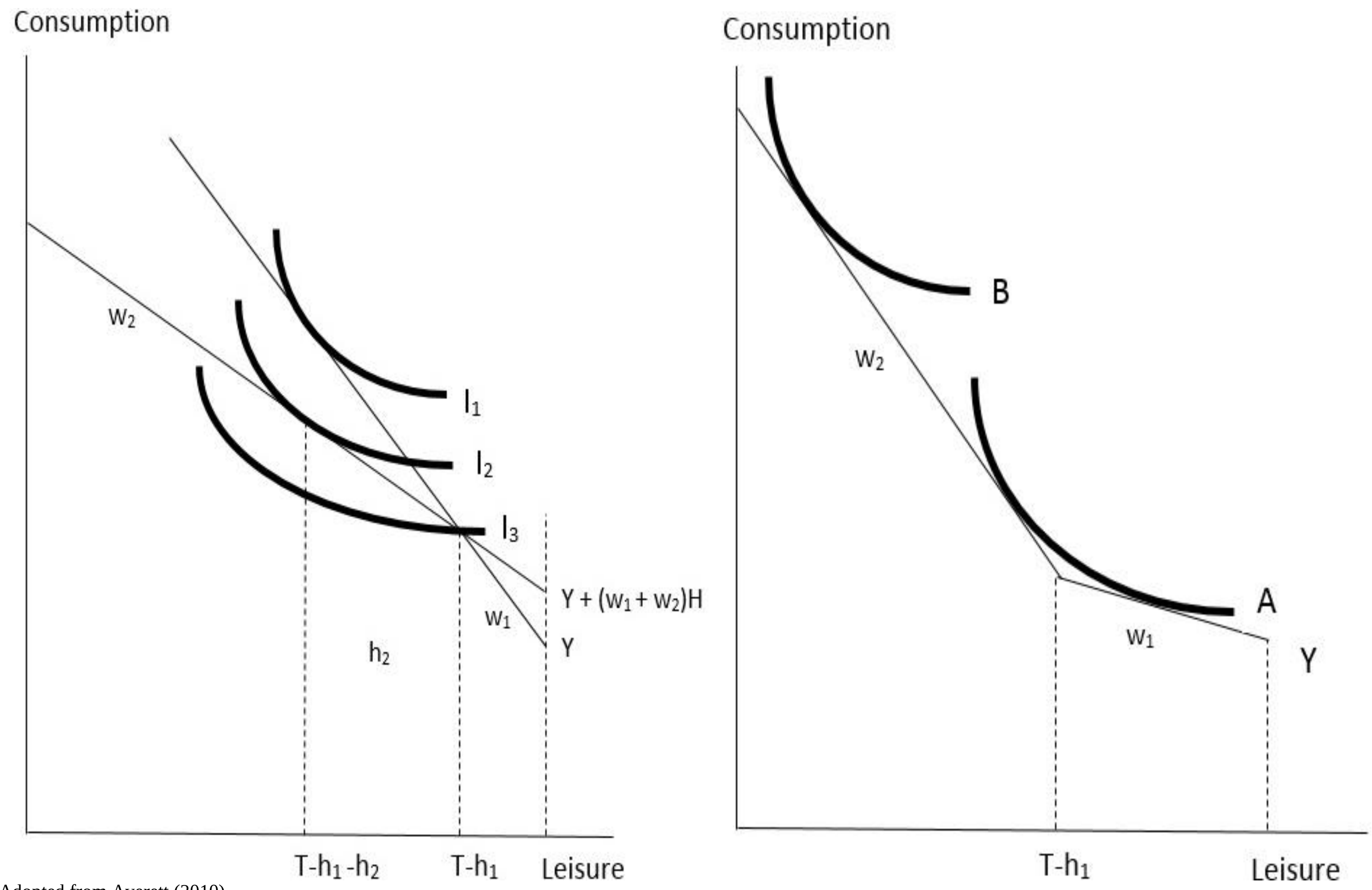
[80] In rural areas, a good example of constrained multiple job holding is the combination of agricultural production with small-scale non-farm entrepreneurial activities. In urban areas, workers may avail part time employment in different elementary occupations (e.g., working as an office cleaner in the morning and as a construction labourer in the evening). On the other hand, a university professor doing part time consultancy jobs in the industry is an example of non-constrained pluriactivity.

Figure 8.1 Constrained and Non-constrained Pluriactivity



Source: Adopted from Averett (2010)

declines as the level of income received from primary job increases. On the other hand, according to the main job insecurity model, workers whose main jobs are vulnerable or exposed to high risk of termination may actively participate in dual job holding to cushion the effects of possible unemployment (Bell et al. 1997). Boheim & Taylor (2004), for instance, found that the presence of a permanent work contract in the primary job, as a proxy indicator of job security, reduces the propensity of looking for a secondary job. Danzer (2011) also provided empirical support for the main job insecurity model by concluding that having a secondary economic activity can be used as a coping strategy to smooth income and ensure uninterrupted employment during wage shocks. Alternatively, according to the heterogeneous job portfolio model, some workers may find incentives to take more than one job because different jobs are not perfect substitutes. This implies that the wage paid and utility lost from foregone leisure may not adequately reflect the benefits and costs of working (Conway & Kimmel 1998; Wu et al. 2009). For example, Renna & Oaxaca (2006) found that some workers have personal preferences for job differentiation, wherein they derive varying levels of satisfaction from different occupations.

The determinants of multiple job holding described above can be summarized by estimating a logistic labour-supply model,

$$ln\left(\frac{p_{it}^{mult}}{p_{it}^{0}}\right) = \theta X_{it} \qquad (8.4)$$

where p_{it}^{0} denotes the probability of having a single job while p_{it}^{mult} denotes the probability of taking multiple jobs, and $\underline{\boldsymbol{X_{it}}}$ is a vector of factors affecting the i^{th} worker's labour supply behaviour. We can further generalize (8.4) to distinguish constrained from non-constrained pluriactivity by estimating a multinomial logistic model denoted by:

$$ln\left(\frac{p_{it}^{l}}{p_{it}^{0}}\right) = \theta X_{it} \qquad (8.5)$$

where $l = 1, 2,$ p_{it}^{1} denotes the probability of being engaged in constrained pluriactivity, while p_{it}^{2} denotes the probability of being engaged in non-constrained pluriactivity.

8.2.2 Socio-Economic Mobility and Multiple Job Holding

In the previous chapters, each household member is assigned with the same level of welfare as measured by the household expenditure per capita. To be able to examine how individual-level occupation affects the socio-economic mobility prospects of a person, the analysis presented in this chapter departs from that convention. In particular, this chapter uses two measures of socio-economic mobility: mobility of employment income and occupational mobility. By using the person's earnings from employment rather than household expenditure per capita, I can focus on individual-level mobility rather than joint socio-economic mobility of household members. On the other hand, including occupational mobility in this context is also important for several reasons. First, even if it were true that multiple job holding provides opportunities to acquire new skills as hypothesized, it is possible that being equipped with new skills could take time before it translates to higher employment income. In some cases, the new skills acquired from pluriactivity first open up employment opportunities before leading to income mobility. Second, the fact that occupational mobility indicators are often less prone to measurement errors than income mobility indicators make the latter an attractive alternative indicator of socio-economic mobility.

Income Mobility

Standard human capital models express income as a function of skills or the capacity to contribute to production for a given rental rate of each unit of skill (Bowles, Gintis & Osborne 2001). Skill is traditionally measured in terms of years of education and labour market experience. Mincer (1974) first formalized this mathematical relationship by expressing log income as a sum of a linear function of years of education and a (quadratic) function of labour market experience such that:

$$ln(Y_{it}) = \alpha_1 E_{it} + \alpha_2 L_{it} + \alpha_3 L_{it}^2 + \varepsilon_{it} \tag{8.6}$$

where Y_{it} is the income of the i^{th} worker at time t, α_1 measures the rate of return to education for each year in school E_{it}, α_2 and α_3 measure the return rate for each year of labour market experience L_{it} and ε_{it} is the stochastic disturbance term. Assuming that the return rates to education and labour market experience are fixed, this model suggests that income growth is a function of change in human capital stock E_{it} and L_{it},

$$\Delta \ln Y_{it} = \alpha_1 \Delta E_{it} + \alpha_2 \Delta L_{it} + \alpha_3 \Delta L_{it}^2 + \xi_{it} \tag{8.7}$$

However, previous studies show that these conventional indicators of human capital stock only explain a small fraction of the total variation in individual income (Atkinson, Bourguignon & Morrisson 1988). In other words, workers with the same amount of human capital can have substantially different incomes. Similarly, changes in human capital stock over time would also explain little variation in income growth. Over the years, researchers have identified that factors like intergenerational reproduction of advantage (e.g., proxied by parental education), unobserved individual heterogeneity (e.g., unobserved variations in effort) and spatial externalities could have stronger effect on income and income growth (Engel, Rigobon, & Ferreira 2007) than changes in schooling and labour market experience. In this study, I extend (8.7) to account for the quality of employment within the context of multiple job holding. As mentioned earlier, I hypothesize that the income mobility-effect of multiple job holding is asymmetric. For instance, for non-constrained multiple job holders, I suspect that the arguments of Paxson & Sicherman (1996) and Panos et al. (2011) may apply. In particular, secondary employment may accelerate the accumulation of skills through additions to the job portfolio. This is because non-constrained multiple job holders have high quality jobs that could induce positive human capital spill-over effects between primary and secondary employment leading to higher productivity. Standard microeconomic theory suggests that increasing productivity will also be compensated with faster income growth (Solow 1956). On the other hand, for constrained pluriactive workers, I suspect that this type of labour supply behaviour is not significantly correlated with increased income mobility. By definition, constrained pluriactive workers do not maximize their income potential since the second job is usually paid at a lower wage rate. In more equal societies where economic growth is uniformly distributed, having a lower initial income may be correlated with faster income growth. However, for societies with high levels of inequality, the inferior quality of the second job is less likely to induce income mobility for constrained multiple job holders. To formally test these hypotheses, this chapter estimates a standard income mobility model denoted by:

$$ln\left(\frac{Y_{it}}{Y_{it-1}}\right) = \gamma Y_{it-1} + \alpha_1 \Delta E_{it} + \alpha_2 \Delta L_{it} + \alpha_3 \Delta L_{it}^2 + \beta^l LS_{it}^l + \xi_{it} \qquad (8.8)$$

where LS^l_{it} is the i^{th} worker's labour-supply behaviour l where $l = 1$ represents constrained pluriactivity and $l = 2$ represents non-constrained pluriactivity. The parameter β^l measures the impact of specific type of labour supply behaviour on income mobility after controlling for initial income and changes in human capital stock.

Occupational Mobility

To be able to examine occupational mobility, it is important to provide a yardstick of job quality.[81] In general, identifying the features of quality employment is not straightforward as the concept may have different meanings for varying levels of development (ADB 2011b). For Filipinos, findings from the World Values Survey show that income and job security are among the most important factors that individuals identify when asked about the qualities they look for in a job. Except for few factors, a stylized pattern also emerges where those in higher income brackets demand more job benefits. However, other than people's subjective beliefs about job attributes that are associated with high quality jobs, there are limited objective data that can capture all of the multidimensional features of job quality. For instance, the LFS only collects basic information about occupation type, wages, and income. A way around this problem is to link the concept of employment quality with the concepts of formal and informal jobs, that is jobs covered by the formal labour market regulations, and those operating outside of such regulations. In this context, one can associate high quality

[81] Under the hours-constraint model of multiple job holding, job quality is gauged with respect to income levels. In other words, I can distinguish constrained from non-constrained pluriactivity by comparing the hourly wage rate of one's primary and secondary job. However, I decided to use the concept of formal and informal jobs to provide a more multi-dimensional concept of job quality.

employment with having a formal job and low quality employment with having an informal job. Certainly, this normative assumption is not without limitations. In some cases, skilled workers voluntarily enter the informal economy for prospects of higher economic returns. In other words, participation in the informal economy could also be an optimal choice for some workers who are capable of getting jobs in the formal economy. This represents voluntary informal employment. On the other hand, workers who have no choice but to take on low quality jobs in the informal economy due to the lack of skills and structural barriers on entry to the formal sector represent involuntary informal employment[82]. Nevertheless, empirical evidence from the Philippines as well as other developing countries suggest that a significant number of informal workers are trapped in jobs with inferior working conditions (WB 2010; ADB 2011b). With significantly lower income, informal workers in the country are more likely to fall into poverty. In addition, a lack of social protection coverage exposes them to greater socio-economic risks that may eventually lead to chronic poverty. This provides a good motivation to use formal and informal employment as a rough measure of quality of employment

To examine the relationship between occupational mobility and labour supply behaviour, occupational mobility can be defined as a multinomial outcome which assumes a value of 0 if a worker keeps the same type of job for two consecutive survey waves, 1 if a worker moves from an informal main job to a formal main job and 2 if a worker moves from a formal main job to an informal main job.

$$ln\left(\frac{p_{it}^{J}}{p_{it}^{0}}\right) = \gamma_j Y_{it-1} + \alpha_{1j}\Delta E_{it} + \alpha_{2j}\Delta L_{it} + \alpha_{3j}\Delta L_{it}^{2} + \beta_j^{l} LS_{it}^{l} + \xi_{it} \qquad (8.9)$$

where p_{it}^{0} denotes the probability of staying in the same type of employment arrangement between time t and $t+1$, p_{it}^{1} denotes the probability of moving from an informal to a formal main job while p_{it}^{2} denotes the probability of moving from a formal to an informal main job.

8.3. Data and Implementation of Concepts

8.3.1 Merged FIES-LFS

The analyses are based on the data from the FIES-LFS conducted by the NSO. As pointed out in Chapter 3, the LFS is a quarterly survey that collects information on household members' employment. Unlike in other chapters where households are used the main units of analysis and they are weighted proportionally to the household size, this chapter uses individual-level data. In particular, the data of all working-age members who are employed for at least two consecutive waves from the 6,519 households that appear in all three waves of FIES-LFS (2003, 2006 and 2009) is

[82] Kucera & Xenogiani (2009) provide a good discussion of voluntary and involuntary informal employment by comparing the quality of formal and informal jobs.

used.[83] Although this data comprises a balanced sample of households, it does not have complete longitudinal information for every member since individuals moving out of a sample household are not tracked over time. As explained in Chapter 3, survey weight adjustments are used to account for the potential bias that may be induced by attrition in all computations.

8.3.2 Measuring Socio-Economic Mobility

While the labour force survey collects various indicators of labour market participation of all sampled household members, the survey collects earnings data from workers in wage or salaried employment only. Employers, self-employed and unpaid family workers do not report any income in LFS. Thus, income mobility can only be estimated for wage workers. In this context, income mobility is defined as the annualized growth in wage workers' earnings.[84] On the other hand, occupational mobility is gauged in terms of formal-informal job transitions.

