Of Milk and Honey: Returns to Education and Migration of Filipinos

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Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. To the best of the author's knowledge and belief, it contains no material previously published or written by another person, except where due reference is made in the text.

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Abstract

The first study in this dissertation shows that standard estimates of returns to education capture the effects of labor characteristics and ability. It finds that accounting mainly for sector, occupation and region reduces returns to education by three-fifths. Accounting for ability using sibling fixed-effects estimation further reduces returns to schooling by almost half, yields no significant returns to primary and incomplete secondary education, and yields increasing returns to higher education. Earnings and returns to schooling are unaffected by education quality when controlling for province and key city fixed effects. Returns to schooling and ability are higher in urban areas and regions considered as economic centers suggesting that internal labor migrants are driven by returns to education and ability.

The second part of this thesis develops a demand and supply model of migration to estimate the impacts of proximate and underlying factors on both permanent and temporary migration from the Philippines using a Vector Auto-Regressive model. Results show that permanent migration is positively related to destination wages but also to domestic wages and employment indicating that they are positively selected from the local labor force. Permanent migration is negatively related to local demand for labor proxied by GDP per capita but also to local labor supply; positively related to destination demand for labor and negatively related to destination labor supply (both lagged two periods). Temporary migration is also positively related to destination and Philippine wages, negatively related to local labor demand and supply, and positively related to destination labor demand. However, temporary migration is also positively related to destination labor supply indicating that they are negatively selected in the destination labor force.

The third study aims to estimate the returns to migration and education for overseas Filipino workers. It finds that earnings of overseas Filipino workers in most key destinations are higher than those of domestic workers, but their returns to schooling are not significantly different from, or are even lower than, those of domestic workers. These findings together with the result of a Heckman selection

model confirm the negative selection of temporary migrants. Apart from purchasing power parity gains to either earnings or returns to schooling, there are also monetary gains in the conversion of foreign earnings to the local currency through the US dollar as in the case of remittances.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Returns to Education

Education is important for individual earnings and national economic growth. With much of the Philippine labor force in the 1980s-1990s having only elementary education, returns to education were highest at the primary level (e.g. Hossain and Psacharopoulos (1994)). The costliness and inaccessibility of higher education meant that returns to higher education were low. Poor education was a cause of slow growth in the Philippines in the 1980s–1990s. On the other hand, the rising share of the labor force with higher education is associated with increasing returns to higher education in recent years. Similarly, the respectable economic performance in the past decade is associated with higher human capital content of labor.

While there have been many studies on returns to education in the Philippines, these have focused on the quantity of education. However, while the Philippines fared better than some of its neighbors in terms of enrollment, it fared poorly in terms of income per capita and economic growth. This suggests that quantity of schooling does not sufficiently explain personal earnings and economic growth. Education quality may be as important as or more important than education quantity. Previous studies found high returns to schooling in the Philippines. This study shows that these are overestimated by the omission of observable demographic and labor characteristics as well as unobserved ability. Moreover, the high returns to primary education documented in the literature defy explanation. I argue that these are due to certain questionable assumptions and may be capturing the effects of education quality and ability.

In light of the foregoing, this paper aims to account for education quality and ability in returns to education in the Philippines. To do this, standard estimates of returns to education are used as a benchmark. Using pooled cross-section data, returns to education are estimated using the human capital earnings function, relating wage to years of schooling, experience and experience squared, controlling for year fixed effects. The basic Mincerian is then augmented by controlling for sex, marital status, region, sector, occupation, class, tenure and urbanity. Measures of primary and secondary education quality are also included and their effect on returns to schooling determined. To account for ability, fixed effects estimation is employed on sibling data. This amounts to relating the difference in wages between siblings to the difference in their education, all other things equal. The idea is that siblings have very similar unobserved "ability" that can be eliminated by differencing. Returns to education are also estimated by education level. While schooling and education quality may be subject to measurement error, this is addressed by using fixed effects instrumental variable estimation.

Estimates from a basic human capital earnings function show returns to schooling of around 12 percent. Controlling for sex, marital status, region, urbanity, sector, occupation, class of work, and tenure reduces returns to schooling by three-fifths and raises the explanatory power of the model from a third to over half of the variation in earnings with sector, occupation, and region accounting for most of the variation. Controlling for province or city fixed effects reduces returns a bit more and raises the explanatory power of the model further. On the other hand, education quality is insignificant to earnings and does not affect returns to quantity of education. However, returns to schooling for the test cohorts are higher than non-cohorts as the former are younger and returns to schooling increase over time.

Accounting for sibling fixed-effects further reduces returns to schooling by almost half, suggesting that most of what were hitherto considered as returns to education are actually returns to ability. This confirms the idea of wage premiums for ability on top of returns to education. Moreover, there are no significant returns to primary education and barely significant returns to incomplete secondary education. Fixed effects instrumental variable estimates are not substantially different from fixed effects estimates suggesting negligible measurement error in observed schooling. Standard estimates for returns to primary and incomplete secondary education turn out to be returns to ability. This means that workers with only basic education are paid not so much for the productive content of their education but for the innate ability that allowed them to pursue primary or secondary education. This suggests that basic education plays a signaling rather than a productivity enhancing role. Truly significant returns to education accrue only starting from secondary education completion, through college, up to post-graduate education. Moreover, returns to ability generally rise as education level increases, consistent with the signaling theory of education where higher education signals higher ability.

Accounting for ability reduces returns to schooling across years, by sex, across marital status, regions, sector, occupation, class of work, tenure, and urbanity. While returns to schooling are higher in urban areas and in regions considered as economic centers, the reductions are also higher with fixed effects estimation. These suggest that migrants are motivated by higher returns to education and have higher ability. With international migration being an alternative to internal migration, international migrants are also driven by higher returns abroad and are likely to be more able than non-migrants. Returns to migration and to the education of migrants are the subject of the third study in this dissertation.

1.2 Determinants of Migration

Before analyzing the returns to education for Filipino migrants, it is important to analyze the reasons that motivate them to migrate. The Philippines is the ninth largest source of international migrants, with 4.3 million Filipino migrants worldwide in 2010. In 1981-2012, there were 1.9 million registered Filipino migrants. The number of Filipino migrants grew from only six per thousand in 1960 to 44 per thousand in 2010, including only those born in the Philippines or those who have Filipino citizenship. Including those not born in the Philippines or those who have foreign citizenship but have Filipino ancestry more than doubles the stock of Filipino migrants. While permanent migrants have the largest share, temporary migrants are the fastest growing and among these, rehires are the largest and fastest growing. Why are increasing numbers of Filipinos migrating? Why is the share of temporary migrants growing faster? Few studies have analyzed the factors motivating Filipino migration. Those that do either lack empirical evidence or analyze a limited set of factors, focusing on push factors without consideration of pull factors.

The second part of this dissertation aims to determine the factors driving migration. Its contribution lies in the analysis of both push and pull factors as well as the analysis of both permanent and temporary migration. The analysis starts with an estimation of the effects of Philippine and key destination income and labor force on migration. The underlying model assumes that wages and employment behave according to changes in labor demand and supply. However, including only income and labor force may generate bias as their effects may be capturing the effects of wages and employment. Moreover, with distortions in the economy such as legislated wages and regulated employment, the effects of changes in labor demand and supply may not be as expected. To account for distortions, the model is augmented by analyzing the effects of wages and employment in the Philippines and key destinations.

Regressing permanent migration on income and labor shows that emigration is positively related to the labor force. As the labor force increases, the corresponding decrease in wages would shift the migrant supply curve outward raising the wage differential between the US and the Philippines. As a result, more Filipino workers are willing to migrate at any given US wage. Emigration is significantly related to Philippine income only when accounting for structural break. However, the positive relationship is contrary to expectation. This is due to wages rising faster than income. Consequently, employment was not rising fast enough and unemployment was growing. This suggests that a migration hump (where migration increases with income) occurs only in as much as wages are growing faster than income thereby depressing employment and motivating migration. Emigration is positively related to lagged US income. As US income increases, the corresponding increase in US wages compels employers to substitute US workers with migrant labor. The lagged effect is understandable given the information and transactions cost for migration. Conversely, emigration is negatively related to lagged US labor force. As the US labor force increases, the resulting decrease in wages would increase the quantity demanded for US labor.

Standard models of migration relate migration to wages and employment in the origin and destination countries. Others model migration as a function of income and labor force underlying labor demand and supply. Both implicitly assume no distortions in the economy and that wages and employment respond to income and labor in a free market. In economies with legislated wages and regulated employment, the effects on migration of changes in income and labor force may not be as expected. Moreover, either set of factors may be capturing the effects of the other, generating biased estimates. Accounting for distortions has an implication on the effects of changes in labor demand and supply on migration.

Controlling for wages, permanent migration is not significantly related to income and labor force. On the other hand, wages have a positive effect even when controlling for income and labor force. Holding income and labor force fixed, an increase in wages creates or increases excess labor supply, motivating migration. Controlling for US wages raises the effects of US income and labor force. An increase in income, controlling for labor force and wages, raises the quantity of labor demanded relative to quantity supplied, thereby increasing migrant demand. An increase in labor force raises the quantity of US labor supplied relative to quantity demanded, holding income and wages fixed, decreasing migrant demand. Emigration is positively related and highly elastic to US wages. Controlling for US income and labor force, an increase in US wages decreases US employment, requiring migrants to fill the decrease in US native employment. Emigration is negatively related to remittances. An increase in remittances increases local labor demand, increasing employment and decreasing the supply of migrants.

Accounting for employment using a vector auto-regression model shows that permanent migration is positively related to domestic wages, holding labor demand and supply and employment fixed. Higher wages raise the quantity of labor supplied creating unemployment even at existing employment levels. Emigration is also positively related to domestic employment, controlling for labor demand and supply and wages. Higher employment reduces wages relative to what workers are willing to accept. Emigration is negatively related to national income. A decrease in income reduces the quantity of labor demanded at the same wage, creating unemployment. Otherwise, employers are willing to pay a lower wage at existing employment levels. Emigration is negatively related to the domestic labor force, with labor demand, wages and employment fixed. With higher labor supply at the same wage, producer surplus rises, increasing the quantity of labor supplied.

Permanent migration increases with destination wages. As US wages increase, the quantity of US labor demanded decreases. If migrants can be paid lower than the wages for US labor, migrants can fill the decrease in US labor. Emigration increases with destination income as this increases the demand for labor; but is undeterred by subsequent declines. Emigration decreases as the destination labor force increases as this creates excess labor supply at prevailing wages and employment levels. Emigration is positively related to remittances. If remittances increase labor demand holding wages constant, the increase in the quantity of labor supplied had wages increased would have to migrate.

Like permanent migration, temporary migration is also positively related to the Philippine labor force but it is not related to income and remittances. Increases in income and remittances would not affect OFW deployment if wages rise proportionately more, making employment and unemployment unchanged. OFW deployment is positively related to lagged Saudi income. As Saudi income increases, Saudi wages increase attracting more migrants. At the same wages, the quantity of labor demanded also increases relative to the quantity supplied increasing the demand for migrant labor. OFW deployment is positively related to lagged Saudi labor force, contrary to expectation. An increase in Saudi labor force would increase OFW deployment if Saudi wages are downward-rigid, with native employment not increasing. The additional labor demand would have to be filled up with migrant labor at lower wages.

Controlling for Philippine wages, Philippine income and remittances are negatively related to OFW deployment, as expected. A decrease in income and remittances, holding wages fixed, would decrease quantity of labor demanded relative to quantity supplied, increasing the supply of migrants. Controlling for lagged Saudi wages, OFW deployment increases with lagged Saudi income. As Saudi labor demand increases, fixed wages increase the quantity of Saudi labor demanded relative to quantity supplied, increasing the demand for migrant labor. OFW deployment is positively related to lagged Philippine and Saudi wages. Controlling for Philippine income, an increase in Philippine wages would increase unemployment, increasing the supply of migrants. An increase in Saudi wages, controlling for income, would decrease the quantity demanded for native Saudi labor. Optimal employment is filled with migrant labor.

Accounting for employment, temporary migration is also positively related to domestic wages, as well as to Saudi wages. However, OFW deployment is not significantly related to domestic employment and Saudi employment. Temporary migration is also negatively related to domestic income and positively related to Saudi income. OFW deployment is also negatively related to the local labor force. On the other hand, OFW deployment is positively related to Saudi labor force. Controlling for wages and employment, the increase in the quantity of labor demanded has to be filled with migrants at lower wages. OFW deployment is also positively related to remittances.

Permanent and temporary migration generally behave alike in response to various push and pull factors. However, there are a few differences. Permanent migration is positively related to domestic employment, controlling for labor demand and supply and wages. On the other hand, temporary migration is not significantly related to domestic employment. Higher employment reduces domestic wages relative to the level that permanent migrants are willing to accept. This suggests that the reservation wage of permanent migrants is higher than that of temporary migrants. This indicates that permanent migrants are positively selected from the local labor force. Permanent migration is negatively related to destination labor force: emigration decreases as the US labor force increases, as this creates excess labor supply at prevailing wages and employment levels. Conversely, temporary migration is positively related to the Saudi labor force: controlling for Saudi wages and employment, the increase in the quantity of labor demanded has to be filled with migrants at lower wages. This suggests that temporary migrants are negatively selected in the destination labor force. Despite this, temporary migration is positively related to Saudi wages. Overseas Filipino workers are still attracted by higher wages in the destination countries.

1.3 Returns to Migration

How much do overseas workers actually gain from working in the destination countries? The third part of this dissertation aims to determine the returns to migration of Filipinos and to the education of Filipino migrants. Most existing migration studies on the Philippines (e.g. Orbeta (2008); Alba and Sugui (2009)) focus on the benefits and motives of remittances. Most existing studies on returns to migration compare wages of migrants across destinations (e.g. Tan (2005, 2006)) but not between migrants and non-migrants. They also estimate returns to education over all destinations, but do not compare returns across destinations and with the Philippines. Clemens et al. (2009) compare wages of of Filipinos in the US and in the Philippines. However, to my knowledge, there is still no study comparing wages and returns to education of Filipinos in various destinations and the Philippines. This is the research gap that this study seeks to fill.

This paper aims to determine the returns to migration and education of overseas Filipino workers. It develops an augmented human capital earnings function relating wages to schooling, experience and its square; migration and its interactions with the first three variables, while controlling for sex, civil status, origin region in the Philippines, and occupation. The model is then modified to account for different returns to migration and education by sex, by major destinations, and for each key destination. Returns are estimated with domestic workers as reference. Data on domestic workers are taken from the Labor Force Survey. Most data on overseas workers are from the Philippine Overseas Employment Administration (POEA). However, these do not include the education of overseas Filipino workers. We derive education data for overseas workers from the Survey of Overseas Filipinos (SOF) using Two-Sample Two-Stage Least Squares regression. In the first stage, schooling is fitted on age, civil status, region and interactions between each key destination country, sex and occupation using the SOF data. In the second stage, the augmented human capital earnings function is estimated using predicted schooling for the same set of explanatory variables in the POEA data.

Results show that overseas Filipino workers earn more than domestic workers. However, returns to schooling is higher for local workers. Male overseas workers generally earn more than their local counterparts, but their return to schooling is lower. Female overseas workers earn more, but return to their schooling is not significantly different from those of their domestic counterparts. Earnings of overseas Filipino workers in top destinations as a group are surprisingly lower than those for local workers. However, returns to schooling in major destinations are higher than in the Philippines. Major destinations put a premium on human capital. In the rest of the destinations, earnings are higher but returns to schooling are lower than in the Philippines. Male overseas workers in major destinations earn less than their local counterparts, but the return to their schooling is higher. On the other hand, female overseas workers in top destinations earn more than their local counterparts, and their return to schooling is higher. In the rest of the destinations, male overseas workers earn less than male local workers, but their return to schooling is higher. Female overseas workers earn more in other destinations than local female workers, but the return to their schooling is lower.

Across key destinations, overseas Filipino workers in Australia, Italy, Japan, Canada, China, Taiwan, USA, Kuwait, Bahrain, Malaysia and the UAE earn more than domestic workers. However, returns to schooling in Bahrain, Canada, Malaysia, and the United States are not significantly different from that in the Philippines. Nevertheless, returns to schooling resembling those of developing countries like the Philippines are already considered high for developed countries considering the stylized fact of decreasing returns to income. Moreover, returns to schooling are lower in Australia, China, Italy, Korea, Kuwait, Japan, Malaysia, and Taiwan than in the Philippines. Return to schooling is higher only in UAE. While earnings are lower in Qatar than in the Philippines, return to schooling is higher. Earnings of Filipino workers in Hong Kong, Korea, Saudi Arabia, Singapore and the U.K. are not significantly different from those of local workers, but returns to schooling in Saudi Arabia, Singapore, and Hong Kong are higher. However, the return to schooling in the U.K. is not significantly different from that in the Philippines, and in Korea it is even lower, and neither are returns to experience significantly different for these two countries.

Earnings for male Filipino workers in Korea, Saudi, Arabia, Singapore and

UAE are higher than those for their local counterparts. Moreover, the return to schooling for male Filipino workers in Singapore is higher than that for male local workers. Almost three-quarters of male workers in Singapore are either managers, executives; professionals; or associate professionals. However, returns to schooling in Korea, Saudi Arabia and UAE are lower than in the Philippines. Earnings and returns to schooling of male Filipino workers in Australia, Bahrain, Canada, China, Italy, Japan, Malaysia and the USA are not significantly different from those in the Philippines. Returns to experience are higher in Canada, China, and Qatar, but not significantly different in Australia, Bahrain, Italy, Japan, Malaysia, and USA. Earnings of male Filipino workers in Hong Kong, Kuwait, Qatar, Taiwan, and the U.K. are lower than those of male local workers. Nevertheless, returns to schooling for male Filipino workers in Hong Kong, Taiwan, and the U.K. are higher than those for their local counterparts. However, the return to schooling for male Filipino workers in Qatar is not significantly different from that for male local workers.

Earnings for female Filipino workers are higher in Japan, Taiwan, U.K., Australia, China, Hong Kong, Italy, Kuwait, and Malaysia. Most female Filipino workers in Hong Kong and Italy, and over a third in Kuwait and Malaysia are laborers and unskilled workers. However, returns to schooling for female Filipino workers in Australia, China, Italy, and Malaysia are not significantly different from that in the Philippines. Earnings of female Filipino workers in Korea are lower than in the Philippines, but return to schooling is higher. On the other hand, earnings for female Filipino workers in Bahrain, Canada, Qatar, Saudi Arabia, Singapore, UAE and USA are not significantly different from that in the Philippines. Nevertheless, returns to schooling for female Filipino workers are higher in Qatar, Saudi Arabia, Singapore, and UAE. This is related to the composition of Filipino labor in these countries. In Saudi Arabia, over half of female Filipino workers are professionals. In Singapore, three-quarters of female Filipino workers are either professionals, managers and executives, or associate professionals and clerks. Returns to schooling for female Filipino workers in Bahrain, Canada, and USA are not significantly different from that in the Philippines. Interestingly, close to three-fourths of female Filipino workers in the United States are even professionals. While the return to experience in Kuwait is higher than that in the Philippines, returns to experience in Bahrain and the USA are not significantly different.

There are no apparent gains to earnings and returns to schooling for the average Filipino worker in the U.K. and Korea; male Filipino workers in Australia, Bahrain, Canada, China, Italy, Japan, Malaysia, and the USA; and female Filipino workers in Bahrain, Canada, and USA. Moreover, few of these have higher returns to experience. This begs the question: what motivates these workers to labor in these countries? Are there gains in differences in costs of living that are not captured by accounting for gains in purchasing power parity (PPP)? If a worker has higher earnings abroad but also has greater spending for the same basket of goods, there appears to be no income gain. However, if the same worker spends less abroad and sends much of his income home as remittances, then exchange rate conversions and differences in cost of living may yield income gains. In fact, there are monetary gains from the conversion of earnings to the the local currency, on top of the income gains identified earlier. Taking the ratio of returns in US dollars to those in PPP shows monetary gains for Filipino workers in Australia, Bahrain, Canada, China, Italy, Kuwait, Japan, Malaysia, Taiwan, USA, and UAE. While there are no real income gains in Korea and Saudi Arabia, there are exchange rate gains. There are also gains in returns to schooling from exchange rate conversions for Filipino workers in Hong Kong, Qatar, Singapore, China, Saudi Arabia, UAE, as well as other destinations. For male Filipino workers, there are exchange rate gains to earnings in Qatar, Taiwan, Hong Kong, Singapore, and UAE, and to returns to schooling in Saudi Arabia and Hong Kong. However, there remain no gains for male workers in Australia, Bahrain, Italy, Japan, Malaysia, and USA. For female Filipino workers, there are exchange rate gains to earnings in Taiwan, China, Hong Kong, Malaysia, Japan, Italy, and U.K.; and to returns to schooling in Qatar, Saudi Arabia, UAE. However, there remain no gains for female Filipino workers in Bahrain, Canada, and the U.S..

The first part of this dissertation compares returns to education across regions in the Philippines in 2007-2010. That study finds that the return to schooling is higher in the national capital region than in the rest of the regions in the country. These estimates may be biased as they do not account for migration. If the more able migrate from the periphery to the capital or abroad, the returns to education in the peripheral regions maybe underestimated while those in the capital may be overestimated. Comparing earnings and returns to schooling for domestic and overseas workers by region for 2011 shows results similar to those of the first part of this thesis. The average return to schooling for local workers in the national capital region is higher than in most other regions. Average earnings for local workers in the capital are also higher than those in most other regions. To address the suspected bias in domestic returns to education across regions, I compare returns to education for overseas workers from different regions, controlling for sex, civil status, occupation and destination country. Results show that earnings of overseas Filipino workers from most regions are not significantly different from the earnings of those from the national capital. Conversely, returns to schooling for overseas workers from several regions are higher than the returns for those from the capital region, while returns to schooling for those from the rest of the regions are not significantly different. This confirms the hypothesis that the higher returns for domestic workers in the capital are due to the migration of workers with higher ability.

With wage and education data contained in separate sources, estimating returns to education relies on strong assumptions. An alternative approach is employed by separately relating earnings and destination to occupation using the POEA dataset and occupation to schooling using the SOF dataset. The probability of working in a particular destination depends on the worker's occupation. Professionals and trade workers have the highest odds of working in Australia, service workers in Canada, technicians in China, professionals in Italy, plant operators in Korea, managers and executives, and services workers in Kuwait, technicians in Japan, service workers in Malaysia, clerks in Qatar, trade workers and clerks in Saudi Arabia, professionals and technicians in Singapore, service workers in Taiwan and UAE, clerks and service wokrers in the UK and the US.

Consequently, earnings of professionals and trade workers in Australia are 3.5 times and 3.2 times higher than counterparts in the Philippines, respectively. Service workers in Canada earn 3.3 times more, technicians in China earn 2.6 times more, and professionals in Italy earn 3.6 times more, than in the Philippines. Plant operators in Korea earn 1.9 times more, managers and executives earn 1.4 times more and service workers earn 92 percent more in Kuwait, and technicians in Japan earn 1.7 times more, than their counterparts in the Philippines. Service workers in Malaysia earn 55 percent more, clerks in Qatar earn 1.4 times more, and clerks in Saudi Arabia earn 51 percent more, than their local counterparts. Professionals and technicians in Singapore earn 2.5 times more, service workers in Taiwan earn 3.9 times more, clerks earn 3.6 times more and service workers earn 2.6 times more in the US, than in the Philippines.

Relating occupation to schooling shows that the likelihood of skilled employment increases with schooling in a few destinations. The odds of working as a professional, service worker, and plant and machine operator in the US and as a plant operator in Japan increases with schooling. On the other hand, the odds of all skilled employment in Australia and most skilled employment in the UK do not rise with schooling. In most major destinations, schooling decreases the likelihood of all or most skilled employment, contrary to expectation.

Chapter 2

Spying Out the Land: Accounting for Ability in Returns to Education in the Philippines

> "But because my servant Caleb has a different spirit and follows me wholeheartedly, I will bring him into the land he went to, and his descendants will inherit it." - Numbers 14:24

This study shows that standard estimates of returns to education capture the effects of labor characteristics and ability. It finds that accounting mainly for sector, occupation and region reduces returns to education by three-fifths. Accounting for ability using sibling fixed-effects estimation further reduces returns to schooling by almost half, yields no significant returns to primary and incomplete secondary education, and yields increasing returns to higher education. Earnings and returns to schooling are unaffected by education quality when controlling for education division fixed effects. Returns to schooling and ability are higher in urban areas and regions considered as economic centers suggesting that internal labor migrants are driven by returns to education and ability.