According to the 17th International Conference of Labour Statisticians, jobs are considered informal if the corresponding employment relationship is, "*in law or in practice, not subject to labour legislation, income taxation, social protection or entitlement to certain employment benefits (advance notice of dismissal, severances of pay, paid annual or sick leave, etc)*" (ILO 2004). In other words, informal work refers to jobs which are typically outside formal labour regulation. However, implementing this definition is not straightforward given data constraints.[85] To operationalize this definition in LFS, this study adopts a classification system that is similar to the one used in Heriawan (2004) and Martinez et al. (2014). In particular, the criteria used in distinguishing formal and informal jobs are based on cross tabulating employment status and type of occupation (Table 8.1). Formal workers correspond to all employers with permanent workers. This includes self-employed workers, who are assisted by family members in the non-agriculture sector. Formal workers also include all government employees and those who are employed as professionals. The rest are classified as informal workers.

[83] BLES defines the working age population as the household population 15 years and over (BLES 2011).

[84] Although it is possible to use the household expenditure per capita as income measure for non-wage workers, it would be hard to directly link the impact of multiple job holding on mobility if such income measure is used.

[85] Depending on the available data, there are various ways of implementing the official definition and each approach may produce different estimates. For example, by treating casual workers and unpaid family workers as informally employed, Cuevas et al. (2009) estimated that at least 29% of all the employed in Indonesia are working in the informal economy based on 2007 Sakernas. However, most sources put the estimates at a much higher level. For example, using the presence or absence of work contracts and information about bookkeeping records reported in the 2009 Informal Sector Survey, ADB and BPS (2011) estimated that 89% of the employed population in the predominantly agricultural province of Yogyakarta is informal, while 76% of total employment in the predominantly urbanized province of Banten has informal employment arrangements. Furthermore, OECD (2010) estimates the informal employment in Indonesia to be at least 70%. On the other hand, according to BPS Indonesia, about 68% of Indonesians were employed in the informal economy in 2009.

Table 8.1 Definition of Formal and Informal Employment

	Professional, technical and related worker	Administrative and managerial worker	Clerical and related workers	Sales workers	Services worker	Agriculture, animal husbandry, forest, fishermen, hunters	Production and related workers, Transport operators and labourers	Others
Own account worker	F	F	F	I	I	I	I	I
Self-employed assisted by family worker	F	F	F	F	F	I	F	I
Employer	F	F	F	F	F	F	F	F
Government worker	F	F	F	F	F	F	F	F
Private worker Casual worker in agriculture Casual worker in non-agriculture	F	F	F	I	I	I	I	I
Unpaid family worker	I	I	I	I	I	I	I	I

Source: Martinez et al. (2014)

8.3.3 Distinguishing between Constrained and Non-Constrained Pluriactivity

As mentioned earlier, constrained pluriactivity refers to instances when a worker is willing to take a second job with inferior quality relative to the characteristics of his/her first job. Non-constrained pluriactivity refers to the opposite case. However, being able to implement this definition depends on data availability. For instance, Martinez et al. (2014) defined that a multiple job holder in Indonesia is engaged in constrained pluriactivity (relative to a single job holder with the same type of primary job) if he/she is either (i) holding a formal main job and an informal secondary job, or (ii) holding two informal jobs. On the other hand, a multiple job holder is engaged in non-constrained pluriactivity if he is either (iii) holding two formal jobs or (iv) holding an informal main job and a formal secondary job. However, following this definition in the Philippine context is problematic for two reasons. First, the LFS data provide limited information about the second job which prevents me from classifying whether the second job has a formal or an informal arrangement. Second, defining constrained and non-constrained pluriactivity in terms of formal and informal job could create circularity problems since our measure of occupational mobility also depends on the formality/informality of a worker's job. In this study, I follow an indirect approach. A worker is considered to be in constrained pluriactivity if he/she has multiple jobs and comes from a household who are consuming more than what they are earning (i.e., household expenditure exceeds household income). This definition is premised on the argument that liquidity constraints affect occupational choices (Giannetti 2011). In particular, those who are exposed to higher risks of liquidity constraint may not have the leisure to choose better quality jobs.

Following the definitions outlined above, survey estimates show that about 7 in 10 workers were informally employed in their main jobs. Among the employed in 2009, approximately 11% had multiple jobs. Of these multiple job holders, about 43% are in constrained pluriactivity while the 57% are in non-constrained pluriactivity.

8.4 Empirical Results

8.4.1 Background on the Philippines's Labour Market Over the Past Decade

One possible reason why the high incidence of poverty and pervasive income inequalities have remained prominent features of the Philippines's development process despite strong economic growth rates is that the quality of jobs held by workers at the bottom of the income pyramid has not improved significantly. Previous studies show that to be able to move forward into a higher and sustained level of development, it is important to expand good quality employment opportunities to the poor (ADB 2011b, WB 2013 and 2014). This section examines how the quality of employment in the country has changed over the past decade.

Table 8.2 provides a summary of the employment trends based on key labour market indicators since 2003. On the positive side, one can find a noticeable drop in the proportion of the labour force without jobs during this period. Despite this progress, underemployment rates or the proportion of employed persons who are either looking for a second job, a new job with longer work hours or wants additional work hours in their current jobs, increased. In a developing country like the Philippines, the underemployment rate is probably a more telling indicator than unemployment rate because the poor which comprises a significant fraction of the population cannot afford to remain unemployed for extended period of time. The results also portray a declining trend in labour participation rates for both men and women. This is in sharp contrast to the trends observed in previous years when labour participation rates, especially among women, were increasing (KILM 2014). Survey estimates suggest that labour participation rate among men dropped from 82% in 2003 to 79% in 2012 while the proportion of working age women entering the labour market declined from 51% to 50% during the same period. Taken in a comparative context, although the Philippines' labour market can be characterized with higher participation rate, higher incidence of unemployment and underemployment are more prominent features of its labour market structure compared to other Asian countries (Montalvo 2006).

Tables 8.3 to 8.5 describe the distribution of the proportion of workers employed by production sector, occupation group and type of employment, respectively. Interestingly, while agriculture remains to be the sector with the highest contribution to total employment, its share has dropped from 35% in 2003 to 30% in 2012. The declining role of agriculture sector has translated to an expanding employment in service-oriented sectors whose share to total employment increased by 5.3 percentage points over the past decade. On the other hand, the contribution of the industry sector has become

Table 8.2 Trends in Key Labour Market Indicators, 2003-2012

Employment Indicator	2003	2006	2009	2012
Labour Force (in million)	34570.8	35464.1	37894	40432
Labour participation rate, total (% of total population ages 15+)	66.7	64.2	64	64.2
Labour participation rate among men	82.2	79.3	78.7	78.5
Labour participation rate among women	51.4	49.3	49.4	50
Unemployment rate (% of the labour force)	11.4	8	7.5	7
Underemployment rate (% of the employed)	17.5	21.5	19.7	20.9

Source: Author's computations using data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009, BLES data and KILM (2014)

stagnant as its share to total employment decreased by roughly 0.5 percentage points. In terms of occupations, the past decade has seen a moderate increase in the number of workers holding managerial positions. This is also accompanied by a consistent increase in the share of clerical and sales. On the other hand, the proportion of employed who are production workers (i.e., trades and related workers, plant and machine operators and assemblers) has declined significantly while the proportion of labourers and unskilled workers has observed a small increase. In terms of type of employment, the previous decade has witnessed a significant shift from self-employment to wage and salaried employment. In particular, self-employment dropped by 7 percentage points from 2003 to 2012 while the proportion of employed in wage and salaried jobs increased by the same amount. However, the country continues to operate with a significant share of unpaid family work. From 2003 to 2012, the proportion of employed people in unpaid work barely changed from 10% to 9%. Overall, while non-agricultural employment is expanding, the pace of reduction of employment in agriculture sector has been much slower compared to the marked shift from agricultural to non-agricultural employment that transpired before the Asian financial crisis (WDI 2014). In addition, the increasing role of the services sector to total employment can be mostly attributed to the higher proportion of persons employed in low-paying service-oriented jobs.

Tables 8.6 and 8.7 provide further insights on how the quality of employment in the country has evolved over the years. For instance, the estimates suggest that real incomes of workers with wage and salary jobs increased by approximately 1.7% per year from 2003 to 2012. Paid workers from family-operated activities noted the fastest annual income growth (3.3%) while those working for private households experienced the lowest rate of increase in income (0.9%). Furthermore, there has also been a gradual increase in the proportion of the labour force who have formal employment arrangements. Interestingly, the proportion of those who take multiple jobs, an approximate indicator of the prevalence of non-standard employment arrangements, comprise a non-negligible portion of the labour force and more importantly, have shown signs of increasing trend.

In summary, a quick examination of key labour force indicators reveals that unlike its macro-economic growth, the country’s performance in the employment front portrays a mixed picture. On the positive side, the statistics show increasing non-agricultural and formal employment. However, the improvement in the quality of jobs held by those who are at the bottom of the occupational ladder has been less remarkable with the unemployment and informal employment rates remaining high. In other words, the issue is less about a significant fraction of the country’s population not having jobs but more on the observed pattern that many of those who are employed remain in low quality employment. Worryingly, a quick examination of the labour force survey also reveals that moving into better jobs is not an easy task. For instance, only about three in five of the initially non-employed (i.e., unemployed and not in the labour force) reported having a job in the succeeding wave.

In addition, not everyone who gets a job always remain employed, wherein approximately 10% of those who initially had a job were found to be either unemployed or not in the labour force in the following survey period. Furthermore, I also find that only about one in five who were initially

Table 8.3 Distribution of Workers (%), by Production Sector of Main Job

Production Sector	2003	2006	2009	2012
Agriculture	35.4	34.7	32.8	30.4
Mining	0.4	0.4	0.5	0.7
Manufacturing	9.9	9.3	8.4	8.3
Electricity, Gas and Water	0.3	0.4	0.4	0.4
Construction	5.4	5.2	5.4	6
Wholesale and Retail Trade	18.5	18.5	19.6	18.8
Hotels and restaurants	2.6	2.7	3.1	4.1
Transport, storage and communication	7.7	7.9	7.6	8.1
Financial intermediation	1	1	1.1	1.1
Real estate, renting, and business activities	2.2	2.3	3.1	3.3
Public administration and defence, compulsory social security	4.7	4.4	5.1	5.2
Education	3	3.1	3.2	3.4
Health and social work	1.2	1.1	1.2	1.2
Other community, social and personal service activities	2.8	2.4	2.6	2.6
Private households with employed persons	4.9	4.9	5.9	6.1

Source: Author’s computations using data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009 and BLES data.

Table 8.4 Distribution of Workers (%), by Main Occupation

Occupation	2003	2006	2009	2012
Officials of government and special interest organizations, corporate executives, managers, managing proprietors, and supervisors	12.3	12.1	14.5	16.1
Professionals	4.3	4.3	4.4	4.9
Technicians and associate professionals	2.8	2.7	2.7	2.8
Clerks	4.3	4.9	5.3	5.7
Service workers and shop and market sales workers	9.3	9.8	10.7	12.6
Farmers, forestry workers and fishermen	18.6	17.6	15.4	12.7
Trades and related workers	9.2	8.1	7.7	6.8
Plant and machine operators and assemblers	7.6	7.7	6.1	5.3
Labourers and unskilled workers	31.3	32.3	32.7	32.9
Special occupations	0.4	0.4	0.4	0.2

Source: Author's computations using data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009 and BLES data.

Table 8.5 Distribution of Workers (%), by Status of Main Employment

Type of worker	2003	2006	2009	2012
Wage and salary workers	**53**	**53.4**	**55.8**	**60.2**
Private household		5.7	5.9	5.6
Private establishment		39.4	41.3	46.1
Government		7.8	8.2	8
Family owned business		0.5	0.3	0.4
Self-employed	**37.1**	**35.1**	**33.6**	**30.4**
Own-account worker		30.4	29.4	26.9
Employer		4.7	4.2	3.5
Unpaid family worker	**10**	**11.5**	**10.6**	**9.4**

Source: Author's computations using data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009 and BLES data.

Table 8.6 Average Daily Basic Pay of Wage and Salary Workers (in 2005 PPP US$)

Type of worker	2003	2006	2009	2012
All Wage and Salary Workers	**10.97**	**11.7**	**12.78**	**12.76**
Private household	5.15	5.22	5.76	5.59
Private establishment	10.3	11.32	12.41	12.02
Government / Government Corporation	18.78	19.48	21.04	22.42
Family-operated business	7.32	7.31	8.17	9.86

Source: Author's computations using data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009 and BLES data.

Table 8.7 Distribution of Employment Status (%), 2003-2009

Type of worker	2003	2006	2009
Single job holder with formal job	22.88	23.09	25.66
Multiple job holder with formal main job	2.59	2.53	2.87
Single job holder with informal job	56.44	55.86	53.28
Multiple job holder with informal main job	6.78	7.27	7.12
Unemployed	11.31	11.23	11.08

Source: Author's computations using data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009

employed in the informal sector finds a job in the formal sector in the following survey wave. These results set the tone for the need to investigate the mechanisms through which social mobility can be facilitated. In this study, I examine the case of non-standard arrangements, particularly, multiple job holding.

8.4.2 Discussion of Empirical Results

Descriptive Trends

Survey estimates suggest that multiple job holding is a significant part of total production in the Philippines, increasing from 10.4% in 2003 to 11.1 in 2009. In 2009, empirical data suggests that about 62% of pluriactive workers in the Philippines were in paid employment in their main jobs while the remaining 38% were in self-employment (including unpaid family work). On the other hand, about 57% of multiple job holders held their main jobs in the agricultural sector, 10% in industry and 33% in service-oriented sectors. Furthermore, 65% of multiple job holders were engaged in elementary occupations for their main jobs (including agricultural work), while 15% were in sales and other service oriented positions. About 20% of multiple job holders in the sample were engaged in professional, administrative and managerial jobs.

Interestingly, 63% of pluriactive workers reported a different secondary occupation, while 37% had the same line of work for their main and secondary jobs. Table 8.8 summarizes what kind of work multiple job holders in the Philippines take as their second jobs. In particular, agricultural work as a secondary activity is quite common among workers especially those holding elementary occupations in their primary jobs. Conversely, combining agricultural work is least common among professionals, technical workers and those holding administrative and managerial positions. This is not surprising considering that professionals and technical workers are more likely to be in urban areas, where agricultural employment is not common. Furthermore, agricultural workers and labourers are more likely to be engaged in the same occupation for their second jobs.[86]

Determinants of Multiple Job Holding[87]

To identify the determinants of pluriactivity, equations (8.4) and (8.5) are estimated using logistic regression with robust standard errors to adjust for the correlation among repeated observations for the same individual. The results show that Filipino men are more likely to have a second job than their female counterparts (Table 8.9). This is different from the findings in other countries which typically report that women are more likely to get a second job than men. Nevertheless, the gender difference in multiple job holding rates has slightly decreased over the years with the proportion of pluriactive women increasing from 8.1% in 2003 to 9.7% in 2009, while that of men increased only from 16.3% to 16.8%. Household composition also seems to matter. As the family size increases, the propensity to take multiple jobs tends decrease but the average age of other household members is negatively correlated with the propensity to be pluriactive. Moreover, the burden of getting a second job is usually left to the head of the household.