2.1 Context and Objectives

The importance of human capital to earnings and economic growth is well known. The literature on human capital is inspired by Schultz (1961) who attributed the bulk of US national income growth to the improvement in human capital, and the large unexplained growth in labor earnings to human capital investment. Conversely, he attributed slow capital absorption among poor countries to slow improvements in human capital. Consistent with this, Balisacan and Hill (2003) identified the eroding comparative advantage in, and quality of, education, together with low saving and investment rates, and slow employment growth, among the proximate causes of the slow growth in the Philippines for the period 1980-2000.

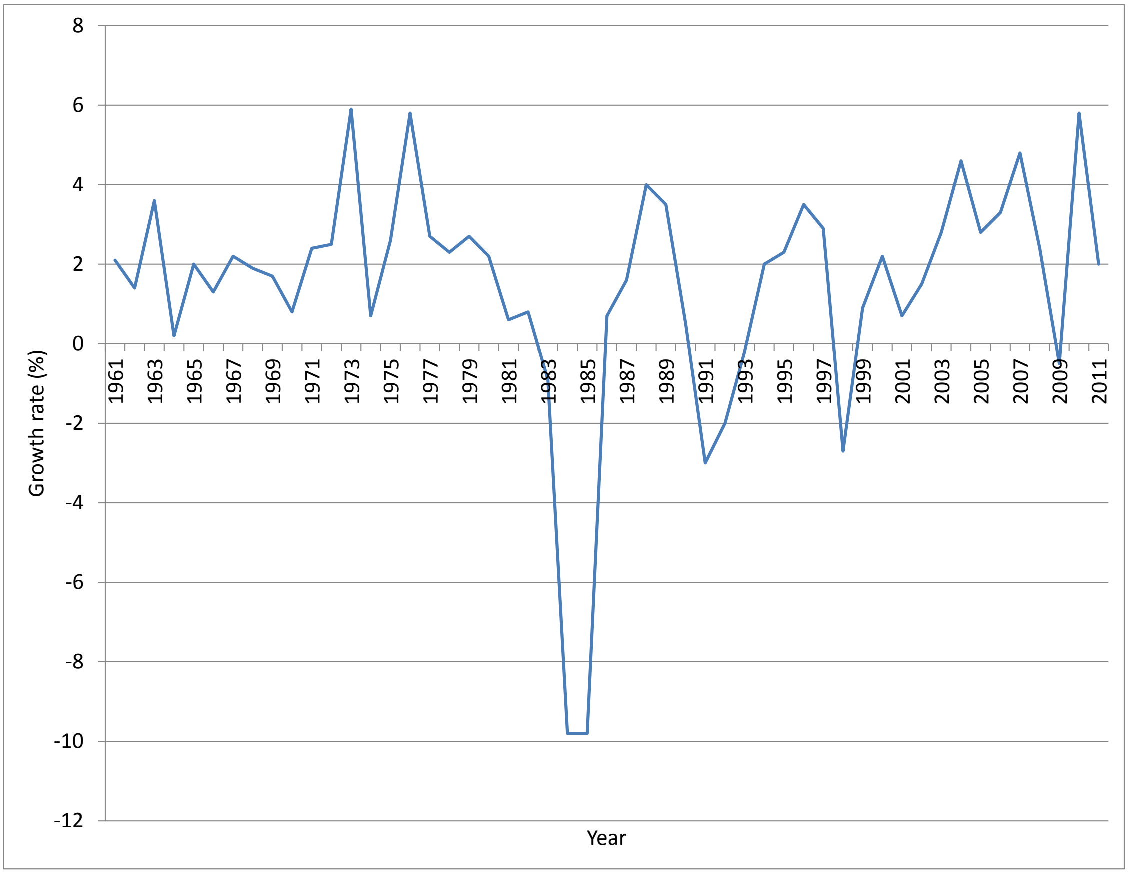
2.1.1 Economic Growth, 1950-2010

The economic performance of the Philippines over the past 50 years is shown in Figure 2.1. Per capita income in the 1960s grew at an average of 1.7 percent. This was followed in the 1970s by an average growth of 3 percent although this was debt-driven growth (Balisacan and Hill, 2003). However, growth then fell to less than 1 percent in the early 1980s, followed by a crash in 1984-1985 due to a political crisis as a result of which per capita income decreased by 9.8 percent in both years. The late 1980s saw a recovery with an average growth of 2 percent. This was not sustained, however, as the economy faced negative shocks in the early 1990s with income declining by an average of 1.7 percent per year in the first three years before recovering to an average of 2.7 percent per year in 1994-1997. Another negative shock occurred in 1998, this time largely external in origin, with income dropping by 2.7 percent. Average growth in the 1990s was just 0.6 percent. The new millennium presents a new dawn to the Philippine economy as growth averaged 2.8 percent in the 2000s, much higher than in the previous two decades, although not quite as high as in the 1970s. While the year-to-year fluctuations in economic growth have been due to shocks to the economy, the underlying trends may be attributed to the changing structure of the economy, in terms of sectoral output and labor composition.

2.1.2 Human Capital

The human capital composition of the labor force has changed much over the last 60 years. The average years of schooling of the Philippine labor force rose from 2.8 years in 1950 to 9 years in 2010. In 1950, the biggest proportion (47 percent) of the labor force had no schooling [Figure 2.2]. 31 percent had only incomplete primary education while 10 percent had only complete primary education. Only 10 percent had either incomplete or complete high school while only 2.5 percent had either incomplete or complete tertiary education. Since 1955, the share of the labor force with only incomplete primary education has declined while the share of those with

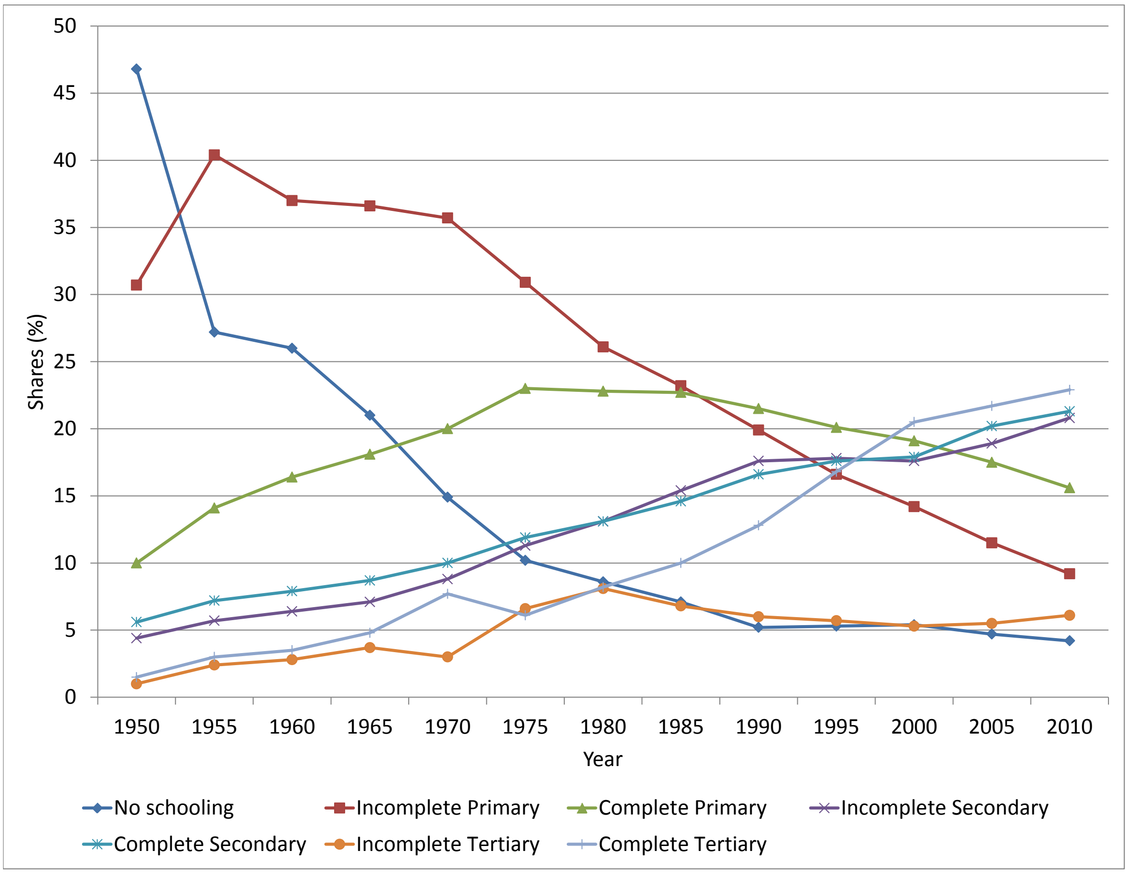
Figure 2.1: Annual Growth of Philippine GDP per capita, 1961–2011



Source: World Development Indicators, The World Bank

higher education rose.

Figure 2.2: Shares of Philippine Labor Force by Highest Grade Completed, 1950–2010



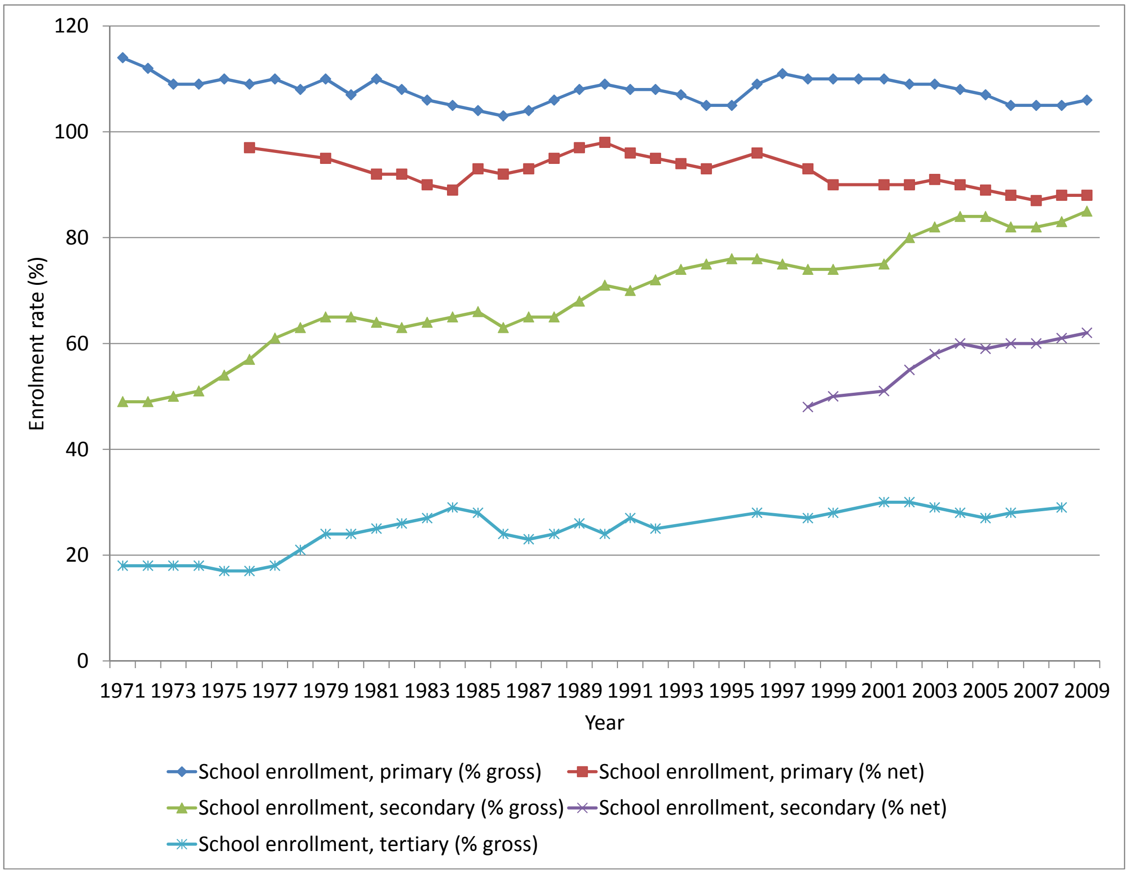
Source of data: Barro and Lee (2010)

The share of the labor force with complete primary education rose to 23 percent in 1975 and remained at this level until 1985. While this figure has declined since then as the shares of labor with higher education rose, it surpassed the share of labor force with incomplete primary education. The shares of the labor force with incomplete and complete secondary education surpassed that with incomplete primary education in the early 1990s and that with complete primary education in early 2000s. The share of the labor force with incomplete tertiary education rose to 8.1 percent in 1980 but declined thereafter. The share of the labor force with complete tertiary education surpassed that with incomplete tertiary education in the early 1980s and then rose steeply into the 1990s, surpassing the shares of the labor force with incomplete and complete primary and secondary education in the late 1990s. By 2010, 23 percent of the labor force had complete tertiary education, 21.3 percent had complete secondary education, 20.8 had incomplete secondary education, 15.6 had complete primary education, 9.2 percent had incomplete primary education, 6.1 percent had incomplete tertiary education, and 4.2 percent had no schooling.

The fact that most of the labor force in the 1950s-1970s and the largest share of the labor force in the 1980s-1990s had only primary education suggests that further education proved too costly relative to the benefits for most and that there were sufficient benefits from primary education as confirmed in the following literature review. On the other hand, the rising share of the labor force with post-primary education and the fact that the share of the labor force with secondary education surpassed that with only primary education in the late 1990s, suggest that there was an increasing relative benefit from secondary education and tertiary education, also evident in the literature. Moreover, while the especially poor economic performance of the Philippines in the 1980s-1990s is associated with low human capital composition of labor, the respectable performance in the 2000s is associated with higher human capital.

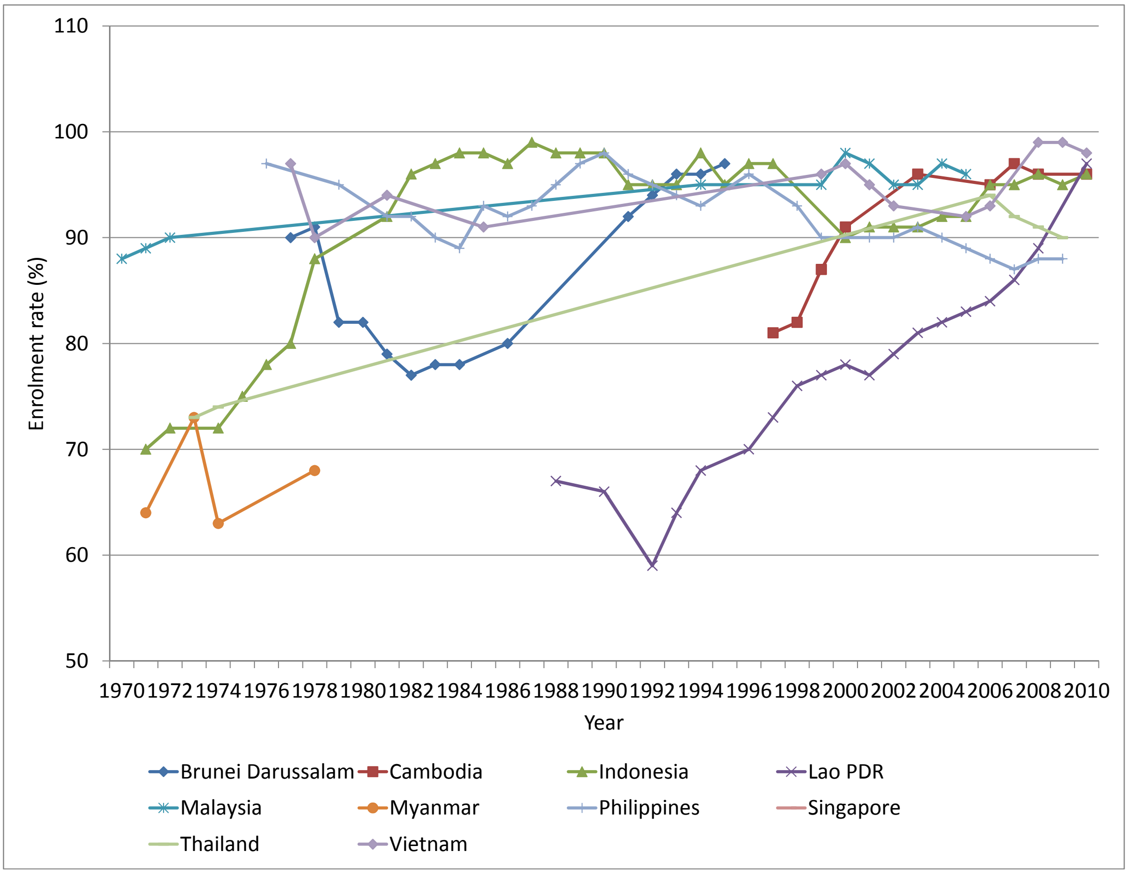
Current enrolment rates determine the future human capital composition of labor. Both gross and net primary enrolments have generally declined since the 1970s (Figure 2.3). Over the last decade or so, net primary enrolment fell from 96 percent in 1996 to 88 percent in 2009. This is lower than net primary enrolment for Vietnam (98%), Laos (97%), Cambodia, Malaysia (2005) and Indonesia (96%) (Figure 2.4). This will raise the proportion of labor force with either no schooling or incomplete elementary education in the future. On the other hand, secondary and tertiary enrolments have generally increased. Gross secondary enrolment rose from 49 percent in 1971 to 85 percent in 2009. Net secondary enrolment rose from 48 percent in 1998 to 62 percent in 2009. This is higher than net secondary enrolment for Myanmar (51%), Laos (40%), Cambodia (35% in 2007) but lower than those for Brunei (97% in 2009), Thailand (72%), Malaysia (68% in 2009), and Indonesia (67%) (Figure 2.5). Gross tertiary enrolment rose from 18 percent in 1971 to 29 percent in 2008. The latest figure is higher than those for Indonesia (23%), Vietnam (22%), Brunei and Laos (17%), Myanmar (11% in 2007) and Cambodia (8% in 2008) (Figure 2.6). However, it has been surpassed by Thailand (46% in 2010), and Malaysia (40% in 2009). The rise in secondary and tertiary enrolment will on the whole increase the human capital composition of labor and returns to education in the future. This would also increase future returns to secondary and tertiary education.

Figure 2.3: Enrolment by educational level, 1971–2009



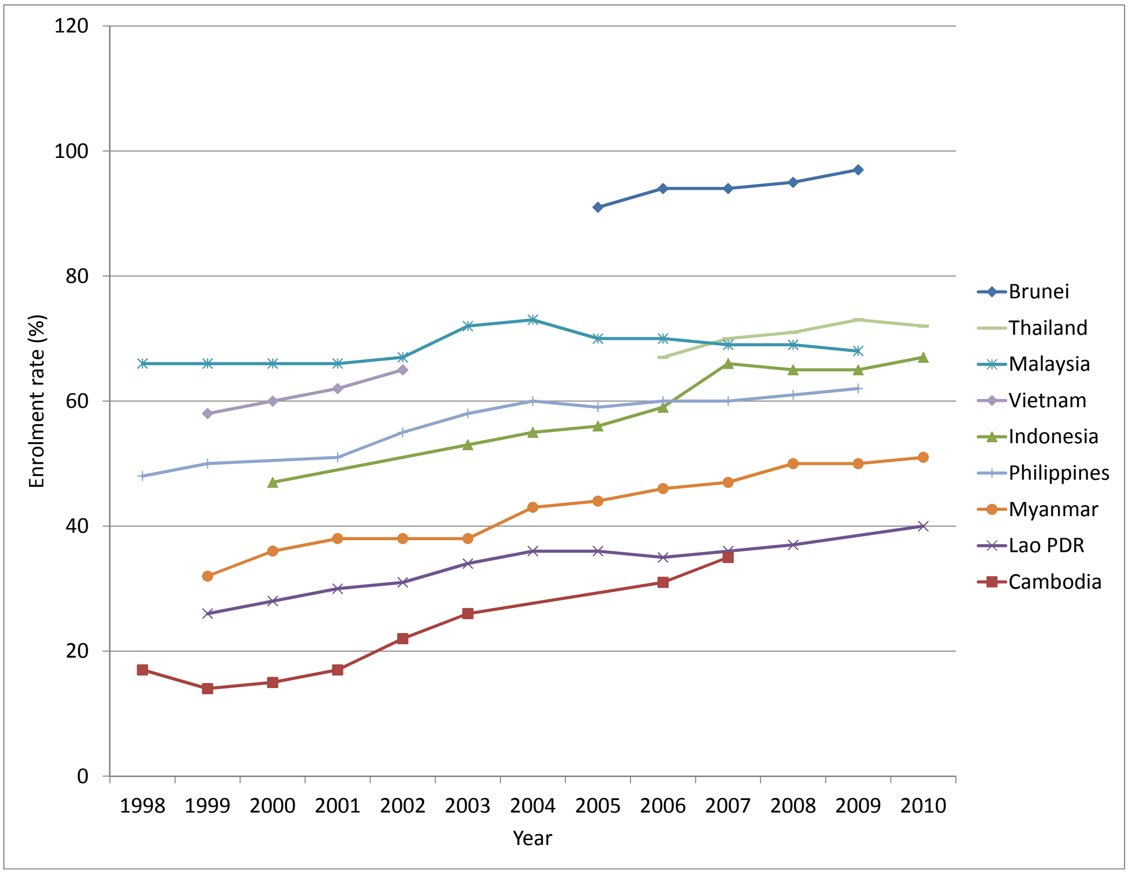
Source: World Development Indicators, The World Bank

Figure 2.4: Net Primary Enrolment Rates, South-East Asia, 1970–2010



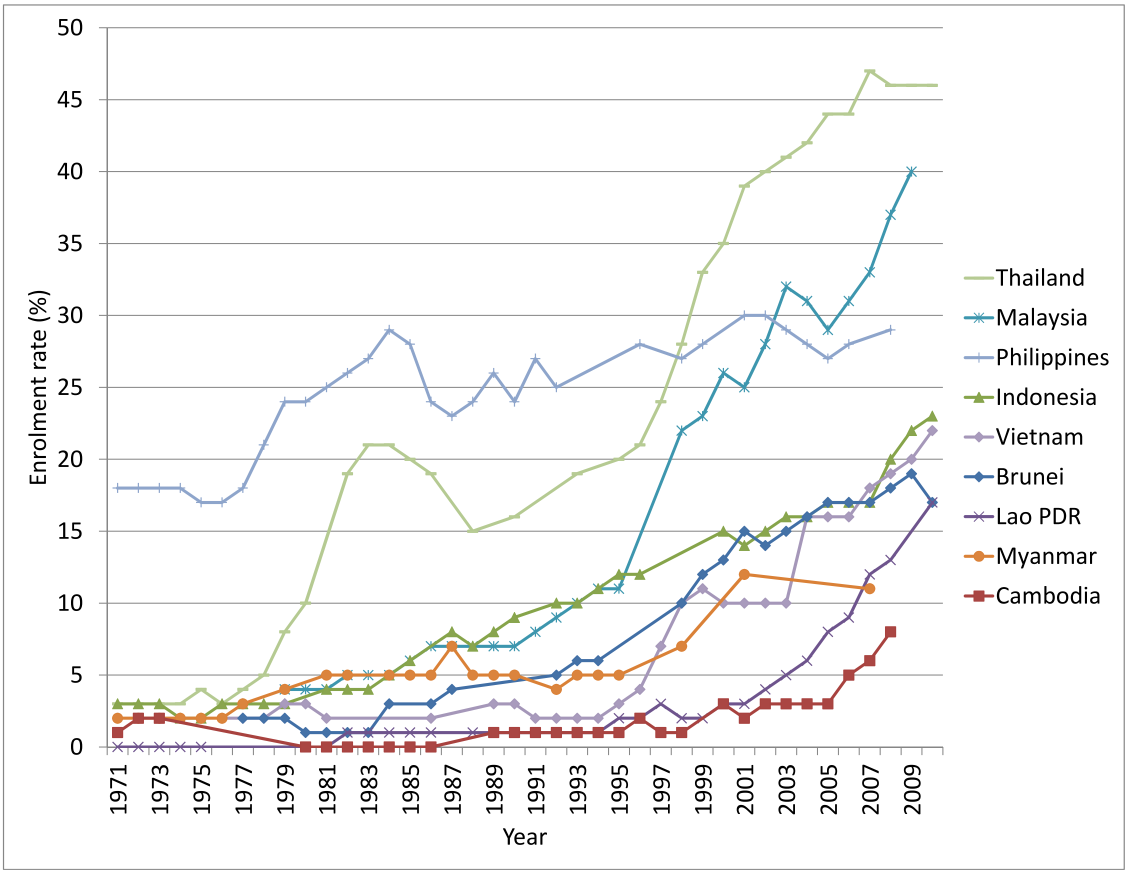
Source: World Development Indicators, The World Bank