Less educated workers are more likely to get a second job in the Philippines. For instance, those who only had primary education were approximately 1.5 times more likely to get a second job than those who had secondary or college education. On the other hand, there is a declining propensity to get a second job as an individual moves up the income ladder – a pattern consistent with the target income model of pluriactivity. In particular, workers from the poorest 20% households are approximately three times more likely to get a second job than workers from the richest 20% households. Nevertheless, the fact that as many as 8% from richest quintile are also engaged in

[86] An interesting avenue for future research is to focus on multiple job holding in the agriculture sector using detailed income data from agricultural sources. In particular, future research may examine the interaction between "push" and "pull" factors and how this affects an individual's income mobility prospects through pluriactivity.
[87] Because of the limited number of survey waves, the statistical models do not control for individual-specific effects.

Table 8.8 Distribution of Multiple Job Holders (%), by Type of Occupation in Main and Secondary Jobs

Main Job \ Secondary Job	Special Occupations	Officials of Government and Special Interest Organizations	Professionals	Technicians and Associate Professional	Clerks	Service Workers	Agricultural Workers	Trades and Related Workers	Plant and Machine Operators and Assemblers	Laborers and Unskilled Workers	# obs
Special Occupations	0	38.46	0	0	0	0	41.03	0	0	18.46	5
Officials of Government and Special Interest Organizations	0	26.96	0.17	1.48	3.14	8.81	30.98	6.72	5.58	16.14	151
Professionals	0	32	6	25.6	0	11.2	22.4	0	2.48	0.54	22
Technicians and Associate Professional	0	2.11	0	9.31	0	19.61	13.73	17.65	7.84	30.39	28
Clerks	0	20.9	0	15.67	5.22	4.85	40.3	0	2.95	9.7	29
Service Workers	0	20.18	0	2.39	0	10.7	21.1	12.23	5.81	27.83	42
Agricultural Workers	0.17	9.85	0	0.83	1.33	3.87	45.56	6.31	3.24	28.83	652
Trades and Related Workers	0	5.73	0	1.86	0	7.28	40.56	10.84	7.74	26.01	83
Plant and Machine Operators and Assemblers	1.73	15.45	0	1.91	0	2.24	39.43	9.96	12.4	16.87	53
Laborers and Unskilled Workers	0.47	4.47	0.43	2.27	0.31	5.62	29.09	6.31	2.52	48.56	420

Source: Author's computations using 2003 data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009
Note: Detailed information about the secondary job is not available from 2006 round onwards.

multiple job holding suggests that dual job holding is not always a matter of constrained pluriactivity as previously inferred. Multiple job holding rates also differ across geographic locations. Workers from urban areas are less likely to take multiple jobs compared to their rural counterparts. In particular, self-employed agricultural workers are more likely to be pluriactive than paid workers in the non-agriculture sectors.

The results also confirm the hours-constraint hypothesis. In general, multiple job holders are more likely to work for less than 35 hours in their main jobs compared to single job holders. Interestingly, while the prevalence of multiple job holding is generally higher among those engaged in fewer hours of work in their primary job, multiple job holding is still quite high for those who are working for at least 35 hours per week in their primary jobs.[88] In particular, about 9.5% of those who are working for at least 35 hours per week in their main jobs are engaged in multiple economic activities.

Consistent with the findings from existing literature, the estimated models show that the motivation to have multiple jobs in the Philippines is generally associated with the presence of constraints in one's primary job. Both income and non-income factors make up such constraints. For instance, both wage employment and the number of hours worked in a person's main job decrease the propensity to be pluriactive while living in rural agricultural areas and being engaged in the agriculture sector tend to increase the propensity of an individual to take multiple jobs. Nevertheless, as pointed out earlier, multiple job holding is not always a case of constrained pluriactivity which could be indicative that the determinants of constrained and non-constrained pluriactivity are different. Estimation of (8.5) allows me to examine this hypothesis. The results suggest that higher educational attainment increases the propensity to be engaged in non-constrained pluriactivity but decreases the odds of becoming a constrained multiple job holder. Wage employment decreases the odds of falling into constrained pluriactivity while self-employment increases it.

Relationship between Economic Mobility and Multiple Job Holding

I argued earlier that being employed is not a sure ticket out of poverty and in most cases, the quality of jobs held is important. However, landing a job with satisfactory quality that is enough to lift poor workers out of poverty is often a function of origins, skills, effort and luck (Piketty 1995; Kochar 1999). To some extent, a worker's decision to be pluriactive could be a sign of effort that is motivated by the desire to improve one's living standards. Moreover, recent evidence from

[88] Compared to industrialized countries, I consider 15% as a high proportion of the population with multiple jobs. In industrialized countries, the incidence of multiple job holding is about 5% to 10% (Australian Bureau of Statistics (ABS) 2009; Wu et al. 2009; Campbell 2011;).

Table 8.9 Regression Coefficients of Logistic and Multinomial Logistic Models on the Propensity to Take Multiple Jobs

Variable	Logistic Model	Multinomial Logistic Model	
	Pluriactive	Non-constrained pluriactivity	Constrained pluriactivity
Urban	-.54***	-.43***	-.74***
Hhld head	.58***	.59***	.53***
Male	.26***	.28***	.28***
Age	.083***	.081***	.087***
Age squared	-.00089***	-.00085***	-.00095***
Educational attainment (base = primary education)			
secondary education	-.026***	-.049***	0.0093
tertiary education	-.072***	0.0045	-.25***
Main job is formal	.53***	.5***	.55***
Employer in main job			
Wage/salaried job	-.041***	-0.0012	-.13***
Self-employed	.19***	.13***	.25***
Unpaid family work	.22***	.056***	.4***
Main job is in agriculture sector			
Manufacturing	-.52***	-.44***	-.64***
Services sectors	-.42***	-.29***	-.6***
Number of hours in main job	-.023***	-.022***	-.026***
Wants to work more hours	1.2***	1.2***	1.2***
Family size	-.014***	-.011***	-.021***
Has spouse	.2***	.092***	.4***
Average age of other household members	-.0099***	-.0039***	-.021***
Income quintile (base = 1st quintile)			
2nd quintile	-.14***	-.17***	-.091***
3rd quintile	-.093***	-.037***	-.13***
4th quintile	-.1***	.032***	-.3***
5th quintile	-.2***	-.096***	-.39***
Intercept	-3.2***	-4***	-3.8***

Source: Author's computations using data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009
Notes: *** - p< 0.01, ** p <0.05, * - p < 0.1

industrialized countries suggest that pluriactivity provides a good venue to acquire new skills or improve existing ones which could eventually open up an avenue of better economic opportunities. Nevertheless, this type of labour supply behaviour may not always result in a worker's improved living standards through acquisition of new skills. For one, high inequalities lead to labour market segmentation wherein access to high quality jobs is limited to a privileged few. This makes the relationship between socio-economic mobility and multiple job holding an empirical issue.

After holding other factors such as changes in sectoral transitions fixed, the results suggest that among workers in wage or salaried jobs, non-constrained multiple job holders experienced faster income growth than either constrained multiple job holders or single job holders. Given that the statistical model from which this conclusion has been drawn is based on data from workers who remain in wage or salaried jobs in two consecutive waves only, one should be cautious in concluding that multiple job holding leads to economic mobility that would allow the poor workers to catch-up with the rest. In the Philippines, more than half of the poorest 40% are workers who are either self-employed or engaged in unpaid family work. To include them in the analyses, I also estimated the occupational mobility model described in Section 8.2. The results suggest that after holding other factors fixed, having multiple jobs is weakly correlated with higher income growth but strongly correlated with formal to informal or informal to formal job transitions. Interestingly, compared to single job holders, unconstrained pluriactivity decreases the odds of moving from informal to formal jobs and increases the odds of moving from formal to informal jobs. On the other hand, constrained pluriactivity increases the odds of both informal to formal and formal to informal job transitions. In other words, the results are indicative that the impact of multiple job holding on Filipino workers' prospects of economic mobility is mixed. For some, multiple job holding leads to faster income growth while for others, this type of labour supply behaviour increases occupational mobility but the accompanying mobility is not necessarily an upward mobility. There are several possible explanations for this. The most intuitive explanation is that having multiple jobs serves as a coping response and tool to avoid experiencing more severe forms of poverty during times of economic uncertainties. It could also be the case that some multiple job holders are more interested in the non-pecuniary benefits of having multiple jobs that is not adequately captured in the model of occupational mobility. For example, a worker may take a second job that is related to his/her personal hobbies. In some cases, having multiple jobs may also lead to more flexible schedule that would allow one to balance work and other personal responsibilities. However, it is hard to test this hypothesis due to data limitations. Another possible reason why pluriactivity is giving mixed signals in terms of its relationship with socio-economic mobility is that our data only allows us to estimate mobility between two time periods that are three years apart. It is possible that the effect of multiple job holding gradually tapers off over time. If this is true, then we may need to rely on longitudinal data which are collected more frequently to be able to draw more conclusive inferences.

8.5 Conclusion and Policy Implications

Amidst rapid economic development, the Philippines confronts the challenges of jobless growth, slow reduction of poverty and income inequalities. These trends could have adverse

Table 8.10 Regression Coefficients of Economic Mobility Models

Variable	Income Mobility Model	Multinomial Logistic Model	
	Wage growth	Informal to Formal Main Job Transition	Formal to Informal Main Job Transition
Urban	0.014	-.11***	0.0061
Hhld head	-.029*	-.066***	.088***
Male	.046***	-0.0055	-.032*
Age	0.0002	.041***	.073***
Age squared	-0.0000094	-.00036***	-.0006***
Educational attainment (base = primary education)			
secondary education	-0.018	.2***	.17***
tertiary education	-0.029**	-0.038***	.15***
Sector of employment remained (main job)			
Moved from agriculture to non-agriculture	.055***	1.7***	-.46***
Moved from non-agriculture to agriculture	-.12***	-.14***	1.5***
Change in family size	0.00049	.01***	.0044*
Change in the proportion of hhld members who are employed	-0.034	.13***	-.36***
Income quintile (base = 1st quintile)			
2nd quintile	.041**	.36***	.22***
3rd quintile	.065***	.52***	.24***
4th quintile	.088***	.88***	.34***
5th quintile	.15***	.73***	.057***
Single job holder			
Non-constrained multiple job holder	.032*	-.065***	.26***
Constrained multiple job holder	0.0034	.023**	.36***
Intercept	-0.0025	-3.6***	-4.6***

Source: Author's computations using data from the longitudinal subsample of FIES-LFS 2003, 2006, 2009
Notes: The dependent variable for the wage growth model is employment earnings.
*** - $p < 0.01$, ** $p < 0.05$, * - $p < 0.1$

consequences for the long-term growth prospects of a country, as well as for a broad range of human welfare outcomes (Wilkinson and Pickett 2009).

Increasing inequalities and labour market segmentation are mutually reinforcing. Thus, labour market policies are important tools for addressing the adverse consequences of increasing inequalities. For this, policymakers need sufficient data to identify the vulnerable workers. Previous studies show that a bulk of these vulnerable workers have non-standard employment arrangements. An important form of non-standard employment practices that has been identified in the literature is multiple job holding. Previous studies suggest that this labour supply behaviour is typically used as a coping mechanism against risk of unemployment or income shortfall. However, recent evidence from industrialized countries suggests that it can also be used as a means to move into better occupations. The present paper adds to the existing literature by offering a detailed examination of multiple job holders in the Philippines – a country for which the empirical evidence of the patterns of pluriactivity is scarce.

The analysis of a nationwide panel data from the FIES-LFS, reveals that multiple job holding is quite prevalent in the Philippines, accounting for more than 10% of the employed between 2003 and 2009. In addition, the results suggest that men, especially those who are head of households, those less educated, rural agricultural workers, underemployed and workers from the lower income quintile are more likely to get a second job. This confirms that the propensity to be pluriactive is primarily driven by socio-economic constraints. In particular, almost half of multiple job holders are engaged in constrained pluriactivity, that is having multiple jobs to be able to make ends meet. Despite the fact that constrained pluriactivity can be a potent tool for avoiding socio-economic vulnerabilities in the short-run, the estimates provided in this chapter show that it is not strongly correlated with better mobility outcomes. Moreover, there is some evidence to suggest that highly skilled workers who are already on top of the socio-economic hierarchy observe immediate increase in income from multiple job holding. If this pattern holds for other forms of non-standard employment, then it can be argued that non-standard employment contributes to further segmentation of the labour market wherein the benefits are being channelled disproportionately to those who are already on top of the socio-economic hierarchy. In this context, the challenge confronting policymakers is to ameliorate the expanding labour market segmentation in the country. This entails improving the working conditions of individuals with non-standard jobs, particularly those who combine multiple precarious employment. For instance, a system could be considered to compensate for the risks associated with non-standard jobs using higher incomes or provision of other non-pecuniary benefits, across all segments of the labour market. Finally, to be able to better respond to the needs of researchers and policy-makers, there is a need to improve existing data collection systems on labour market indicators. In particular, there is a need to collect more reliable indicators of working conditions within the context of continuously changing labour markets.

Chapter 9 Evaluating the Feasibility of Using Pseudo-Panel Data to Measure Income Mobility

9.1 Introduction

Using the Philippines as case study, the previous chapters underscored the usefulness of income mobility analysis for understanding how income distribution evolves over time. Despite the advantages of examining income mobility, it was almost an uncharted field in developing countries until recently and most of the existing studies (including this thesis) cover short periods of time only (Fields 2011). One of the main factors that contribute to the dearth of income mobility studies in developing countries is the high cost of collecting panel data from where information on the income of each person or household, and changes in income over time, can be derived (Deaton 1997; Bourguignon, Goh & Kim 2004; Antman & McKenzie 2007; Fields et al. 2007; Cuesta, Nopo & Pizzolitto 2011). In this chapter, I evaluate the performance of different pseudo-panel estimation techniques that have been proposed in the literature in measuring different income mobility indicators when panel data is not available. Moreover, I further develop these methods to estimate a wider range of mobility indices in addition to the ones that these methods were originally designed to measure.

Over the years, a number of researchers have attempted to reconcile the need for examining income mobility with the lack of panel data by exploiting the information provided by other data sources. In particular, methodological research has focused on exploring the usefulness of repeated cross-sectional surveys because many developing countries regularly collect income (and non-income) indicators of development at the micro-level through cross-sectional surveys. The main issue in working with cross-sectional surveys in the context of income mobility analysis is that it is not straightforward to measure the amount of temporal dynamics in each person's or household's income given that cross-sectional surveys do not follow the same set of respondents over time.

To address this issue, researchers proposed a methodology called pseudo-panel estimation which entails constructing synthetic panels from repeated cross-sectional survey data. There are several variants of pseudo-panel estimation. Four of the most recent developments in the literature are the methods proposed by Bourguignon, Goh & Kim [BGK] (2004), Antman & McKenzie [AM] (2007), Dang, Lanjouw, Luoto & McKenzie [DLLM 1] (2011) and Dang, Lanjouw, Luoto & McKenzie [DLLM 2] (2014). These methods employ different procedures for creating synthetic panels and are originally designed to measure different aspects of income mobility. For instance, the AM approach is designed to examine the origin-independence perspective by extending the procedure initially proposed by Deaton (1985) which entails grouping all observations into different mutually exclusive and exhaustive cohort groups. The characteristics of interest are then averaged for each cohort group, and in turn, the cohort averages serve as the pseudo-panels. On the other hand, the BGK, DLLM 1and DLLM 2 approaches are designed to measure poverty dynamics or the amount of income movements at the low-income range. All three approaches involve estimating structural models to impute the unobserved incomes of respondents from a specific cross-sectional survey wave while maintaining the original respondents as the units of analysis. The main objective of this study is to demonstrate how these four methods can be extended to be able to estimate a wider array of income mobility measures.[89] In particular, the chapter addresses the following questions:

(i) Are the proposed pseudo-panel techniques useful for measuring income mobility? In general, which of the techniques are most desirable?

(ii) Does the performance of the pseudo panel techniques' depend on the type of income mobility measure being estimated?

(iii) How can the existing pseudo-panel techniques be improved?

9.2 Developments in Income Mobility Estimation using Repeated Cross-Sectional Data

Several researchers have proposed a variety of statistical techniques which use information from repeated cross-sectional surveys to create synthetic panel data. This section reviews the methodological developments in measuring income mobility using pseudo-panel methods. The discussions begin with a review of the classical pseudo-panel estimation methodology pioneered by Deaton (1985) followed by the presentation of four contemporary pseudo-panel approaches that are designed to answer specific income mobility-related questions.[90]

9.2.1 What is Pseudo-Panel Estimation?

In general, the pseudo-panel approach refers to a class of statistical and econometric methods that use repeated cross-sectional surveys to estimate indices or models that are typically suitable for longitudinal studies. For exposition, consider the following time-indexed static model

$$Y_{it} = \beta X_{it} + f_i + \varepsilon_{it} \qquad i = 1, 2, \ldots, N, \quad T = 1, 2, \ldots, T \tag{9.1}$$

where Y_{it} is the response outcome for unit i at time t, $\underline{\boldsymbol{X}}_{it}$ is a vector of explanatory variables, f_i is an unobserved unit specific effect and ε_{it} is a random disturbance term. Conventionally, the parameters of this model can be estimated using fixed-effects (FE) or random effects (RE) methods when longitudinal data is available.[91] However, estimation complexities arise when only repeated cross-

[89] A similar study has been done by Cruces, Fields & Violaz (2013) which examined the usefulness of AM, BGK and DLLM 1 methods in estimating various indices of mobility using Chilean panel data. This chapter extends Cruces et al. (2013) in several ways. First, in addition to the three methods that they examined, I also included DLLM 2 in the analysis. Second, I used a wider set of income mobility indices. Third, I explained in greater detail how these pseudo-panel estimation approaches can be extended to construct synthetic micro-based income data.

[90] Another strand of literature in pseudo-panel estimation is based on Age-Period-Cohort (APC) models. The APC models are generally used for assessing the impact of age, period and cohort for demographic and epidemiological variables such as disease incidence or mortality rates. Since the APC model is not used for poverty estimation, I do not discuss it here. Interested readers may refer to Yang, Fu & Land (2004) and Mason and Wolfinger (2002).

[91] Even in the presence of genuine panel data, ordinary least squares (OLS) estimation of (9.1) will produce inconsistent estimates for β if f_i is correlated with X_{it} . On the other hand, even if f_i can be reasonably assumed to be orthogonal with X_{it}, OLS estimators will still be non-optimal due to the serial correlation induced by the term f_i. In lieu of this, a fixed effects (FE) (or a random effects in the

sectional survey (RCS) data is available because in such case, Y_{it} and $\underline{\mathbf{X}}_{it}$ are not fully observed. As an alternative to (9.1), one can consider the following model,

$$Y_{i(t)t} = \beta X_{i(t)t} + f_{i(t)} + \varepsilon_{i(t)t} \quad i(t) = 1, 2, \ldots, N_t, \quad T = 1, 2, \ldots, T \qquad (9.2)$$

Notice the change in subscripts used to denote the sampled units when comparing (9.1) and (9.2). The subscript i(t) corresponds to the i^{th} respondent at the t^{th} cross-sectional survey wave while the subscript t correspond to the time period t. Conventional RCS designs imply that $i(\tau)t \neq i(\Psi)t$ for every pair $(i(\tau)t, i(\Psi)t)$ in $\{1,2,\ldots,N_t\}$, $t = \{\tau, \Psi\}$. In other words, the i^{th} sampled unit at time period τ is not necessarily the same with the i^{th} unit at time period Ψ. If we simply use the pooled RCS data and proceed to ordinary least squares (OLS) estimation of the model, the parameter estimates will be inconsistent if $f_{i(t)}$ is correlated with $X_{i(t)t}$. One way of addressing this issue is to find suitable instruments for $X_{i(t)t}$, i.e., variables that are correlated with $X_{i(t)t}$ but are asymptotically uncorrelated with the unobserved terms of (1). In a seminal work, Deaton (1985) proposed an approach which uses cohort-averaging as an indirect form of instrumentation. In particular, Deaton (1985) proposed the following model,

$$\bar{Y}_{ct} = \beta \bar{X}_{ct} + \bar{f}_{ct} + \bar{\varepsilon}_{ct} \quad c = 1, 2, \ldots, C, \; T = 1, 2, \ldots, T \qquad (9.3)$$

where

$$\bar{Y}_{ct} = \frac{1}{n_{c_t}} \sum_{i=1}^{n_{c_t}} Y_{it}, \quad \bar{X}_{ct} = \frac{1}{n_{c_t}} \sum_{i=1}^{n_{c_t}} X_{it}, \quad \bar{f}_{ct} = \frac{1}{n_{c_t}} \sum_{i=1}^{n_{c_t}} f_i, \quad \bar{\varepsilon}_{ct} = \frac{1}{n_{c_t}} \sum_{i=1}^{n_{c_t}} \varepsilon_{it}$$

This approach groups the sampled units into C mutually exclusive classes such that each class is always represented from every cross-sectional survey round and that class membership is fixed over time. Since we do not observe the same set of units in RCS, the term f_{ct} is not fixed over time.[92] Thus, we cannot readily rely on conventional panel data estimation techniques such as the FE estimator to difference out this term. However, when n_c is sufficiently large (in proportion to N_c, the number of individuals in the population who are in the c^{th} class), Deaton (1985) argued that we can conveniently assume that the term f_{ct} will be constant. In such case, it will be straightforward to remove this term using data transformation. Moreover, Deaton (1985) introduced further adjustments to the conventional FE estimator to take into account that Y_{ct} and X_{ct} are error-ridden estimators of their population counterparts. Furthermore, Verbeek & Nijman (1993) proposed a general class of estimators that can be considered when estimating (2). This class of estimators employs a "within transformation" on the pseudo-panel and adjusts the moment matrices in the least squares to account for measurement error due to data aggregation. Verbeek & Nijman (1993) also improved Deaton's

case that f_i is uncorrelated with X_{it}) estimator can be considered. The FE estimator implements a data transformation that removes the correlation between the explanatory variables X_{it} with the unobserved terms of (9.1).

[92] Note that at the population-level, this term is fixed under the assumption that the population is closed.

estimator after showing that the latter performed poorly in terms of the mean squared error when the cohort sample size is small.

The static model described in (9.1) can be extended to include a lagged term of the dependent variable (9.4). There are two estimation issues for (4). First, the term $Y_{i(t)t-1}$ is unobserved when using RCS dara. Second, $f_{i(t)}$ is likely to be correlated with both $Y_{i(t)t-1}$ and $X_{i(t)t}$ prompting the need to find suitable instruments.

$$Y_{i(t)t} = \alpha Y_{i(t)t-1} + \beta x_{i(t)t} + f_{i(t)} + \varepsilon_{i(t)t} \tag{9.4}$$

To be able to estimate (4), Moffitt (1993) ignored the term $f_{i(t)}$ and proposed using an instrument for $Y_{i(t)t-1}$ in the form of (9.5) where $W_{i(t)t-1}$ is vector of exogenous variables whose historical time-series are provided in the data and $Z_{i(t-1)}$ is a vector of time-invariant exogenous variables. In other words, Moffitt's (1993) idea is to first estimate a static model and use the predicted values as instrument for $Y_{i(t)t-1}$.

$$\widehat{y}_{i(t)t-1} = \widehat{\delta}_1 W_{i(t)t-1} + \widehat{\delta}_2 Z_{i(t-1)} \tag{9.5}$$

Moffitt's approach is anchored on a strong data requirement that the historical time-series of $X_{i(t)t}$ is observed. This is hardly satisfied in most of the existing RCS designs. In turn, Collado (1997) improved Moffitt's (1993) approach by using less stringent data requirements and going back to the conventional cohort-based approach. In particular, Collado (1997) proposed a Generalized Method of Moments (GMM) estimator corrected for measurement error for the following model,

$$\bar{y}_{c(t)t} = \alpha \bar{y}_{c(t-1)t-1} + \beta \bar{x}_{c(t)t} + \bar{f}_{c(t)} + \bar{\varepsilon}_{c(t)t} \tag{9.6}$$

Unlike Moffitt (1993), Collado (1997) did not assume that the unit-specific effects cancel out at the cohort-level. The author also argued that in the cohort-based approach, there is a trade-off between the number of cohort groups and the sample size per group. In particular, when the number of sampled units per cohort becomes large, the issue on measurement error becomes less relevant. However, this may have potential costs on efficiency since in finite sample sizes, increasing the number of units per cohort calls for fewer cohort groups to be formed.

Like Moffitt (1993), Girma (2000) departed from the conventional cohort-based approach and argued that a unit-based estimation method (i.e., maintaining the original observations as the units of analysis) will better optimize the use of available information from repeated cross-sectional data. Although he still grouped the units into cohorts, he did not involve transforming the data to cohort averages. Instead, he argued that different units within the same cohort (even across different time periods) exhibit non-zero correlations. In turn, such information can be used to find a suitable instrument when estimating (9.4). In particular, he proposed a pairwise quasi-differencing approach for the following model,

$$y_{i(t)t} = \alpha y_{j(t-1)t-1} + \beta x_{i(t)t} + f_{i(t)} + \eta_{i(t)t} \qquad (9.7)$$

where i and j are units from the same cohort group. Implicitly, (9.7) suggests that any past and present value of y and x can be used as instruments. Without imposing other conditions, this would create an infinite number of candidate instruments. However, subsequent studies argued that relying on arbitrarily chosen units from the same cohort as instruments could be a noisy approximation of the unobserved value of $y_{i(t)t-1}$ which might lead to inaccurate estimation of (9.4) (Verbeek & Vella 2005).

McKenzie (2004) extended (9.4) to allow for different covariate effects across cohorts. This heterogeneous dynamic pseudo-panel model can be denoted by (9.8) and its corresponding cohort-level model is denoted by (9.10). The author also argued that a GMM estimator similar to the one adopted by Collado (1997) which is consistent as the number of cohort groups increases, may not work since the number of parameters to be estimated also increases with the former. Instead McKenzie (2004) used an approach analogous to the Arellano-Bond estimator typically used in genuine panel models wherein $\bar{y}_{c(t-2)t-2}$ is used as an instrument for $\bar{y}_{c(t-1)t-2}$ which in turn as unbiased estimator of $\bar{y}_{c(t)t-2}$. Although this instrumentation approach addresses the bias arising from the measurement error induced by not observing the same individuals for each time period, the author pointed out that this estimator may be less efficient relative to the OLS estimator. In other words, an OLS estimator may still be superior (with lower variability) unless the number of time periods and the cohort sample sizes are both large.

$$y_{i(t)t} = \alpha_c y_{i(t)t-1} + \beta_c x_{i(t)t} + f_{i(t)} + \varepsilon_{i(t)t} \qquad (9.8)$$

$$\bar{y}_{c(t)t} = \alpha_c \bar{y}_{c(t)t-1} + \beta_c \bar{x}_{c(t)t} + \bar{f}_{c(t)} + \bar{\varepsilon}_{c(t)t} \qquad (9.9)$$

Inoue (2008) further extended the discussion of pseudo-panel estimation of dynamic models by considering a model that contains time-invariant unit-specific and (cohort) group-specific fixed effects denoted by (10) where $Z_{c(t)}$ are cohort-level explanatory variables and δ_c is the time-invariant group specific effect. Inoue (2008) proposed a GMM-based estimator for (9.10) which is consistent under some stringent orthogonality and rank conditions.

$$\bar{y}_{c(t)t} = \alpha_c \bar{y}_{c(t)t-1} + \beta \bar{x}_{c(t)t} + \gamma Z_{c(t)} + \bar{f}_{c(t)} + \delta_c + \bar{\varepsilon}_{c(t)t} \qquad (9.10)$$

In summary, there are two broad types of pseudo-techniques that have been proposed in the literature. The first type or what I refer to as Type I method in the succeeding discussions, uses cohort-averages as a form of instrumentation. In particular, all sampled units are grouped into mutually exclusive and exhaustive cohort classes. The cohort averages of the characteristics of interest are then used as the analytical units. In this context, the cohort averages act as the pseudo-panels. The approaches proposed by Deaton (1985), Verbeek & Nijman (1993), Collado (1997), McKenzie (2004) and Inoue (2008) can be considered as Type I methods. On the other hand, what I refer to as

Type II methods maintain the original sampling units as the analytical units. Following this definition, the approaches developed by Moffitt (1993) and Girma (2000) can be considered as Type II methods. Overall, each type has its own advantages and limitations. For instance, the main advantage of Type I method is that its underlying statistical theory, particularly how the model parameters can be estimated consistently, has been discussed extensively in the literature (Verbeek 2008). However, aggregating the units into cohorts can lead to significant loss of information. In particular, it becomes less straightforward to examine variations of the characteristics of interest within cohorts. On the other hand, Type II method addresses this limitation as it maintains the original observations as the units of analysis. However, unlike the Type I methods, the underlying statistical theory of Type II methods has not been extensively discussed in the literature. Over the years, both methods have been used in different empirical applications. In the next section, I discuss four recently proposed pseudo-panel techniques falling under either Type I or Type II method, that are specifically designed to measure income mobility.

9.2.2 Estimation of Income Mobility using Pseudo-Panel Data

Antman & McKenzie's (AM) Approach

As pointed out in Chapter 1, one of the ways of viewing mobility is to conceptualize it as the temporal dependence between previous and current income. There are two ways of measuring temporal dependence. First, we can estimate the correlation between previous and current income. Subtracting this correlation from unity yields the Hart's index described in Chapter 1. Alternatively, we can use income elasticity which entails expressing each unit's current income $Y_{i(t)}$ as a function of its lagged income $Y_{i(t)t-1}$, a vector of socio-demographic characteristics $X_{i(t)t}$ and a unit-specific effect $f_{i(t)}$. This is the approach followed by Antman & McKenzie (2005 and 2007) in measuring income mobility in Mexico. Equation (9.11) shows the underlying statistical model. Here, α is the mobility parameter of interest. In general, a large absolute value for α portrays strong temporal dependence, i.e., low mobility, while small values mirror weak relationship between previous and current incomes, i.e., high mobility.

$$\bar{y}_{c(t)t} = \alpha\bar{y}_{c(t-1)t-1} + \beta\bar{x}_{c(t)t} + \bar{f}_{c(t)t} + \lambda_{c(t)t} \tag{9.11}$$

where

$$\lambda_{c(t)t} = \alpha[\bar{Y}_{c(t)t-1} - \bar{Y}_{c(t-1)t-1}]$$

McKenzie (2004) argues that the term $\lambda_{c(t)t}$ can be ignored when the number of sampled units for every cohort is sufficiently large. Noticeably, (9.11) is an extension of (9.6). Thus, as can be inferred from the discussions in the previous section, consistent estimation of the parameters of (9.11) depends on the assumptions about the unobserved unit-specific effect as well as the sample size for each cohort.[93] Following Antman & McKenzie (2005 and 2007), a number of studies have applied this approach in estimating the temporal dependence-based concept of income mobility (Calonico 2006; Navarro 2006; Cuesta et al. 2011).