Figure 2.5: Net Secondary Enrolment Rates, South-East Asia, 1998–2010



Source: World Development Indicators, The World Bank

Figure 2.6: Gross Tertiary Enrolment, South-East Asia, 1971–2010



World Development Indicators, The World Bank

2.1.3 Sectoral Output, Employment and Productivity

The structure of the economy has significantly changed over the last 50 years. The share of agriculture to total output has been declining from its peak of 31 percent in 1974 to a low of 12.3 percent in 2010 (Figure 2.7). The share of agricultural employment has declined from 52 percent in 1980 to 35 percent in 2009 (Figure 2.8). Industry has also also not done well, with its share of output decreasing from 39 percent in 1983 to 30 percent in 2010 and its employment share decreasing slightly from 15.4 percent in 1980 to 14.6 in 2009. Growth occurred in the service sector, with its output share rising from a low of 34 percent in 1977 to 57 percent in 2011 and its employment share rising from 33 percent in 1980 to 50 percent in 2009.

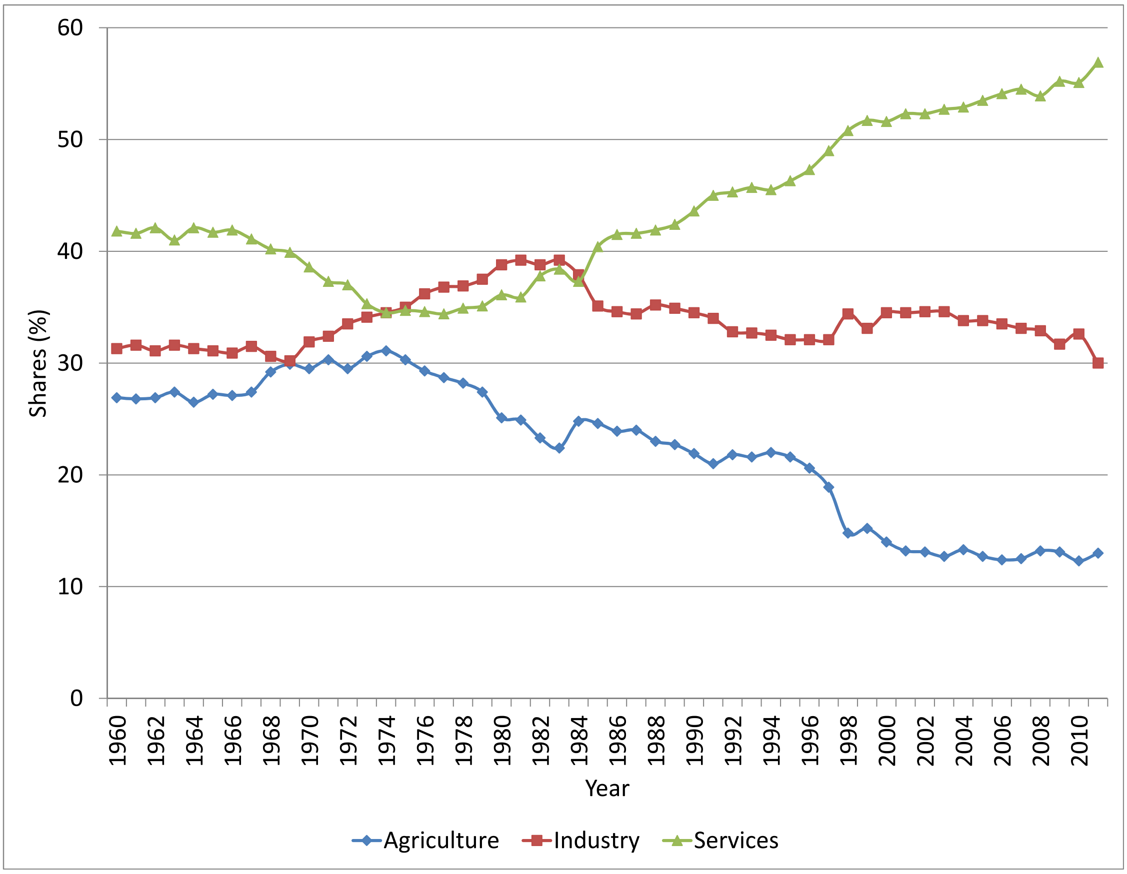
Labor productivity reflects sectoral output and employment growth. The average product of labor in agriculture has been low ($1460 in 1980) and declining ($1300 in 2008) (Figure 2.9). While the average product of labor in industry decreased from around $8300 in the early 1980s to $5073 in 1996, it has rebounded and reached $7728 in 2008. The average product of labor in services has steadily increased from $2640 in 1985 to $3755 in 2008. Moreover, while the average product of labor in services is lower than that in industry, the marginal product of labor in services is not necessarily lower, assuming higher capital intensity in industry. Wages and returns to education are expected to be higher in growing sectors of the economy and lower in the declining sectors. Therefore, wages and returns to education in agriculture are expected to be low and those in industry and services higher.

Recent Philippine economic growth rates have been rising, driven by services (i.e. telecommunications, finance and business process outsourcing) and consumption (Bocchi, 2008). The growth in consumption appears to be driven by overseas employment and remittances. On the other hand, the growth in services appears to be related to higher returns to education in the sector (di Gropello et al., 2010). Overseas employment also entails a high level of human capital as seen in the fact that "most emigrating Filipinos are professionals", i.e. 35.5 percent of emigrating workers were professionals prior to migration.

2.1.4 Unemployment and Underemployment Rates

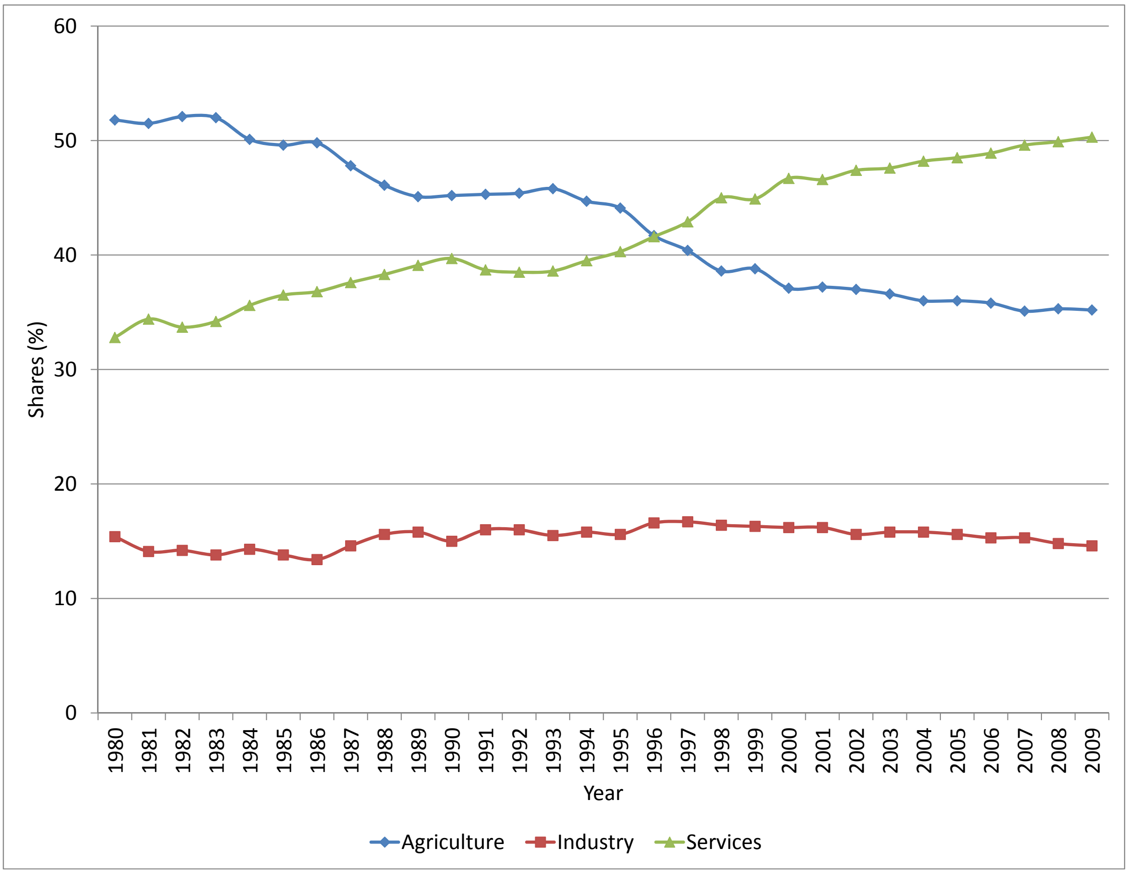
Apart from the sectoral distribution of output and labor, relative employment rates/labor intensities can also indicate the competitiveness of labor across sec-

Figure 2.7: Sectoral Shares to GDP, 1960–2011



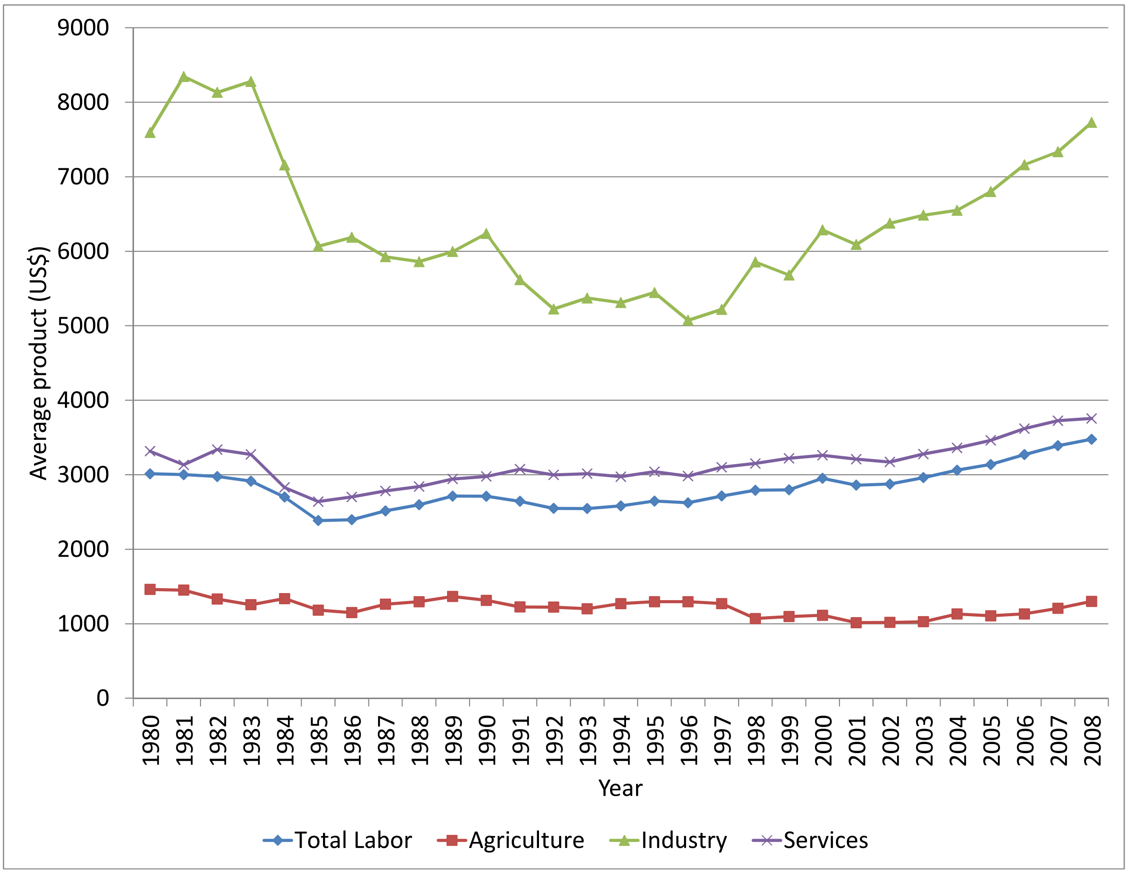
Source: World Development Indicators, The World Bank

Figure 2.8: Sectoral Shares to Total Employment, 1980-2009



Source: World Development Indicators, The World Bank

Figure 2.9: Average Product of Labor (constant 2000 US$), 1980–2008



Source of basic data: World Development Indicators, The World Bank tors. The lower the unemployment/underemployment rate in a sector, the higher the relative demand for labor in that sector. Sectors with a high demand for labor may provide a wage premium to attract labor. However, they would ensure maximum productivity from the wage premium they pay and make sure they hire the most able workers. For this reason, unemployment rate would be negatively related to ability across sectors. Over the past years, the unemployment rate for males is slightly higher than that for females suggesting a lower wage premium. Across sectors, the underemployment rate in 2011 is highest in agriculture (75.3 percent) indicating high excess labor and therefore a low wage premium for ability. The lower underemployment rate of 49.6 percent in services indicates less excess labor and a higher wage premium. Industry has the lowest underemployment rate (38.7 percent) suggesting that it has the highest wage premium.