Bourguignon, Goh & Kim's (BGK) Approach

Bourguignon, Goh & Kim (2004) proposed a method of estimating the probability of falling into poverty using the following model,

$$Y_{i(t)t}^{c} = \beta_t^c X_{i(t)t}^{c} + \varepsilon_{i(t)t}^{c}$$
$$\varepsilon_{i(t)t}^{c} = \rho^c \varepsilon_{i(t)t-1}^{c} + e_{i(t)t}^{c} \qquad (9.12)$$

where $Y_{it(t)}^{c}$ is the income of unit *i* from (cohort) group *c* at time *t*, $X_{it(t)}^{c}$ is a vector of explanatory variables, β_t^c is the corresponding vector of covariate effects and $\varepsilon_{i(t)t}^{c}$ is and AR(1) error term such that $V(e_{i(t)t}^{c}) = \sigma_{ect}^2$. With RCS data, $\varepsilon_{i(t)t}^{c}$ and $\varepsilon_{i(t)t-1}^{c}$ are not observed simultaneously. Nevertheless, the authors argued that the parameters of (9.12) can be estimated using RCS data using the variance of the residuals as shown in (9.13).

$$\sigma_{\varepsilon ct}^2 = (\rho^c)^2 V(\varepsilon_{i(t)t-1}^{c}) + \sigma_{ect}^2 \qquad (9.13)$$

In particular, for each group *c* and time *t*, (9.12) can be estimated using OLS. The variance of the resulting residuals from (9.12) can then be used to estimate (9.13) while the residuals of (9.13) can be used as estimates of σ_{ect}^2. Given these parameter estimates and under the assumption that $e_{i(t)t}^{c} \sim N(0, \sigma_{ect}^2)$, then the probability of falling into poverty at time *t+1* is given by

$$P(Y_{i(t)t+1}^{c} < z \mid x_{i(t)t}^{c}, \hat{x}_{i(t)t+1}^{c}, \hat{\beta}_{t+1}^{c}, \hat{\sigma}_{ect+1}^{2}) = \Phi\left(\frac{z - \hat{\beta}_{t+1}^{c}\hat{x}_{i(t)t+1}^{c} - \hat{\rho}^{c}\hat{\varepsilon}_{i(t)t}^{c}}{\hat{\sigma}_{ect+1}^{2}}\right) \qquad (9.14)$$

While the estimation methodology is quite straightforward to implement, there are several issues with this approach. First, estimating heterogeneous models with varying parameters across cohort groups reduces the effective sample size. If some cohort groups comprise only few observations, then the corresponding parameter estimates might not be reliable. Second, to be able to estimate the probability of falling into poverty in the future, the formula calls for the availability of estimates for β_{t+1}^{c}, X_{it+1}^{c} and σ_{ect+1}^{2}. In the absence of this information, a simple approach is to assume that these parameters and variables are time-invariant throughout the observation period.

[93] In the next section, I adopt the simplifying assumption that conditional on previous income, there is no persistent unit-specific effect. Hence, the model parameters can be estimated using OLS.

Dang, Lanjouw, Luoto & McKenzie's (DLLM 1) Approach

Like Bourguignon, Goh & Kim, Dang, Lanjouw, Luoto & McKenzie (2011) focused on measuring dynamics in the low income range. In particular, consider the following models,

$$Y_{i(1)1} = \beta_1 X_{i(1)1} + \nu_{i(1)1} \tag{9.15}$$

$$Y_{i(2)2} = \beta_2 X_{i(2)2} + \nu_{i(2)2} \tag{9.16}$$

where Y is individual (or household) income and $\underline{\boldsymbol{X}}$ is a vector of individual (or household) characteristics whose values are fixed over time. These models can be estimated using two waves of RCS. However, to be able to estimate indicators of poverty dynamics, we need either $Y_{i(1)2}$ or $Y_{i(2)1}$, both of which are unobserved in RCS data. Thus, the main idea behind the DLLM approach is to impute the values of $Y_{i(2)1}$ or $Y_{i(1)2}$ using the information provided in (15) and (16). Without loss of generality, I will focus on the imputation of $\mathrm{Y}_{\mathrm{i(2)1}}$.Following the approach initially developed by Elbers, Lanjouw and Lanjouw (2003) for small area estimation of poverty, DLLM (2011) proposed the "out-of-sample" imputation formula depicted in (9.17) which assumes that the explanatory variables are constant over time (i.e., $\mathrm{X}_{\mathrm{i(t)t}} = \mathrm{X}_{\mathrm{i(t)t+1}}$).

$$\begin{aligned}\widehat{Y}_{i(2)1} &= \hat{\beta}_1 X_{i(2)1} + \tilde{v}_{i(2)1} \\ &= \hat{\beta}_1 X_{i(2)2} + \tilde{v}_{i(2)1}\end{aligned} \tag{9.17}$$

In addition to β_1 and $X_{i(2)2}$, (17) calls for an estimate of the error term $v_{i(2)1}$. To do this, DLLM (2011) first assumed that ($v_{i(2)1}$ and $v_{i(2)2}$) ~ $BVN(0, \sum_\vartheta)$ such that[94]

$$\textstyle\sum_\vartheta = \begin{bmatrix} \sigma_{\vartheta 1}^2 & \rho\sigma_{\vartheta 1}\sigma_{\vartheta 2} \\ \rho\sigma_{\vartheta 1}\sigma_{\vartheta 2} & \sigma_{\vartheta 2}^2 \end{bmatrix} \tag{9.18}$$

The parameters $\hat{\sigma}_{\vartheta 1}^2$ and $\hat{\sigma}_{\vartheta 2}^2$ can be estimated from (9.15) and (9.16). On the other hand, the authors adopted a naïve approximation for ρ by assuming that it is either equal to zero or one. This produces lower and upper bounds for different indicators of poverty dynamics (DLLM 2011) as shown below.

$$\emptyset\left(\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, \frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 0\right) \leq \mathrm{P}(\hat{Y}_{\mathrm{i(2)1}} < \mathrm{z}, \mathrm{Y}_{\mathrm{i(2)2}} < \mathrm{z}) \leq \emptyset\left(\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, \frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 1\right) \tag{9.19}$$

$$\emptyset\left(\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 1\right) \leq \mathrm{P}(\hat{Y}_{\mathrm{i(2)1}} < \mathrm{z}, \mathrm{Y}_{\mathrm{i(2)2}} > \mathrm{z}) \leq \emptyset\left(\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 0\right) \tag{9.20}$$

$$\emptyset\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, \frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 1\right) \leq \mathrm{P}(\hat{Y}_{\mathrm{i(2)1}} > \mathrm{z}, \mathrm{Y}_{\mathrm{i(2)2}} < \mathrm{z}) \leq \emptyset\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, \frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 0\right) \tag{9.21}$$

$$\emptyset\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 0\right) \leq \mathrm{P}(\hat{Y}_{\mathrm{i(2)1}} > \mathrm{z}, \mathrm{Y}_{\mathrm{i(2)2}} > \mathrm{z}) \leq \emptyset\left(-\frac{z-\beta_1 X_{i(2)2}}{\sigma_{\vartheta 1}}, -\frac{z-\beta_2 X_{i(2)2}}{\sigma_{\vartheta 2}} \mid \rho = 1\right) \tag{9.22}$$

[94] DLLM (2011) also proposed an analogous non-parametric approach.

Dang, Lanjouw, Luoto & McKenzie's (DLLM 2) Approach

The DLLM 1 approach which entails constructing lower and upper bounds using $\rho = 0$ and $\rho = 1$ for poverty dynamics is intuitive. A value of zero for ρ implies that after accounting for correlates of income, the temporal fluctuations in each unit's income are independent. This (temporal) independence is expected to induce more mobility, i.e., more movements into or out of poverty. On the other hand, if ρ is equal to one, then there is perfect inertia in the temporal fluctuations in one's income which is expected to minimize mobility, i.e., less movements into or out of poverty.

The good thing about DLLM 1 approach is that it maintains the original observation as the unit of analysis, making it straightforward to estimate the bounds depicted in (9.19) to (9.22) for different sub-population groups which in turn, enriches the analysis.[95] In addition, since this approach allows for heterogeneous covariate effects wherein the parameters β_1 and β_2 are estimated separately, it may be able to capture structural changes in the income distribution[96]. However, one of the obvious limitations of DLLM 1 method is that it does not provide point estimates for the different poverty indicators. In addition, the width of the bounds depend on how much income variation can be attributed to differences in time-invariant individual or household characteristics. As the model fit improves (higher R^2), the bounds become narrower (DLLM 2011). However, R^2 is high when the underlying income distribution regime is rigid wherein differences in time-invariant characteristics are the primary determinants of income variation. In other words, when much of the income variations arise from factors other than these fixed characteristics, the DLLM 1 approach may not provide optimal estimates of poverty dynamics. To address this issue, Dang et al. (2014) proposed a point estimator for ρ which they derived as follows

$$\rho\left(Y_{i(2)1}, Y_{i(2)2}\right) = \frac{Cov(Y_{i(2)1}, Y_{i(2)2})}{\sqrt{V\left(Y_{i(2)1}\right)V((Y_{i(2)2})}}$$

$$\rho\left(Y_{i(2)1}, Y_{i(2)2}\right) = \frac{Cov(\beta_1' X_{i(2)1} + \vartheta_{i(2)1}, \beta_2' X_{i(2)2} + \vartheta_{i(2)2})}{\sqrt{V\left(Y_{i(2)1}\right)V((Y_{i(2)2})}}$$

$$= \frac{\beta_1' V(X_{i(2)})\beta_2 + \rho\sqrt{\sigma_{\vartheta_1}^2 \sigma_{\vartheta_2}^2}}{\sqrt{V\left(Y_{i(2)1}\right)V((Y_{i(2)2})}}$$

$$\rho = \frac{\rho(Y_{i(2)1}, Y_{i(2)2})\sqrt{V(Y_{i1})V(Y_{i2})} - \beta_1' V(X_i)\beta_2}{\sigma_{\vartheta_1}\sigma_{\vartheta_2}}$$

95 Intuitively, this is subject to the sample size available for the sub-population group under consideration.

96 For instance, if the level of importance that a (social) opportunity structure attributes to fixed individual characteristics like race, ethnicity, religion and parental education changes significantly over time, then such changes are implicitly incorporated in the estimation of the model parameters.

$$\hat{\rho} = \frac{\hat{\rho}_{\bar{y}_{c1}\bar{y}_{c2}}\sqrt{V(Y_{i1})V(Y_{i2})} - \hat{\beta}_1' V(X_i)\hat{\beta}_2}{\hat{\sigma}_{\vartheta 1}\hat{\sigma}_{\vartheta 2}} \tag{9.23}$$

As shown in (9.23), the point estimator is a function of the parameter estimates of (9.15) and (9.16), variance of the observed incomes as well as the variance of the cohort means of the observed incomes. To arrive at this formula, the authors used the correlation between the two sets of cohort averages as a rough approximation of $\rho(Y_{i(2)1}, Y_{i(2)2})$. Furthermore, it is straightforward to show that when $\hat{\beta}_1' = \hat{\beta}_2$, $\hat{\rho}$ can be re-expressed as a function of the correlation between the cohort means and the coefficient of determination of each cross-sectional model. In addition to (9.24), Dang et al. (2014) also provided more informative lower and upper bounds for ρ as shown in (9.25) and (9.26). In turn, formula analogous to (9.19) to (9.22) can be derived using the estimated values of ρ.

$$\hat{\rho} = \frac{\hat{\rho}_{\bar{y}_{c1}\bar{y}_{c2}} - \sqrt{R_1^2 R_2^2}}{\sqrt{(1-R_1^2)(1-R_2^2)}} \tag{9.24}$$

$$\hat{\rho}_{LB} = \hat{\rho}_{\bar{y}_{c1}\bar{y}_{c2}} \tag{9.25}$$

$$\hat{\rho}_{UB} = \frac{\hat{\beta}_1' V(X_i)\hat{\beta}_2}{\sqrt{V(Y_{i1})V(Y_{i2})}} \tag{9.26}$$

9.2.3 Extending Pseudo-Panel Methods to Measure Broad Class of Income Mobility Measures

Can the pseudo-panel estimation methods discussed in the previous section be used to measure a broader class of mobility indicators other than those for which these methods are originally designed to measure? A previous study by Cruces et al. (2013) asked the same question and found that the AM, BGK and DLLM 1 did not perform well in capturing the income mobility patterns in the Chilean panel data. Whether this provides conclusive proof undermining the usefulness of pseudo-panel methods in estimating income mobility merits further investigation. For one, the Chilean panel data is not representative of the population of data sets to which the pseudo-panel techniques can be applied. In other words, this panel data could have specific characteristics that make pseudo-panel techniques less attractive. To further investigate this issue, I completed a similar exercise using the panel data from the Philippines.

As explained earlier, the AM, BGK, DLLM 1 and DLLM 2 methods are designed to answer different income mobility-related questions. In particular, the AM approach answers the question, "*up to what extent can previous income predict current income*?" On the other hand, the BGK approach is designed to answer the question, "*what is the risk of falling into poverty in the future*," while both DLLM 1 and DLMM 2 approaches answer "*what is the probability of staying, moving into or moving out of poverty?*" (Cruces et al. 2013). Similar to Cruces et al. (2013), the objective of this study is to examine the feasibility of using these approaches in estimating a wider array of income mobility measures. To do this, it is essential to first construct a micro-based pseudo-panel data of incomes. For simplicity, suppose we have two cross-sections denoted by $\{Y_{i(1)1}\}$ and $\{Y_{i(2)2}\}$. The main task is to provide imputed values for either $\{Y_{i(1)2}\}$ or $\{Y_{i(2)1}\}$ that can be used to estimate any mobility measure denoted by $M(Y_{i(1)1}, Y_{i(1)2})$ (or $M(Y_{i(2)1}, Y_{i(2)2})$). This section provides the step-by-step procedures of extending the algorithms of AM, BGK, DLLM 1 and DLLM 2 to be able to estimate other mobility indices which these techniques were not originally designed for.

AM Approach

Step 1: For each time period $t = 1, 2$, group all sampled units into different cohort groups.[97]
Step 2: Compute the average income of each cohort. Do the same for other characteristics of interest.
Step 3: Estimate the model $\bar{y}_{c(t)t} = \alpha\bar{y}_{c(t-1)t-1} + \varepsilon_{c(t)t}$ using OLS (Note: This model can be expanded to include other control factors).
Step 4: Compute the variance of the residuals $V(\hat{\varepsilon}_{c(t)t})$.
Step 5: Estimate $\hat{Y}_{i(1)2} = \hat{\alpha}Y_{i(1)1} + \tilde{\varepsilon}_{i(1)2}$ where $\tilde{\varepsilon}_{i(1)2}$ is a randomly drawn data point from $N(0, Var(\hat{\varepsilon}_{c(t)t}))$.
Step 6: Estimate the mobility measure $M(Y_{i(1)1}, \hat{Y}_{i(1)2})$.
Step 7: Repeats Steps 5 and 6 for R times.
Step 8: Take the average and standard deviation of $M(Y_{i(1)1}, \hat{Y}_{i(1)2})$ across all iterations.