2.1.5 Research Objective and Questions

This study aims to determine the returns to education in the Philippines over the past decade. Is the human capital composition of labor associated with returns to education? How much of returns to education can be attributed to quality of education? How do comparative growth, employment and productivity across regions and sectors determine relative wages and returns to education? Are there wage premiums to ability as relative unemployment / underemployment rates suggest? How do these wage premiums vary across regions, sector, and occupations. This study shows that standard estimates of returns to education are capturing the effects of labor characteristics and abilities. It provides unbiased estimates of returns to education by accounting for education quality and unobserved ability using sibling fixed-effect estimation. It also provides unbiased estimates of returns to education by sex, marital status, region, sector, occupation, class of work, tenure and urbanity.

2.2 Literature Review

2.2.1 Returns to Education: Estimation Methods

Determining the profitability of human capital investment is similar to estimating the rate of return on general investments. The rate of return is the discount rate that equates the net present value of the benefit from that investment over another activity to the net present value of the cost of that investment (Becker, 1964). There are three methods of estimating returns to education (Psacharopoulos and Ng, 1994).

The full-discounting method entails finding the discount rate, r, from the formula:

$$\sum_{t=m+1}^{n} \frac{(Y_b - Y_a)_t}{(1+r)^t} = \sum_{t=1}^{m} (Y_a + C_b)_t (1+r)^t$$

where $(Y_b - Y_a)_t$ is the difference in earnings between a person b with more education and a person a with less education, C_b is the direct cost of schooling, and Y_a is foregone earnings. When only the private cost of schooling is considered, the resulting discount rate is referred to as the private rate of return to education. The social rate of return to education can be estimated by including the public costs of education. While the full-discounting method is considered as the"most appropriate method of estimating the returns to education" as it considers an individual's earning history, it has a high demand for data on earnings as well as costs (Psacharopoulos and Ng, 1994). It requires sufficient data on earnings by age for various education levels as well as direct private and public costs of education. The short-cut method of estimating returns to education is given by the following formula:

$$r = \frac{(Y_b - Y_a)}{m(Y_a)}$$

where $(Y_b - Y_a)$, as earlier, is the difference in earnings between a person b with more education and a person a with less education, Y_a is foregone earnings and m is the difference in the years of schooling between a and b (Psacharopoulos and Ng, 1994; Psacharopoulos, 1995). While this method is easy to use, it assumes constant earnings across time. That is, it presents age-earnings profiles as flat; earnings vary only by educational attainment but not by age or experience.

Another method is the human capital earnings function, due to Mincer (1974):

$$lnE_t = lnE_0 + rs + \beta_1 t - \beta_2 t^2$$

where E_t is current earnings, E_0 is initial earnings without schooling and work experience (lnE_0 is the intercept log wage), s is the number of years of schooling, t is the number of years of work experience[1], r is the return to each year of schooling, β_1 is the return to a year of work experience and $-\beta_2$ is the rate of decline in the

[1]Using age alone would lead to omitted variable bias which would underestimate the return to schooling: $lnE_t = lnE_0 + rs + \beta_1(A - s - b) - \beta_2(A - s - b)^2$

$$lnE_t = \left[lnE_0 - \beta_1(A-b) - \beta_2\left(-2Ab + b^2\right)\right] + \left[r - \beta_1 - \beta_2\left(-2A + s + 2b\right)\right]s + \beta_1 A - \beta_2 A^2$$

Therefore, the return to schooling, r, is underestimated by $\beta_1 + \beta_2\left(-2A + s + 2b\right)$.

return to experience. While earnings are expected to increase with experience, the rate of increase is expected to decline.

2.2.2 Estimation Issues

Earnings can be measured in annual, weekly or hourly terms, usually in logarithm. However, returns to schooling may be higher for annual or weekly earnings as the estimated return includes the effect of time spent at work (Card, 1999; Chiswick, 1997).[2] The use of hourly wages is thus preferred as the estimated returns are free from the effects of work effort.

Chiswick (1997) argues that the coefficient of schooling is "not the rate of return from schooling" but the mean percentage change in earnings per year of schooling, which is the product of rate of return and the ratio of schooling investment to potential earnings.[3] The schooling coefficient can be interpreted as the rate of return to schooling only if the cost of schooling equals potential earnings. Assuming no direct costs, if the opportunity cost of schooling is less than potential earnings, the schooling coefficient would underestimate the rate of return. Conversely, if direct and foregone costs exceed potential earnings, the schooling coefficient would overestimate the rate of return.

The earnings function can be extended by transforming the years of schooling into a series of dummy variables representing levels of education (Psacharopoulos and Ng, 1994).

$$lnY_i = \alpha + \beta_1 PRIM_i + \beta_2 SEC_i + \beta_3 UNIV_i + \gamma_1 EX_i + \gamma_2 EX_i^2 + e_i$$

This specification allows for non-linear returns to schooling and can show whether returns to schooling are constant, increasing or decreasing across levels. Non-linear returns can also be tested by relating the natural logarithm of earnings as a quadratic function of schooling or by including a dummy variable for each year of schooling.

Implicit to the human capital earnings function is the idea that education enhances productivity. Contrary to this, Arrow (1973) argues that higher education does not add to productivity but acts as a "screening device", sorting individuals by ability. Employers do not know the productivity of individuals and so use educa-

[2] $E_a = E_h W^\gamma H^\delta$; in logs: $LnE_a = LnE_h + \gamma LnW + \delta LnH$ where E_a is annual earnings, E_h is hourly earnings, W is weeks worked, and H hours worked per week.

[3] $b = rK$, $K = C_t/E_{t-1}$ where b is the schooling coefficient, r is the rate of return to schooling, K is the ratio of schooling investment to potential earnings, and C_t is the sum of foregone earnings, C_f, and direct costs, C_d. Social rate of return, r^*, considers public cost of schooling, C_s, in K^*.

tional certification to convey expected productivity. Similarly, Spence (1973) argues that education acts as an instrument for signaling ones ability. Employers offer particular wages for the expected ability from any given level of education. These wage offers determine returns to education which in turn determine investment in education. People will choose higher education if the signaled productivity of higher education is greater than the costs.

However, Layard and Psacharopoulos (1974) argue that the hypothesis that schooling raises earnings not because it raises productivity but because it certifies ability is unverified, citing that returns to education for U.S. males who completed high school and bachelor's degree are no higher than those of drop-outs. This may be due to failure of screening hypothesis models to account for sheepskin effects (Riley, 1979) considering log wages as a linear function schooling, not allowing for returns to education to rise disproportionately at completion years. To test for sheepskin effect, Hungerford and Solon (1987) specified a spline function with discontinuities at 8, 12, and 16 years of schooling (i.e. used years of schooling with interaction terms for completion years) and found substantial "sheepskin effects" at each level.[4] While their specification allows for discontinuities at completion years, they had no data on actual degree attainment. Jaeger and Page (1996) argued that this leads to biased estimates of sheepskin effects as some individuals finish high school or college earlier or later than the normal years of schooling or not finish even with those years of schooling. With data on diplomas received, they estimated for sheepskin effects while controlling for years of schooling. They found sheepskin effects over twice bigger than when using years of schooling alone. The returns to receiving a high school diploma (11%) and a bachelor's degree (31%) are much larger than when using years of schooling alone (3% and 11%, respectively).

2.2.3 Quality of Education

Hanushek and Woessmann (2007) argue that, despite countries' efforts to bridge the gap in educational attainment, disparities in incomes remain and schooling fails to deliver the expected learning outcomes. They cite evidence suggesting that the quality of education, more than the quantity of education, affects incomes and growth.

[4] The model is

$$lw = \alpha + \beta_1 S + \beta_2 D_8 + \beta_3 D_8 \cdot (S-8) + \beta_4 D_{12} + \beta_4 D_{12} \cdot (S-12) + \beta_5 D_{16} + \beta_6 D_{17} + \beta_7 D_{18} + \delta_1 X + \delta_2 X^2$$

where lw is log wage, S is schooling, D_8, D_{12}, and $D16$ are dummy variables for $S \geq 8$, $S \geq 12$, and $S \geq 16$, respectively; D_{17} and D_{18} are dummies for $S = 17$ and $S = 18$, respectively; and X is experience.

In this regard, poor countries are more disadvantaged in education than earlier thought. Further evidence shows that the quality of education greatly affects earnings, controlling for educational attainment. Quality is also positively related to quantity. Moreover, the effect of education quality appears to be greater for poorer countries.

In the United States, returns to education differ significantly across individuals from different states and of different cohorts (different dates of birth) (Card and Krueger, 1992). Much of the difference is due to variations in school quality. Return to schooling among individuals is higher where schools have lower pupil-teacher ratios and have higher teacher salaries. Return to schooling increases by 0.4 percentage-points as pupils per teacher decreases by 5. Return to schooling increases by 0.1 percentage-points as teacher salaries increase by 10 percent. Murnane et al. (2000) studied the effect of cognitive skills on earnings. They find that a one-point increase in high school math scores increases earnings by 1.5 to 2 percent among males and 1.3 to 1.7 percent among females. Over fifty percent of the difference in earnings between black and white males is due to differences in math scores. Effective school reforms can raise earnings by 3.5 percent. However, even accounting for cognitive skills, the model explains less than a third of the variation in earnings. This may be due to limitations in the measurement of skills, or the presence of other relevant factors in the labor market.

Hanushek and Woessmann (2007) survey the studies on the effect of education quality on individual incomes and find that in the United States, an increase in mathematics score by one standard deviation raises earnings by 12 percent. Citing Altonji and Pierret (2001), they state that the effect of achievement on earnings increases with experience. They also cite studies finding significant returns to numeracy and literacy in the UK and Canada. Surveying the evidence for developing countries, they conclude that returns to education quality may be larger than those for developed countries. They also find that educational attainment and school quality are complementary. Citing Hanushek and Zhang (2009), they show that the average returns to schooling for thirteen countries (mostly developed ones) decreases from 6 percent to 4.9 percent when controlling for education quality.