BGK Approach

Step 1: For each time period $t = 1, 2, 3$, group all sampled units into different cohort groups.
Step 2: For each cohort group c, estimate $Y^c_{i(1)1} = \beta^c_t X^c_{i(1)1} + \varepsilon^c_{i(1)1}$, $Y^c_{i(2)2} = \beta^c_t X^c_{i(2)2} + \varepsilon^c_{i(2)2}$ and $Y^c_{i(3)3} = \beta^c_t X^c_{i(3)3} + \varepsilon^c_{i(3)3}$.
Step 3: Retrieve the residuals $\hat{\varepsilon}^c_{i(1)1}$, $\hat{\varepsilon}^c_{i(2)2}$, $\hat{\varepsilon}^c_{i(3)3}$ from the models estimated in Step 2. Compute their respective variances $\hat{\sigma}^2_{\varepsilon_{c1}}$, $\hat{\sigma}^2_{\varepsilon_{c2}}$, $\hat{\sigma}^2_{\varepsilon_{c3}}$.
Step 4: For each cohort c, estimate $\sigma^2_{\varepsilon ct} = (\rho^c)^2 V(\varepsilon^c_{i(t)t-1}) + \sigma^2_{ect}$.
Step 5: From the model in Step 4, retrieve the residuals $\hat{\sigma}^2_{ect}$.
Step 6: Estimate $Y^c_{i(1)2} = \hat{\beta}^c_2 X^c_{i(1)1} + \hat{\rho}^c \hat{\varepsilon}^c_{i(1)1} + \tilde{e}^c_{i(t)t}$ where $\tilde{e}^c_{i(t)t}$ is a randomly drawn data point from $N(0, \hat{\sigma}^2_{ect})$[98].
Step 7: Estimate the mobility measure $M(Y_{i(1)1}, \hat{Y}_{i(1)2})$.
Step 8: Repeats Steps 6 and 7 for R times.
Step 9: Take the average and standard deviation of $M(Y_{i(1)1}, \hat{Y}_{i(1)2})$ across all iterations.

DLLM 1 Approach

Step 1: For each time period t, estimate $Y_{i(t)t} = \beta_t X_{i(t)t} + \vartheta_{i(t)t}$. Retrieve the parameter estimates $\hat{\beta}_t$, and the residuals $\hat{\varepsilon}_{i(t)t}$.
Step 2: Compute the mean and the variance of the residuals, $\hat{\mu}_{\vartheta_t}$ and $\hat{\sigma}^2_{\vartheta_t}$.
Step 3: Set the residual correlation $\hat{\rho}_j$, $j \in \{LB, UB\}$, such that $\hat{\rho}_{LB} = 0$ and $\hat{\rho}_{UB} = 1$.
Step 4: Sort the residuals $\hat{\varepsilon}_{i(2)2}$ from lowest to highest.

97 As discussed earlier, cohort grouping should be mutually exclusive and exhaustive. In addition, cohort membership should be fixed over time. Furthermore, it is ideal to strike a balance between the number of cohorts and the sample size per cohort. A common approach used in the literature is to form cohorts based on gender and year of birth.
98 This assumes that $X^c_{i(1)1} = X^c_{i(1)2}$

Step 5: Draw n_2 pairs of residuals $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ from BVN$(0, \hat{\Sigma}_\vartheta)$ where

$$\hat{\Sigma}_\vartheta = \begin{bmatrix} \hat{\sigma}_{\vartheta 1}^2 & \hat{\rho}_j \hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2} \\ \hat{\rho}_j \hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2} & \hat{\sigma}_{\vartheta 2}^2 \end{bmatrix}$$

Rank the residual pairs $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ in ascending order according to the values of $\tilde{\varepsilon}_{i(2)2}$.

Step 6: Pair the first element $\tilde{\varepsilon}_{i(2)1}$ of each sorted residual pair $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ with the sorted $\hat{\varepsilon}_{i(2)1}^{j}$.
Step 7: For each j ∈ {Est, LB, UB}, estimate $\hat{Y}_{i(2)1}^{j} = \hat{\beta}_1 X_{i(2)2} + \tilde{\varepsilon}_{i(2)1}^{j}$.
Step 8: Estimate the mobility measure $M_j(\hat{Y}_{i(2)1}^{j}, Y_{i(2)2})$.
Step 9: Repeats Steps 5 to 8 for R times.
Step 10: For each j ∈ {LB, UB}, take the average and standard deviation of $M_j(\hat{Y}_{i(2)1}^{j}, Y_{i(2)2})$ across all iterations.

DLLM 2 Approach

Step 1: For each time period t = 1, 2, group all sampled units into different cohort groups. Compute the correlation of $\bar{Y}_{c(1)1}$ and $\bar{Y}_{c(2)2}$ and denote it by $\hat{\rho}_{\bar{y}_{c1}\bar{y}_{c2}}$.
Step 2: Compute the variances $V(Y_{i(1)1})$ and $V(Y_{i(2)2})$.
Step 3: For each time period t, estimate $Y_{i(t)t} = \beta_t X_{i(t)t} + \vartheta_{i(t)t}$. Retrieve the parameter estimates $\hat{\beta}_t$, residuals $\hat{\varepsilon}_{i(t)t}$, and the coefficients of determination R_t^2.
Step 4: Compute the mean and the variance of the residuals, $\hat{\mu}_{\vartheta_t}$ and $\hat{\sigma}_{\vartheta_t}^2$.
Step 5: Compute the residual correlation $\hat{\rho}_{est}$, $\hat{\rho}_{LB}$, and $\hat{\rho}_{UB}$.

$$\hat{\rho}_{est} = \frac{\hat{\rho}_{\bar{y}_{c1}\bar{y}_{c2}} \sqrt{V(Y_{i1})V(Y_{i2})} - \hat{\beta}_1^{'} V(X_i) \hat{\beta}_2}{\hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2}}$$

$$\hat{\rho}_{LB} = \hat{\rho}_{\bar{y}_{c1}\bar{y}_{c2}}$$

$$\hat{\rho}_{UB} = \frac{\hat{\beta}_1^{'} V(X_i) \hat{\beta}_2}{\sqrt{V(Y_{i1})V(Y_{i2})}}$$

Step 6: Rank the residuals $\hat{\varepsilon}_{i(2)2}$ from lowest to highest.
Step 7: Draw n_2 pairs of residuals $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ from BVN$(0, \hat{\Sigma}_\vartheta)$ where

$$\hat{\Sigma}_\vartheta = \begin{bmatrix} \hat{\sigma}_{\vartheta 1}^2 & \hat{\rho}_j \hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2} \\ \hat{\rho}_j \hat{\sigma}_{\vartheta 1} \hat{\sigma}_{\vartheta 2} & \hat{\sigma}_{\vartheta 2}^2 \end{bmatrix}$$

Rank the residual pairs $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ in ascending order according to the values of $\tilde{\varepsilon}_{i(2)2}$.

Step 8: Pair the first element $\tilde{\varepsilon}_{i(2)1}$ of each sorted residual pair $(\tilde{\varepsilon}_{i(2)1}, \tilde{\varepsilon}_{i(2)2})$ with the sorted $\hat{\varepsilon}_{i(2)1}^{j}$.
Step 9: For each j ∈ {Est, LB, UB}, estimate $\hat{Y}_{i(2)1}^{j} = \hat{\beta}_1 X_{i(2)2} + \tilde{\varepsilon}_{i(2)1}^{j}$.
Step 10: Estimate the mobility measure $M_j(\hat{Y}_{i(2)1}^{j}, Y_{i(2)2})$.
Step 11: Repeats Steps 7 to 10 for R times.
Step 12: For each j ∈ {Est, LB, UB}, take the average and standard deviation of $M_j(\hat{Y}_{i(2)1}^{j}, Y_{i(2)2})$ across all iterations.

9.3 Data

Consistent with the existing literature on pseudo-panel data, the final sample is restricted to households whose heads were born between 1933 and 1978, or equivalently, those who were aged 25 to 70 in 2003. The reason for doing this is to be able to have a relatively in-scope population. If I included younger or older households, I would be dealing with households that can change dramatically in the succeeding time periods. It would then be difficult to identify which population is being represented by the results. From the panel sample consisting of 6519 households, I drew independently a smaller (50%) random subsample for each wave, to create cross-sectional data to be used in pseudo-panel estimation. I decided not to use the full cross-sectional data of FIES so that I can treat the estimates based from the panel subsample as the actual values of the target "population" parameters.

Following the convention in the previous chapters, the household expenditure per capita is used as the income measure. For the AM approach, the cohorts are constructed by grouping households according to the heads' year of birth and gender. In particular, I followed the approach of Cruces, Fields & Viollaz (2013) which uses two-year span to be able to strike a balance between the number of cohorts and sample size per cohort. In estimating the conditional models, I included the cohort's average family size, average proportion of household members less than 15 years old, average proportion of household members who are employed and proportion of households relying on agricultural income. For the BGK, DLLM 1 and DLLM 2 approaches, the income correlates included in the model are provincial dummies, household head's age and its square, gender of the household head and educational attainment of the household head. Furthermore, estimates of poverty dynamics are based on US$2/day poverty line.

9.4 Discussion of Empirical Results

Following the procedures outlined in Section 9.2.3, I estimated four measures of poverty dynamics which include the proportion of population moving into poverty, moving out of poverty, staying in poverty and staying non-poor. In addition, I also estimated seven of the most commonly used income mobility indices as described in Chapter 1. They cover three different mobility concepts – movement (average rank jump, Fields-Ok's, King's indices), temporal dependence (Hart's index) and equalizer of income (CDW, Fields' and Shorrocks' indices). Before proceeding to the discussion of the results, some remarks are in order. First, when computing income mobility from time t to $t+1$, I always chose a reference period. For the chosen reference period, the actual income data from FIES is used. On the other hand, the income values for the other time period are imputed following the approach outlined in Section 9.2.3. In general, the choice of reference period is different for each method. For the AM and BGK approaches, the initial time period is always chosen as the reference period while the income values for the final time period are imputed. In contrast, the DLLM 1 and DLLM 2 approaches use the final time period as the reference while the income values for the initial time period are imputed. Given that the final sample for each cross-sectional wave is representative of the same population, I suspect that the differences in the estimates will not depend on the choice of reference period. Second, unlike the original AM, BGK, DLLM 1 and DLLM 2 methods which strictly use either parametric or non-parametric procedures, I adopt a semi-parametric approach. As outlined in Section 9.2.3, the semi-parametric algorithm for estimating income mobility entails iteratively drawing random disturbance terms from the Gaussian distribution with pre-specified parameters. For each mobility index, every iteration corresponds to an estimated value. The results provided in the succeeding discussions are based on 100 replicates. Third, I derived a point estimate for the DLLM 1 approach by taking the midpoint of the lower and upper bounds. Fourth, to be able to fine-tune the estimates for the DLLM 1 and DLLM 2 approaches, I introduce a structure preserving technique that takes into account the rank of the residuals from the reference period. Lastly, there are three components that contribute to the estimated standard error of the mobility estimates - sampling error, model error and the iterative sampling procedure for the stochastic disturbance term.

Dynamics in the Low Income Range

As noted in Chapter 5, the gross outflow from US$2/day poverty from 2003 to 2009 is approximately 10% of the population while the gross inflow accounts for 9% (Table 9.4). The proportions of the population who remained poor and non-poor during these two periods are 34% and 47%, respectively. Tables 9.1 to 9.3 compare the estimated proportion of each category of poverty status across the different pseudo-panel methods. The performance of the AM approach is not consistent. For some years, the pseudo-panel estimates are reasonably close to the estimates based on actual panel data but there are cases when both the unconditional and conditional pseudo-panel estimates are quite different from the proportions estimated from the actual panel data. Interestingly, the unconditional estimates for the poverty outflow and inflow are generally lower than the actual panel data-based estimates while the proportion of persistent poverty and non-poverty are consistently higher. A slightly different pattern emerges when we look at the conditional estimates of the AM approach. In particular, pseudo-panel estimates of poverty outflow and persistence of non-poverty are consistently higher while poverty inflow and poverty persistence are consistently lower than the panel estimates. On the other hand, the performance of the BGK approach yields mixed results. For instance, while the pseudo-panel estimates for poverty inflow and persistence of non-poverty are quite close to the estimates derived from actual panel data, the pseudo-panel estimates for poverty outflow and persistence of poverty are quite disparate. Compared to the AM and BGK approaches, the DLLM 1 and DLLM 2 methods performed better. For instance, the estimates using the actual panel data fall in between the estimated lower and upper bounds produced by DLLM 1. While these bounds could be restrictively wide as pointed out by Cruces et al. (2013), taking its midpoint yields estimates that are quite close to the actual panel-based estimates. Furthermore, the bounds estimated using the DLLM 2 method are much narrower compared to that of the DLLM 1. This is expected given that the DLLM 2 approach uses more informative estimates of the residual correlation. The point estimates using the DLLM 2 approach are also reasonably close to the actual panel-based figures. Nevertheless, it is worth noting that the point estimates of the DLLM 2 approach are always lower for movements into and out of poverty and always higher for poverty immobility.

Other Dimensions of Income Mobility

As pointed out in the earlier chapters, from 2003 to 2009, average per capita consumption barely moved, changing by approximately 2%. This is also accompanied by a small reduction in income inequality where the Gini coefficient changed from 0.44 in 2003 to 0.43 in 2009. However, turning to a broader set of income mobility measures, I find a much more dynamic income distribution over the six-year period, especially when viewed in terms of income movements. In particular, the mean absolute percentage change in per capita consumption is about 36%. This is equivalent to a 14-step change in income ranks, on the average. On the other hand, mobility is less pronounced when viewed in terms of temporal dependence and equalizer of income. For instance, the correlation of the logarithm of incomes in 2003 and 2009 is about 0.8. Furthermore, the observed income mobility reduces long-run inequality by only 6%.

Tables 9.4 to 9.6 compare the estimated values of different mobility indices using the actual panel and pseudo-panel data. For the AM approach, I find that the estimates derived from the conditional models are closer to the actual panel-based figures for indices designed to gauge movement and temporal dependence of incomes. In contrast, the unconditional models performed better than the unconditional models in estimating income mobility indices under the equalizer of income perspective. On the other hand, the pseudo-panel estimates computed using the BGK approach are at least twice as high than the values estimated using actual panel data. Turning to the DLLM 1 and DLLM 2 approaches, I find that the values of all mobility indices using actual panel data fall in between the lower and upper bounds estimated using the pseudo-panel approach. Unlike the indices of poverty dynamics for which DLLM (2011) provided a theoretical proof that the approach produces valid lower and upper bounds, we have not done so for the mobility indices considered in this section. Thus, this result is encouraging. In other words, it provides us reason to believe that the DLLM 1 and DLLM 2 approaches can also be useful for estimating mobility indices other than what they were originally designed to measure. Furthermore, comparing the midpoint of the bounds derived using DLLM 1 with the DLLM 2's point estimator, I find that for 2003-2006 and 2006-2009 periods, the estimated values from DLLM 1 are quite a bit closer to the movement-based indices computed using the actual panel data. For the rest, the DLLM 2 estimates performed better. In addition, I find that the midpoints from the DLLM 1 approach consistently overestimate mobility while the DLLM 2's point estimates are usually lower than the values of indices computed from actual panel data.

In summary, the results of these analyses allow me to address the three research questions:

1. *Are the proposed pseudo-panel techniques useful for measuring income mobility? In general, which of the pseudo-panel techniques are most desirable?*

Overall, the results using Philippine data suggest that the DLLM 1 and DLLM 2 approaches performed reasonably well in estimating poverty dynamics and other measures of mobility. On the other hand, the AM and BGK approaches provided satisfactory results for selected indicators only; the proportion of population moving into poverty and proportion of population remaining non-poor for BGK and indices under the equalizer of income perspective for AM. There are several possible explanations for this. For instance, the pseudo-panel approaches considered in this study are not originally designed for estimating varied income mobility measures. Rather, these methods are proposed for specific mobility indicators only. If the structural parameters of the underlying models are not flexible enough, it would not be surprising to note that the pseudo-panel estimators will not always perform well for all types of income mobility measures. Of the four pseudo-panel methods considered here, I argue that the DLLM 1 and DLLM 2 approaches use more flexible model specifications than the AM and BGK methods.

2. *Do the pseudo panel techniques' performance depend on the type of income mobility measure being estimated?*

My empirical findings suggest that in most cases, the pseudo-panel methods performed better when estimating indices under the mobility as income movement perspective. On the other hand, indices measuring temporal dependence of income and its inequality-reducing effect are harder to impute using the pseudo-panel methods considered here. A possible reason why this is the case is that unlike the temporal dependence and equalizer of income-based measures, most of the movement-based indices are less sensitive to the detailed features of the joint temporal distribution of incomes.

3. *How can the existing pseudo-panel techniques be improved?*

Compared to the findings by Cruces et al. (2013) using the Chilean panel data, the use of pseudo-panel methods especially the DLLM 1 and DLLM 2 approaches in estimating income mobility in the Philippines produced more encouraging results. I suspect that the differences in the characteristic features of the income distributions of the two countries contribute to the diverging findings about the usefulness of the pseudo-panel methods. For instance, the Chilean panel data spans a ten-year period while the Philippine data covers a shorter six-year period. Given this, it is reasonable to expect that there is more mobility in the Chilean panel data than in the Philippine data. However, as I have initially pointed out, the use of time-invariant variables in DLLM 1 and DLLM 2 are probably more suitable when the true income mobility regime is low because it imputes the value of permanent income. This could potentially justify why I have noted more satisfactory results than Cruces et al. (2013) found. Nevertheless, it is difficult to provide a conclusive explanation without doing further studies. To be able to move forward, I recommend doing simulation studies that will outline a more objective characterization of the performance of each pseudo-panel method considered in this paper.

There are several areas for improvement that could be explored further. First, it would be worthwhile to extend the BGK, DLLM 1 and DLLM 2 algorithms to allow the use of time-varying correlates of income in the model specification. Adding time-varying correlates may significantly improve the prediction power of the models and in turn, improve the pseudo-panel estimates of income mobility. Second, incorporating structural preserving techniques in the existing pseudo-panel algorithms may prove useful in estimating a wider array of income mobility indices. At present, it appears that income mobility measures which are sensitive to the overall structure of the income distribution are harder to impute than indices which focus on capturing movements of individual incomes. Third, statistical inference will enrich the income mobility analysis because it will allow comparison of income mobility across space and over time. However, much of the existing discussions are centred on estimation of mobility indices. Thus, further research is needed to be able to provide a theoretical framework that will serve as a practical guide for conducting statistical inference in the context of income mobility estimation using pseudo-panel data.

9.5 Summary and Future Directions

Measures of income mobility are commonly used in socio-economics literature as analytical tools for examining the evolution of the income distribution. In general, proponents of these measures believe that incorporating a longitudinal perspective enriches the analysis of income distribution. In particular, they argue that income mobility measures provide a more dynamic perspective of the evolution of a country's living standards than simply examining changes in cross-sectional indices of poverty and inequality over time. Panel data that tracks the incomes of the same set of households or individuals is the appropriate data source for measuring income mobility. However, factors like cost and risks of attrition often lead to the use of cross-sectional data.

Unlike panel surveys, cross-sectional surveys do not necessarily follow the same set of households or individuals. Recently, several pseudo-panel estimation methods have been proposed in estimating different concepts of mobility. The development of pseudo-panel methods reconciles the need for incorporating a longitudinal perspective when examining income distribution with the absence or lack of panel data. In particular, it offers researchers with the opportunity to depart from conventional methods of examining static indicators of well-being and delve deeper into the multi-dimensional issue of equality of socio-economic opportunities using cross-sectional survey data.

There are several ways of creating synthetic or pseudo-panels out of repeated cross-sectional data. This chapter reviewed four recent developments in the pseudo-panel estimation of income mobility literature. The first method proposed by AM (2007) entails transforming the unit-level data into cohort averages. These cohort averages serve as the synthetic panels. On the other hand, the approaches proposed by BGK (2004), DLLM (2011) and DLLM (2014) estimates income models while maintaining individuals or households as the units of analysis. Originally, these methods are designed to answer varying concepts of mobility. In this study, I outlined algorithms which extend these approaches to be able to measure a wider array of income mobility indices. The results suggest that the proposed methods by DLLM (2011) and DLLM (2014) which employ the weakest assumption about the structural parameters and functional form of the income models performed satisfactorily in terms of estimating different mobility concepts. Nevertheless, several areas for improvement remain. These include exploring techniques that would accommodate time-varying correlates for the BGK, DLLM 1 and DLLM 2 income models, employing structural preserving strategies to provide better estimates of mobility indices which are sensitive to the overall structure of the income distribution and outlining the framework for carrying out statistical inferences.

Table 9.1 Estimates of Poverty Dynamics in the Philippines, 2003-2006

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM 1 (A)	midpt	DLLM 1 (B)	DLLM 2 (A)	DLLM2 (B)	DLLM2 (C)
Poverty outflow	6.19	2.65	5.52	19.21	2.81	8.41	14	6.25	7.79	10.61
Poverty inflow	9.11	2.18	7.76	11.58	1.98	10.18	18.38	5.98	8.39	12.68
Stay in Poverty	35.08	39.16	33.57	22.12	25.1	33.3	41.5	30.8	35.08	37.49
Stay Non-Poor	49.62	56.02	53.15	47.09	42.52	48.12	53.72	45.92	48.73	50.27

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Table 9.2 Estimates of Poverty Dynamics in the Philippines, 2006-2009

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM 1 (A)	midpt	DLLM 1 (B)	DLLM 2 (A)	DLLM2 (B)	DLLM2 (C)
Poverty outflow	10.49	0.85	6.92	22.84	8.9	13.36	17.82	11.43	13.03	14.61
Poverty inflow	5.93	8.39	10.95	11.31	0.38	8.42	16.46	4.33	7.32	10.39
Stay in Poverty	33.7	34.82	32.26	20.36	23.69	31.73	39.77	29.76	32.83	35.82
Stay Non-Poor	49.88	55.94	49.88	45.48	42.03	46.49	50.95	45.24	46.82	48.42

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Table 9.3 Estimates of Poverty Dynamics in the Philippines, 2003-2009

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM 1 (A)	midpt	DLLM 1 (B)	DLLM2 (A)	DLLM2 (B)	DLLM2 (C)
Poverty outflow	10.22	1.15	1.19	20.63	7.07	11.79	16.52	10.59	12.3	13.43
Poverty inflow	8.58	7.48	7.41	11.54	0.62	8.81	16.99	5.91	9.25	11.17
Stay in Poverty	31.05	33.85	33.92	20.7	23.16	31.34	39.53	28.97	30.89	34.24
Stay Non-Poor	50.15	57.52	57.48	47.13	43.34	48.06	52.78	46.42	47.55	49.26

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Table 9.4 Estimates of Income Mobility in the Philippines, 2003-2006

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM1 (A)	midpt	DLLM1 (B)	DLLM2 (A)	DLLM2 (B)	DLLM2 (C)
Movement										
Ave. Rank Jump	11.78	3.51	10.17	23.13	4.17	13.63	23.1	8.87	11.71	16.7
Fields-Ok	31.77	9.33	28.18	126.55	11.87	36.4	60.92	24.07	31.44	44.52
King	29.87	8.68	24.85	61.91	13.75	32.12	50.49	24.28	30.29	40.01
Temporal dependence										
Hart	15.08	1.2	12.9	72.8	2.39	27.01	51.63	8.32	14.05	27.82
Equalizer of income										
CDW	1.61	-0.88	7.83	-32.82	-2.62	2.22	7.06	-1.44	-0.33	2.45
Fields	1.31	-0.91	8.63	-27.91	-3.46	1.91	7.27	-2.31	-1.22	1.78
Shorrocks	6.58	0.56	6.37	41.64	1.17	11.71	22.25	3.82	6.36	12.35

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Table 9.5 Estimates of Income Mobility in the Philippines, 2006-2009

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM1 (A)	midpt	DLLM1 (B)	DLLM2 (A)	DLLM2 (B)	DLLM2 (C)
Movement										
Ave. Rank Jump	11.8	4.91	13.34	24.35	4.33	14.23	24.13	10.9	14.38	17.83
Fields-Ok	31.59	17.63	35.26	142.41	19.81	40.6	61.38	31.14	38.71	46.72
King	29.63	9.88	30.1	62.05	13.39	31.52	49.65	27.45	33.89	39.84
Temporal dependence										
Hart	15.27	2.27	19.66	77.81	2.4	28.88	55.36	12.35	20.81	31.41
Equalizer of income										
CDW	5.43	9.57	11.5	-22.86	-0.43	4.75	9.93	1.74	3.41	5.46
Fields	5.37	9.66	11.51	-16.91	-1.08	4.93	10.93	1.22	3.1	5.45
Shorrocks	6.66	2.56	9.51	47.12	1.09	12.46	23.83	5.54	9.24	13.85

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Table 9.6 Estimates of Income Mobility in the Philippines, 2003-2009

Indicator	PANEL	PSEUDO-PANEL								
		AM (A)	AM (B)	BGK	DLLM1 (A)	midpt	DLLM1 (B)	DLLM2 (A)	DLLM2 (B)	DLLM2 (C)
Movement										
Ave. Rank Jump	13.9	5.1	5.1	23.61	5.15	14.5	23.86	11.9	15.57	17.63
Fields-Ok	36.13	16.19	16.19	129.34	17.95	39.13	60.3	32.16	40.63	45.54
King	32.76	10.56	10.6	60.28	16	32.84	49.69	29.55	36.26	39.73
Temporal dependence										
Hart	19.86	2.52	2.53	74.8	3.41	28.81	54.21	14.66	24.34	30.77
Equalizer of income										
CDW	4.72	6.88	6.86	-20.91	-0.76	4.13	9.01	1.53	3.41	4.64
Fields	4.7	7.68	7.65	-18.68	-1.58	4.32	10.21	0.97	3.14	4.63
Shorrocks	8.69	2	2	44.76	1.55	12.48	23.42	6.57	10.83	13.62

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Appendix Table A9.1 Standard Error of Estimates of Poverty Dynamics, 2003-2006 (standard deviation across iterations)

Indicator	PSEUDO-PANEL							
	AM (A)	AM (B)	BGK	DLLM 1 (A)	DLLM 1 (B)	DLLM 2 (A)	DLLM2 (B)	DLLM2 (C)
Poverty outflow	0.2534	0.2286	0.2333	0.1546	0.5406	0.4751	0.5733	0.5244
Poverty inflow	0.2652	0.2669	0.2697	0.2865	0.5965	0.4719	0.5303	0.596
Stay in Poverty	0.2652	0.2669	0.2333	0.5965	0.2865	0.596	0.5303	0.4719
Stay Non-Poor	0.2534	0.2286	0.2697	0.5406	0.1546	0.5244	0.5733	0.4751

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Appendix Table A9.2 Standard Error of Estimates of Poverty Dynamics, 2006-2009 (standard deviation across iterations)

Indicator	PSEUDO-PANEL							
	AM (A)	AM (B)	BGK	DLLM 1 (A)	DLLM 1 (B)	DLLM 2 (A)	DLLM2 (B)	DLLM2 (C)
Poverty outflow	0.1604	0.3033	0.2629	0.5229	0.5994	0.6331	0.608	0.6562
Poverty inflow	0.4075	0.2902	0.2152	0.0856	0.6226	0.4414	0.5588	0.5147
Stay in Poverty	0.4075	0.2902	0.2629	0.6226	0.0856	0.5147	0.5588	0.4414
Stay Non-Poor	0.1604	0.3033	0.2152	0.5994	0.5229	0.6562	0.608	0.6331

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Appendix Table A9.3 Standard Error of Estimates of Poverty Dynamics, 2003-2009 (standard deviation across iterations)

Indicator	PSEUDO-PANEL							
	AM (A)	AM (B)	BGK	DLLM 1 (A)	DLLM 1 (B)	DLLM 2 (A)	DLLM2 (B)	DLLM2 (C)
Poverty outflow	0.2404	0.2152	0.2227	0.3586	0.6503	0.5557	0.5706	0.6197
Poverty inflow	0.3927	0.39	0.2814	0.1017	0.5658	0.4808	0.5234	0.6384
Stay in Poverty	0.3927	0.39	0.2227	0.5658	0.1017	0.6384	0.5234	0.4808
Stay Non-Poor	0.2404	0.2152	0.2814	0.6503	0.3586	0.6197	0.5706	0.5557

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Appendix Table A9.4 Standard Error of Estimates of Income Mobility, 2003-2006
(standard deviation across iterations)

Indicator	PSEUDO-PANEL							
	AM (A)	AM (B)	BGK	DLLM1 (A)	DLLM1 (B)	DLLM2 (A)	DLLM2 (B)	DLLM2 (C)
Ave. Rank Jump	0.0644	0.0724	0.0799	0.0581	0.3343	0.1589	0.2152	0.286
Fields-Ok	0.1619	0.1336	0.3415	0.2303	0.8638	0.3897	0.4724	0.7788
King	0.201	0.1306	0.1835	0.3335	0.7313	0.6343	0.7348	0.6688
Hart	0.0371	0.1039	0.1763	0.0663	1.283	0.2561	0.4382	0.8969
CDW	0.2281	0.0832	0.553	0.2475	0.808	0.3507	0.4218	0.631
Fields	0.244	0.1072	0.4779	0.3303	0.7042	0.4582	0.5394	0.6992
Shorrocks	0.0179	0.0495	0.1085	0.0471	0.548	0.1261	0.2008	0.4104

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Appendix Table A9.5 Standard Error of Estimates of Income Mobility, 2006-2009
(standard deviation across iterations)