2.2.4 Omitted-ability bias

One problem in estimating returns to schooling is omitted-ability bias (Griliches, 1977). Assuming that the true equation is:

$$y = a + \beta S + \gamma A + u$$

where S is schooling and A is ability, omitting ability leads to an upward bias in the returns to schooling, β:

$$E\left(b_{ys}\right) = \beta + \gamma b_{AS} = \beta + \gamma \frac{Cov(AS)}{Var(S)}.$$

The bias results from the exogenous positive effect of ability on wages ($\gamma > 0$) and the positive relationship between schooling and ability (b_{AS}), assuming no other omitted variables. Griliches notes that there are two views on "ability". One equates "ability" to IQ, another considers it as an "unobserved latent variable that both drives people to get relatively more schooling and earn more income", and he variably describes it as "energy" and "motivation". To deal with omitted-ability bias, he suggests including a measure of "ability" such as IQ, or some other test score as an additional variable, or using other variables (and other tests scores) as instruments.[5] Using the National Longitudinal Survey for Young Men, Griliches finds that including ability reduces the returns to education by only 0.3 to 0.9 percent from 6.8 percent, depending on the measure of ability, a rather small contribution. He notes that measures of ability are quite unreliable and presents an alternative. As some unobservables are common among siblings, each can be an "instrument" for another.

Using measures of cognitive skills from the International Adult Literacy Survey for 13 OECD countries in 1994, 1996, and 1998, Hanushek and Zhang (2009) found that controlling for ability reduced returns to education in all countries. This is in part due to the positive effect of cognitive skills on wages. As literacy scores increased by one standard deviation, annual earnings rose by 24 percent in the US, and by between 5 to 15 percent in the other countries.

[5] First stage: $IQ = \alpha + \beta * Schooling + \gamma * Test2 + \delta * X + \epsilon$; Second stage: $log\,(wage) = \alpha + \beta * Schooling + \gamma * IQ + \delta * X + \epsilon$.

2.2.5 Measurement error

Another problem identified by Griliches (1977) is error in the measurement of schooling. Given the true wage equation:

$$y = \beta S^{*} + \gamma A + u$$

where S^{*} is the "true" unobserved schooling while observed schooling is $S = S^{*} + e$, where e is the measurement error. Omitted ability and measurement error together lead to the following estimate of returns to schooling:

$$E\left(b_{ys}\right) = \beta + \gamma b_{AS} - \lambda\beta = \beta + \gamma\frac{cov(A,S)}{\sigma_s^2} - \beta\frac{\sigma_e^2}{\sigma_s^2}$$

where λ is the proportion of the variation in observed schooling due to measurement error. Assuming $\beta > 0$, a positive variance in the measurement error leads to a downward bias in the estimated returns to schooling. Including ability in the equation yields the following estimate of β:

$$E\left(b_{ys}\right) = \beta - \lambda\beta/(1 - r_{AS}^2)$$

increasing the negative bias due to measurement error. As more variables related to schooling are included in the equation, the greater the bias due to measurement error.

2.2.6 Endogeneity of schooling

A problem related to ability bias is the endogeneity of schooling (Griliches, 1977). In maximizing wealth, which is essentially cumulated earnings which depend primarily on schooling and ability, the individual equates the present value of marginal income from additional schooling to the foregone income from spending a unit of time on schooling.[6] A uniform subsidy on the cost of schooling raises optimal schooling uniformly.[7] However, if more able persons obtain more human capital for additional

[6] The earnings function is $Y = e^{\beta S + \gamma A + u}$. The marginal benefit equals the marginal costs to schooling:

$$\frac{\partial Y}{\partial S} = \beta y\left(S\right) = ry\left(S\right),\ and\ \beta = r.$$

[7] A subsidy of TR reduces the cost of schooling: $\beta Y = r(Y - TR)$, raising optimal schooling to $S^{*} = \frac{1}{\beta}\left[-log\frac{r-\beta}{r} + logTR - \gamma A\right]$

schooling, optimal schooling rises with ability.[8] Assuming shocks to expected income and temporary changes in foregone income, optimal schooling will be negatively affected by unexplained variability in earnings, creating a downward bias in the estimate to returns to schooling.[9]

Card (1993) notes that educational attainment is not randomly distributed across the population but decided upon by individuals. As a result, return to schooling may be over- or under-estimated. Card (2001) developed a model in which individuals maximize lifetime utility which depends on consumption, schooling, and work; subject to an intertemporal budget constraint that equates consumption to earnings based on prior schooling plus earnings given current schooling less tuition cost. The first order conditions identify the marginal benefit and marginal cost of schooling, which, when equated, define optimal schooling. Differences in schooling can therefore arise both from differences in marginal benefits and differences in marginal costs of schooling. From the marginal benefit, Card derived a model for log earnings with an individual-specific intercept and schooling coefficient. He shows how individual heterogeneity in both the intercept and slope results in an inconsistent and biased estimate of returns to education. If the distributions of the individual-specific initial wages (with no schooling) and marginal returns to schooling are highly skewed/asymetric, schooling will be correlated with the error term in an ordinary least squares estimation and returns to schooling will be overestimated. People with greater returns to schooling have a motivation to obtain more education, which results in an upward bias in the returns to schooling. Even when there is no heterogeneity in the slope, OLS estimates still suffer omitted variable bias due to the correlation between ability and marginal cost of schooling. If marginal costs are less for people who can earn more for any given schooling, returns to education would be overestimated.

2.2.7 Instrumental variables

A standard solution to the endogeneity problem is Instrumental Variable regression where an instrumental variable affects education but not ability or the error term

[8] Greater ability reduces the cost of schooling: $\beta Y = r(Y - TR - \delta A)$ and can have a positive net effect on optimal schooling: $S^* = \frac{1}{\beta}\left[-log\frac{r-\beta}{r} + log(TR + \delta A) - \gamma A\right]$

[9] Expected income is subject to future shocks: $EY = Y_p \cdot e^u$; net foregone income is subject to current shocks: $FY = Y_p \cdot e^t - TR - \delta A$; permanent income is subject to unobserved factors μ_i: $Y_p = e^{\beta S + \gamma A + \mu_i}$; and optimal schooling is negatively related to shocks to permanent and expected income. $S^* = \frac{1}{\beta}\left[-log\frac{r-\beta}{r} + \log(TR + \delta A) - \gamma A - \mu_i - log\frac{1}{r}(re^{t_i} - be^{u_i})\right]$

in the earnings function (Card, 1999, 2001). Griliches (1977) uses test scores on "knowledge of the world of work", IQ, and family background as instruments and found that OLS underestimated returns to schooling. Unobserved ability or education may be related to family background characteristics such as parents education. Using data from the 1972-1996 General Social Survey, Card (1999) finds that completed education rises by 0.2 and 0.4 years for each additional year of schooling of either parent or both parents, respectively. About 30 percent of the observed variation in education is due to parents' education. However, it is unclear whether family background characteristics are valid instruments for education. If unobserved ability is correlated with schooling and family background, omitting family background will overestimate returns to education. Even when controlling for family background or using it as an instrument for education, return to education is still prone to upward bias unless ability and family background are uncorrelated.

While Griliches (1977) focuses on demand-side instruments for schooling, Card (2001) reviews the literature on the the supply-side determinants of schooling. Among the instruments used in recent literature are institutional differences in schooling, school leaving age, tuition, and school proximity. While the use of instruments is sufficient to ensure consistent estimates of returns to schooling, stronger assumptions are required in the case of heterogeneity, such as that instruments be uncorrelated with individual abilities and the schooling residual (Card, 2001). However, this is violated when instruments represent institutional factors that affect the relationship between ability and schooling. For instance, Card (2001) finds different correlation between schooling and IQ for men who grew up near a college and men who did not.

Angrist and Krueger (1991) used quarter of birth (i.e. quarter of the year) as an instrument for education. Quarter of birth determines when individuals start schooling and compulsory schooling laws identify when they can leave school. Individuals born later in the year on average have more schooling than those born earlier in the year and are more likely to graduate from high school. As post-secondary education is not bound by compulsory schooling laws, the quarter of schooling does not affect educational attainment beyond high school. Individuals born later in the year also have greater earnings. However, returns to schooling from instrumental variable regression are not statistically different from the OLS estimates.

Card (1993) uses college proximity as an instrument for educational attainment. Based on his finding that men who grew up near a college have higher education and earnings, he argues that college proximity reduces the costs and raises the benefits of schooling especially among the poor. Various OLS regressions including education, experience, race, region, family background (father and mother's education and their interaction), and family structure produce stable estimates of returns to schooling. However, these are subject to bias as schooling may be related to the disturbance in the earnings function for the reasons identified by Griliches (1977). Instrumental variable estimation with college proximity as an instrument for schooling raises returns to schooling by 25-60 percent over ordinary least squares. This suggests that returns to education are higher among the poor. Testing this indirect effect of college proximity on earnings via education against the direct effect on earnings, he concludes that college proximity has an exogenous effect on schooling.

An alternative solution, which is a generalization of the instrumental variable estimation, is the control function approach (Card, 1999). The residual of the regression of schooling on the instrumental variable is included as a regressor in the earnings function, leaving the relation between log earnings and schooling unaffected by the the unobserved heterogeneity. The control function approach makes certain assumptions regarding the relationships between ability and observed variables and includes terms that account for these (Card, 2001). Another alternative, the maximum likelihood approach, allows returns to schooling to vary flexibly with individual ability.

2.2.8 Fixed-effects estimation

As mentioned earlier, measures of ability can be unreliable (Griliches, 1977). If unobserved ability is common among siblings, each can be an "instrument" for another. Ashenfelter and Krueger (1994) estimate returns to education by relating the wage differential between twins to the difference in their schooling, eliminating the effect of unobserved family attributes that would be correlated with schooling. The econometric model is:

$$y_{1i} = \alpha X_i + \beta Z_{1i} + \mu_i + \varepsilon_{1i} \tag{2.1}$$

$$y_{2i} = \alpha X_i + \beta Z_{2i} + \mu_i + \varepsilon_{2i} \tag{2.2}$$

where y_{1i} and y_{2i} are the log wages for the twins, X_i are variables common to twins such as age, race, family background; Z_{1i} and Z_{2i} are variables that differ between twins such as education; μ_i is the unobserved component of wage common to twins; ε_{1i} and ε_{2i} are the unobserved individual components. The twins' education is related to unobserved family effects:

$$\mu_i = \gamma Z_{1i} + \gamma Z_{2i} + \delta X_i + \omega_i \tag{2.3}$$

where the coefficients γ measure the "selection effect". Substituting 2.3 into 2.1 and 2.2 and collecting terms:

$$y_{1i} = [\alpha + \delta]X_i + [\beta + \gamma]Z_{1i} + \gamma Z_{2i} + \varepsilon'_{1i} \tag{2.4}$$

$$y_{2i} = [\alpha + \delta]X_i + \gamma Z_{1i} + [\beta + \delta]Z_{2i} + \varepsilon'_{2i} \tag{2.5}$$

where $\varepsilon'_{1i} = \omega_i + \varepsilon_{1i}$ and $\varepsilon'_{2i} = \omega_i + \varepsilon_{2i}$. $\gamma > 0$ if families with higher wages are more likely to educate their children. Differencing equations 2.1 and 2.2 or 2.4 and 2.5 yields:

$$y_{1i} - y_{2i} = \beta(Z_{1i} - Z_{2i}) + \varepsilon_{1i} - \varepsilon_{2i}. \tag{2.6}$$

where the "fixed-effects" estimator, β, measures the structural (or selection-corrected) effect of the observables on earnings. Differencing eliminates the family effect in equations 2.1 and 2.2 and the selection effect in equations 2.4 and 2.5.

While fixed-effects estimation addresses omitted ability bias, it is subject to bigger measurement error. Considering the schooling of sibling n as reported by sibling m:

$$S_n^m = S_n + v_n^m$$

where S_n is the true schooling, v_n^m is measurement error. The OLS estimator is downward biased by an amount equal to the proportion of the variance in reported schooling due to the measurement error, $\frac{\sigma_v^2}{\sigma_v^2+\sigma_S^2}$, called the reliability ratio:

$$E(b) = \beta(1 - \frac{\sigma_v^2}{\sigma_v^2 + \sigma_S^2})$$

The fixed-effects estimator is:

$$E(b) = \beta(1 - \frac{\sigma_v^2}{(\sigma_v^2 + \sigma_S^2)(1 - \rho_s)})$$

where ρ_s is the correlation between the schooling of twins. The downward bias caused by measurement error is increased by the association between the twins' schooling. To reduce the bias due to measurement error, average reported schooling can be used as an instrument for self-reported schooling.

Ashenfelter and Krueger (1994)'s results show an OLS estimate of 8.4 percent and a fixed-effects estimate of 9.2 percent. The higher fixed-effects estimate suggests a negative relationship between schooling and ability contrary to expectation. Instrumental variable estimate range from 11.7 to 16.7 percent, up to almost twice as much as the least squares estimate. This suggests substantial downward bias in OLS and fixed-effects estimates due to measurement error.