Indicator	PSEUDO-PANEL							
	AM (A)	AM (B)	BGK	DLLM1 (A)	DLLM1 (B)	DLLM2 (A)	DLLM2 (B)	DLLM2 (C)
Ave. Rank Jump	0.0777	0.1026	0.0798	0.0368	0.3356	0.1863	0.2448	0.291
Fields-Ok	0.1963	0.2119	0.2984	0.8715	0.8957	0.5402	0.5716	0.745
King	0.212	0.213	0.2366	0.289	0.7626	0.559	0.6368	0.7498
Hart	0.0694	0.2192	0.1765	0.0749	1.3768	0.3781	0.627	0.9206
CDW	0.1672	0.1226	0.6153	0.2981	1.0647	0.4849	0.6193	0.7303
Fields	0.1871	0.1401	0.497	0.3486	0.8058	0.5625	0.6505	0.6995
Shorrocks	0.0683	0.0982	0.1368	0.0344	0.5921	0.17	0.2715	0.4013

Source: Author’s computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Appendix Table A9.6 Standard Error of Estimates of Income Mobility, 2003-2009
(standard deviation across iterations)

Indicator	PSEUDO-PANEL							
	AM (A)	AM (B)	BGK	DLLM1 (A)	DLLM1 (B)	DLLM2 (A)	DLLM2 (B)	DLLM2 (C)
Ave. Rank Jump	0.086	0.085	0.0786	0.0505	0.3344	0.2157	0.2695	0.3188
Fields-Ok	0.232	0.229	0.3121	0.5556	0.8119	0.4715	0.6141	0.7583
King	0.223	0.2143	0.2305	0.2588	0.6528	0.5806	0.6293	0.6621
Hart	0.0784	0.078	0.1695	0.0813	1.2445	0.4731	0.7185	0.9356
CDW	0.2004	0.201	0.5555	0.2296	0.7547	0.389	0.5784	0.5644
Fields	0.2442	0.243	0.5096	0.2926	0.631	0.4636	0.6451	0.6106
Shorrocks	0.0679	0.0723	0.1424	0.039	0.5633	0.2169	0.3089	0.4213

Source: Author's computations using household expenditure per capita data from the longitudinal subsample of FIES 2003, 2006, 2009

Chapter 10 Summary and Conclusion

10.1 Introduction

The primary objective of this study was to measure and examine income mobility in the Philippines using longitudinal data from the redesigned Family Income and Expenditure Survey and Labour Force Survey. The study highlights the importance of taking a longitudinal perspective when examining a country's income distribution and going beyond cross-sectional indicators of mean income, poverty and inequality. One of the main advantages of examining income mobility using longitudinal data over the conventional cross-sectional perspective that is commonly adopted in many income distribution studies is that the former is able to differentiate between persistent and transient poor, and between those who experience stable income stream and those who have fluctuating income flows. Empirical evidence of these patterns provides more accurate insights for policy planning.

10.2 Motivation and Research Goals

Over the recent years, the Philippines has shown strong economic growth which even exceed economists' initial growth forecasts. From 2009 to 2012, for instance, its GDP per capita grew at annual rate of 4.1% (WDI 2014). Due to this apparent rosy economic performance, several major global international credit rating agencies awarded the country an investment grade. As improved credit ratings usually translate to lower debt interest payments, experts forecast that the Philippines will attract more foreign investment and encourage stronger domestic consumption (ADB 2013c). These factors can potentially propel the country into a virtuous economic growth regime in the coming years, a welcome outcome for a country that has long been regarded as the "Sick Man of Asia" due to slow economic growth since the 1980s. However, such an outcome is not pre-ordained considering that average income, poverty and inequality are not improving. This could be indicative that the benefits of growth bypass those who are most disadvantaged. Using the longitudinal data that has recently become available through the country's improved household survey system, this study describes income mobility patterns in the country and identifies the offsetting forces that contribute to trivial changes in the Philippines's conventional income indicators despite its transition into faster economic growth regime over the past decade.

The first three chapters of this study set the tone by reviewing the important analytical tools typically used for examining income mobility of Filipino households. The following six chapters are motivated by specific research questions, which have attracted a lot of interest among policymakers and yet have been given little attention in empirical research due to limited panel data needed to carry out such type of research.

10.3 Main Findings

There is significant income mobility in the Philippines despite stagnant income poverty rates and inequality levels.

One of the key findings of this study is that the distribution of household income in the Philippines is much more dynamic than what is commonly presumed due to slow poverty reduction and stubbornly high levels of income inequality. For instance, as demonstrated in Chapter 4, more than half of the household population moved into a different income quintile from 2003 to 2009. This implies that a simple examination of temporal trends in cross-sectional indicators of poverty and inequality in the Philippines will fall short in providing a comprehensive picture of how the country's income distribution has evolved throughout the years.

There are various offsetting forces that contribute to minimal changes in cross-sectional income poverty and inequality.

The results from Chapter 4 provide evidence that for every household that experienced upward (absolute) income mobility of a certain magnitude, there is approximately one household that experienced downward income mobility of the same magnitude. Furthermore, the analysis in Chapter 7 reveals that improvement in socio-economic capital levels seem to have been washed out by the deterioration of economic returns to those capitals.

Filipino households have experienced widely varied income mobility trajectories, with the poor households experiencing slightly faster income growth rates than the rest.

Results from Chapters 4 and 6 indicate that lower income households were more likely to experience faster income growth rates than the rest of the population. In particular, if Filipinos were classified according to their initial household incomes, Chapter 6 demonstrates that lower income households were more likely to experience consecutive episodes of upward income mobility while middle income households were more likely to register slower income movements. Higher income households experienced the most erratic income mobility trajectories. Although these mobility patterns portray convergence of income and relatively pro-poor growth, temporal income fluctuations partially drive this result. In particular, when households are classified according to longitudinally-averaged income instead of their initial incomes, evidence of income convergence becomes weak.

Majority of poor Filipinos are persistently disadvantaged but economic vulnerability also exacerbates the country's problem on poverty.

Although there is evidence that lower income households observed faster income growth, Chapter 5 shows that poverty in the Philippines is still mostly characterized by long episodes of income shortfall below the poverty line. Furthermore, a significant fraction of the Filipinos who are not persistently poor are economically vulnerable and are at risk of falling into poverty from time to time. For instance, about 10% to 15% of the non-poor households (based on the US$2/day poverty line) in a specific year transitioned into poverty in the succeeding survey period. Furthermore, the proportion of the poor who are in transient poverty increases as the poverty line decreases or as the poverty measure becomes more sensitive to the illfare of the poorest of the poor.

The quality of employment plays key role in facilitating a positive income mobility regime.

The statistical models used in this study identify employment to be one of the most important correlates of income mobility. Results from Chapters 5 to 8 highlight that holding good jobs minimizes the risk of falling into long episodes of poverty while transition into better jobs increases the odds of upward income mobility.

Pseudo-panel estimation provides an alternative tool for examining welfare dynamics in the absence of panel data.

Examining welfare dynamics in developing countries is often constrained by the lack of suitable panel data that track the living standards of people over time. The pseudo-panel estimation approach discussed in Chapter 9 which use repeated cross-sectional data to impute income trajectories can be considered as a welcome addition to the modern methods of mobility analysis.

10.4 Broad Policy Implications

The findings underscore the need for more effective policies that will facilitate more sustainable gains in poverty reduction and equitable distribution of socio-economic opportunities created by economic growth. There is no one-size-fits-all policy that can be implemented to meet this objective. In a country like the Philippines where the economic growth is not distributionally-neutral, the focus should be on finding ways to make growth more responsive to poverty reduction and equally distributed socio-economic opportunities.

There are several channels through which growth can be more inclusive for the persistently poor and more sustainable for those who periodically move into and out of economic hardships. To achieve a pro-poor growth, changes in the socio-demographic structure of the Philippines need to be examined to ensure that economic returns to higher skills will not deteriorate. In other words, as the country invests in socio-economic capital development, such an initiative has to be buttressed by an effective management of the economic returns to these forms of capital. This study also finds that employment plays a key role in driving household income distribution outcomes. Worryingly, unemployment rate in the Philippines remains high at 7 percent. In addition to the need to generate more jobs, the country also confronts the challenge of ensuring that these will be productive and good-quality jobs. In addition, since poverty is still very much an agricultural phenomenon, creating more jobs in the non-agriculture sector where labour productivity is much higher could have the enabling capacity of reducing poverty rates. However, this is easier said than done. I have mentioned in Chapter 8 that if the current labour market trends continue, economists from ILO forecast that employment-to-population ratio in the Philippines will decrease by 0.1 percentage point between 2010 and 2015 while labour productivity is expected to drop by 1.1 percentage point over the same period. This is likely to lead to minimal changes in poverty rates in the coming years unless the bottlenecks toward the creation of more vibrant employment opportunities can be addressed so that poor people are able to use labour as a vehicle out of economic dearth.

Since living conditions in developing countries are usually plagued by socio-economic risk, the role of income shocks in the evolution of the household income distribution should also be underscored. My findings that income shocks in the country have a poverty-increasing effect from 2003 to 2009 may be a cause of concern. Given that access to adequate insurance and social protection coverage facilitates effective management of risks and their negative consequences for income distribution outcomes, it is important to ensure that social protection systems are working. However, studies suggest that while the Philippine government has a wide range of programs offering social safety nets especially to the poor and the vulnerable segments of the population, most of these programs are fragmented and thus, do not provide sustainable protection from socio-economic risks. If left unaddressed, income shocks may continue to have debilitating effects on the poor. This prompts the need to evaluate the effectiveness of existing social protection infrastructure in the country.

10.5 Limitations and Future Directions

This study has advanced the existing socio-economic development literature in the Philippines by providing a benchmark for examining income mobility. However, it has a number of limitations that are also worth pointing out. First, income mobility is not a perfect measure of equality of socio-economic opportunities. For instance, this study showed that mobility can be inflated by transitory income fluctuations and thus, it will not be safe to assume that higher levels of mobility are always desirable. The existing literature has proposed a number of alternative measures of equality of opportunities, some of which are based on calculating the income growth rates with a declining weight on growth amongst the rich (Palmisano & Peragine 2014). Future research can explore how these alternative measures fare relative to the mobility measures discussed in this study. Second, well-being is measured mainly in terms of household expenditure per capita. Since the 1970s, there has been a lot of contention on how well-being should be measured. One of the commonly used alternatives to expenditure is income (or earnings). Chapters 1 and 3 have discussed the advantages and disadvantages of using one over the other and identified this study's motivation for using consumption expenditure. Nevertheless, I have carried out robustness analysis using income rather than expenditure data. What I find from these robustness checks is that there are slightly higher levels of mobility when income is used instead of expenditure. This can be attributed to the fact that the temporal distribution of income is less stable than expenditure. All other results are qualitatively similar. What I have not done in this thesis, however, is to probe beyond the income dimension and look at non-monetary measures of well-being. Over the recent years, there has been increasing recognition that understanding living standards and well-being requires shifting the focus of inquiry from one-dimensional income-based poverty measures to multidimensional poverty measures that tap other important life domains. This approach emerged from the paradigm on social exclusion and deprivation proposed by Townsend (1979) and Sen's notion of functioning and capabilities (Sen 1985). However, much of the empirical application of this framework has focused on data from developed countries. Some of the results emerging from these studies suggest that there is a relatively low degree of overlap between income poverty and multidimensional poverty. If income poverty is not necessarily the same as multidimensional poverty, this difference should affect how poverty-reduction programs are designed. Whether the same pattern holds true in the context of developing countries like the Philippines is a promising avenue for future studies. This can be done if we improve the existing data collection systems in developing countries to incorporate not only a longitudinal perspective but also shift from the conventional income-based measures to more holistic and more direct measures of living standards. In the case of the Philippines, combining the data from the Annual Poverty Indicators Survey which collects information about non-monetary measures of well-being with the FIES-LFS data could be explored, although much care should be taken to ensure the comparability of data between these surveys.

Furthermore, to be able to advance research about poverty and disadvantage, it is important to collect more contextually relevant indicators. For instance, there are some studies from developed countries following a life-course perspective which find that the relationship between disadvantage and social status is becoming weaker while life course events are becoming more important determinants of socio-economic pathways. To be able to determine how life course events shape the poverty risks of people in the context of developing countries, we need to start collecting such data.

The third potential limitation of this study is the limited number of time points used in the analyses. Nationwide panel data is scarcely available in the Philippines. Some longitudinal studies which have significantly longer observation periods cover only limited areas. Since I worked with limited time points, there has been a preference to use relatively simple approaches, particularly when estimating the mobility of permanent and transitory income. Nevertheless, in most of my analyses, I examined the robustness of the results to chosen methodologies and measurement parameters up to the extent that could be afforded using the available data.

The fourth potential limitation relates to how I addressed the issue of non-coverage bias when working with the panel subsample of FIES-LFS. As explained in Chapter 3, I reweighted the panel subsample to make it comparable with the cross-sectional sample. While the resulting average income, poverty and inequality rates are comparable to that of the full cross-sectional sample, the standard errors are also slightly inflated not only because of the smaller sample sizes but also due to the use of additional survey weight adjustments. Thus, when comparing groups with respect to some key characteristics of interest, larger differences are needed to be able to detect significant findings.

The fifth limitation is that most of the mobility estimates are presented at the national and broad regional levels only. This approach is mainly dictated by the sample size limitations. There is a need for future studies to provide a more disaggregated set of mobility estimates especially on poverty dynamics as a number of previous studies have highlighted the significant spatial variations in the Philippines in terms of socio-economic development. Perhaps, a better approach is to present mobility estimates at the administrative level (e.g., village, municipal or provincial levels), which local government units could use as inputs for policy planning. However, this would require the use of other computationally-intensive statistical techniques such as small area estimation which is beyond the scope of this study.

Sixth, there is only limited discussion in the thesis on how the mobility estimates for the Philippines can be viewed in an international comparative context. If the country is to be the next Asian Tiger, it is important to gauge where the Philippines stands in terms of the socio-economic mobility relative to other strong candidates within Developing Asia. This analysis is reserved for future research.

Finally, this study is neither a full account of the economic history of the Philippines over the past decade nor a comprehensive diagnostic or prescriptive examination of what went wrong and what has to be done for rapid economic growth to translate into significant poverty reduction and equitable distribution of opportunities. It is an initial study to investigate the usefulness of utilising longitudinal data and provide a benchmark for future. In addition, the attempt to showcase the usefulness of taking a longitudinal perspective when examining a broad range of topics about the income distribution may have led to a less detailed discussion of the policy implications of the results.

In summary, the Philippines has made a substantial progress in accelerating economic growth over the past decade. However, it seems to be failing short in achieving some of the goals set forth in the MDGs, particularly in reducing poverty. For instance, in 1991, about 30% of the country's population lived with less than \$1.25 a day and the proportion dropped to 18% in 2009 which is still 3 percentage points less than the 2015 MDG target of 15%. Although it is possible that the Philippines will hit the target just in time based on the trends observed over the past ten years, many of its neighbouring countries with similar or even slower pace of economic growth have attained their respective poverty targets much earlier (UNDP 2013). This is indicative that there is ample room for improvement for the country's poverty reduction efforts. As we start tackling how to address this "unfinished agenda" and reflect on how we should move forward after 2015, it is hoped that this study will bring to the attention of researchers, policymakers and other key stakeholders the need to invest in the collection and statistical analysis of appropriate indicators that would allow a more dynamic examination of people's well-being over time. This is the first step in identifying intervention policies that could improve the living standards of those who remain extremely poor, minimize the vulnerability of the transiently poor and ensure that the benefits of economic growth are accessible for everyone.

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