Ashenfelter and Zimmerman (1997) relate the difference earnings between brothers, and fathers and sons, to the difference in their schooling. As members of the same family are more likely to share the same abilities and backgrounds than unrelated individuals, the technique effectively controls for unobserved family effects. The objective is to determine whether family attributes account for relationship between wages and education. They use data from the National Longitudinal Survey for 1978 and 1981 for brothers and sons, and 1966 for fathers. Their results for brothers show an upward bias of 25% in OLS estimates of return to education due to omitted family effects, and for fathers and sons an upward bias of 30% due to the omission. However, measurement error results in a downward bias of similar magnitude, resulting in small net bias. Ashenfelter and Rouse (1998) find fixed-effects estimates of returns to schooling for twins to be 30 percent lower than OLS estimates. In South Africa, Hertz (2003) found fixed-effects estimates to be 80.5% lower than OLS estimates for husband-wife pairs, 70.6% for parent-child pairs, and 63.2% for sibling pairs.

2.2.9 Previous estimates for the Philippines

A review of previous studies on returns to education in the Philippines is given in Table 2.1. Early studies found high returns to education in the Philippines in the 1980s-1990s (Table 2.2). Hossain and Psacharopoulos (1994) found the Mincerian returns to schooling to be 11.9 percent in 1988. Gerochi (2002) found even higher returns to schooling in 1995 at 14 percent. However, these figures are based on the elaborate method and the basic Mincerian neither of which control for other factors, thus leading to omitted-variable bias.

Nevertheless, these figures are comparable to those for some neighboring countries (Table 2.3). Returns to schooling were 12.4 percent in Thailand and 13.5 percent in South Korea in 1986, and 13.1 percent in Singapore in 1998. These figures are consistent with the global pattern of diminishing returns to income: returns to education decrease as a country's per capita income increases (Psacharopoulos and Patrinos, 2002). Psacharopoulos and Patrinos estimate the average returns to

Table 2.1: Previous Studies on Returns to Education in the Philippines

Author(s)	Year	Data	Method	Controls, IVs
Tan and Paqueo (1989)	1985	FIES	Elaborate (Private, Social), Mincerian	
Hossain and Psacharopoulos (1994)	1988	FIES, DECS	Elaborate (Private, Social), Mincerian	
Maluccio (1998)	1974, 1983, 1994	Bicol Multipurpose Survey (panel)	Mincerian, 2SLS	Schooling > HS, Age & Square, Male, Rural; IVs: Distance to schools, father's & mother's education, own farmland
Gerochi (2002)	1988, 1990, 1995	LFS, FAPE	Elaborate (Private, Social), Mincerian	
Schady (2000)	1998	APIS	Discontinuous Spline Function	Father's & Mother's education, Province
di Gropello et al. (2010)	1988-2006	LFS, FIES	Extended Mincerian	Male
Luo and Terada (2009)	2003-2007	LFS	Extended Mincerian	Sex, Sector, Occupation, Region, Time

Table 2.2: Mincerian Rates of Return to Education in the Philippines, Previous Studies

	Schooling	Primary	Secondary	Tertiary	Source
1985	8.1***				Tan and Paqueo (1989)
1988	11.9***	18.6***	10.2***	11.0***	Hossain and Psacharopoulos (1994)
1990 1995	14.2*** 14.0***				Gerochi (2002)
1994	7.3*** (OLS) 12.3*** (2SLS)	2.3	2.3	12.2***	Maluccio (1998)
1998	12.6*** (Basic) 11.0*** (+Prov.) 12.3*** (+Par.Ed)	14.2*** 25.2 1.9	15.8*** 39.5* 6.9	10.5*** 32.0*** 4.6*	Schady (2000)
1988-2006		8.0***	10.0***	18.0***	di Gropello et al. (2010)
2003-2007		2.0***	7.3***	15.3***	Luo and Terada (2009)

note: *** p<0.01, ** p<0.05, * p<0.1

schooling for low and high income countries at 10.9 and 7.4 percent, respectively. The world average return to a year of schooling is 10 percent. While diminishing returns to income has become a stylized fact, there does not seem to be an explicit justification. I proffer that the higher returns for developing countries are capturing greater heterogeneity in education quality, while estimates for developed countries may be "pure" returns assuming less heterogeneity in education quality and perhaps better data.

Earlier studies on returns by education level show that in the Philippines, primary education has the highest rate of return. Using the human-capital earnings function, Hossain and Psacharopoulos (1994) found returns to primary education at 18.6 percent against 10.2 for secondary and 11.0 for tertiary education in 1988. They find similar estimates using the Elaborate Method (Table 2.2). Using the Elaborate Method, Gerochi (2002) found returns to primary education at 24 percent, compared to 14.3 percent for secondary and 15.8 for tertiary education in 1995. This is consistent with Psacharopoulos (1993) and Psacharopoulos and Patrinos (2002) who find that primary education has the highest rate of return across all regions. The correspondingly high social returns to primary education (Table 2.4) have led some (e.g. Hossain and Psacharopoulos (1994)) to argue for prioritizing primary

Table 2.3: Rates of Return to Education in other countries in South-East Asia

Country	Year	Rate of Return	Source
Indonesia	1981 Susenas - Controls: experience and its square, education-experience, dummies for various education levels;	OLS: 15.0-17.0	Byron & Takahashi (1989)
	1995 SUPAS - Controls: Region of birth, cohort of birth	OLS: 7.0	Duflo (2000)
Singapore	1974	13.4	Psacharopoulos (1994)
	1998 Labor Force Survey - Controls: Experience and its square	OLS: 13.1	Sakellariou (2001)
South Korea	1974	12	Ryoo, Nam and Carnoy (1993)
	1976	6.5	Patrinos (1995)
	1979	14.1	Ryoo, Nam and Carnoy (1993)
	1980	11.1	Patrinos(1995)
	1986	13.5	Ryoo, Nam and Carnoy (1993)
Thailand	1971	10.4	Psacharopoulos (1994)
	1986	12.4	Patrinos (1995)
	1989	11.5	Patrinos (1995)
Vietnam (South)	1964	16.8	Psacharopoulos (1994)

Source: Psacharopoulos (1993); Psacharopoulos and Patrinos (2002) education. However, returns to primary education are based on the assumption that there are no foregone incomes below the age of ten. This assumption is questionable for poor countries like the Philippines where many early primary school age children work instead of going to schooling or do both.

Table 2.4: Private and Social Returns to Education, previous studies

	1985	1988	1990	1995
Private				
Primary	18.2	18.3	27	24
Secondary	13.8	10.5	14.3	14.3
University	14	11.6	15.5	15.8
Social				
Primary	11.9	13.3	15.1	15.5
Secondary	12.9	8.9	13.5	13.5
University	13.3	10.5	14.6	15.6
Source	Tan and Paqueo (1989)	Hossain and Psacharopoulos (1994)	Gerochi (2002)	Gerochi (2002)

Controlling for age and its square, sex, and urbanity, Maluccio (1998) finds return to schooling of 7.3 percent for the Bicol region in the Philippines in 1994. However, when treating schooling as endogenous, using distance to schools, father's and mother's education, own farmland as instruments, Maluccio finds a higher return to education of 12.6 percent. However, his study is not representative as it is limited to one poor region.

More recent studies find increasing returns to education in the Philippines from the late 1990s (Table 2.2). Unlike earlier studies, these use the extended earnings function, addressing non-linearities in returns to education. Schady (2000) found returns to primary education at 9.4 percent, lower than those for secondary (10 percent) and tertiary (16.7 percent) education. Controlling separately for father's and mother's education, and province, he finds returns to primary education as low as 6.2 percent. Similarly, di Gropello et al. (2010) found lower returns to primary education (6-8 percent), and rising returns to secondary (5-10 percent) and tertiary (16-18 percent) education between 1988 and 2006, controlling for sex.

Why have returns to primary education decreased and that for higher education increased? The former has been linked to rising enrolment and graduation rates (Asian Development Bank, 2007). This could mean that the increase in supply of labor with only primary education is driving down low-skill wages. The latter has been attributed to the effects of "globalization and skill-biased technological change" (di Gropello et al., 2010). Moreover, the rise in returns to secondary and tertiary education accrues mostly to the service sector, especially in emerging industries where professionals earns 3-4 times more than unskilled workers, compared to 2-2.5 times in traditional industries (Asian Development Bank, 2007).

Controlling for sex, major sectors, major occupations, and major regions, Luo and Terada (2009) found even lower returns to primary education at 2 percent compared to secondary (7.3 percent) and tertiary (15.3 percent) education for 2003-2007. However, classifying the sample into only three sectors (agriculture, manufacturing and service), three occupations (worker/laborer; officials, managers, executives; and professionals), and four regions (National Capital, other Luzon, Visayas, and Mindanao) may not capture much of the variation in earnings across the sample.

Previous studies on returns to education in the Philippines have focused on the quantity of education. However, while the Philippines fared better than some of its neighbors in terms of enrollment, it fared poorly in terms of income per capita and economic growth. This suggests that quantity of schooling does not sufficiently explain personal earnings and economic growth. Education quality may be as important as or more important than education quantity. Hanushek and Woessmann (2007) show that the Philippines is on the bottom rung of international student achievement test scores. This may explain poor economic growth in the 1980s-1990s. Moreover, the high returns to schooling and to primary education documented in the literature defy explanation. I argue that these are due to certain questionable assumptions and are capturing the effects of education quality and ability. Unlike previous studies, this study aims to account for quality of education, unobserved heterogeneity (i.e. ability bias) and the endogeneity of education (education and wages are jointly determined by unobserved factors) in the estimation of returns to education in the Philippines.

2.3 Model and Methodology

I begin by constructing age-earnings profiles for various education levels by regressing wage on age for different levels of education, with no constant, and controlling for year fixed effects (to account for inflation, putting estimates in 2001 prices). We then estimate returns to education using the short-cut method:

$$r_p = \frac{(\overline{Y_p} - \overline{Y_n})}{S_p(\overline{Y_n})};\ r_s = \frac{(\overline{Y_s} - \overline{Y_p})}{S_s(\overline{Y_p})};\ r_c = \frac{(\overline{Y_c} - \overline{Y_s})}{S_c(\overline{Y_s})};\ and\ r_g = \frac{(\overline{Y_g} - \overline{Y_c})}{S_g(\overline{Y_c})} \tag{2.7}$$

where $\overline{Y}$ is the average earnings across ages, S is the length of school cycle, and r is the rate of return on investment - for the subscripted level of education: n for no schooling, p for primary, s for secondary, c for college, and g for post-graduate where $S_p = 6$, $S_s = 4$, $S_c = 4$, and $S_g = 2$ are assumed.

I then estimate returns on education using the full-discounting method with the formula:

$$\begin{aligned}
\sum_{t=12}^{65} \frac{(Y_p - Y_n)_t}{(1+r_p)^{t-12}} &= \sum_{t=6}^{12} (Y_n)_t (1+r_p)^{t-6} \\
\sum_{t=16}^{65} \frac{(Y_s - Y_p)_t}{(1+r_s)^{t-16}} &= \sum_{t=12}^{16} (Y_p)_t (1+r_s)^{t-12} \\
\sum_{t=20}^{65} \frac{(Y_c - Y_s)_t}{(1+r_c)^{t-20}} &= \sum_{t=16}^{20} (Y_s)_t (1+r_c)^{t-16} \\
\sum_{t=21}^{65} \frac{(Y_g - Y_c)_t}{(1+r_g)^{t-21}} &= \sum_{t=21}^{22} (Y_c)_t (1+r_g)^{t-21}
\end{aligned} \tag{2.8}$$

where Y is average earnings for persons with the subscripted education at a particular age t. The return on education is the rate of return that equates the net present value of the income gain from a particular education to the net present value of the cost of that education. For example, benefits to primary education accrue to individuals at ages 12 to 65 while costs accrue at ages 6 to 11. As in the literature, we assume foregone earnings as the only costs of education.

I then fit a basic human capital earnings function (Mincer, 1974) relating the natural logarithm of wage on years of schooling (S), experience (T), and experience squared (T^2). Following this, we include control variables X in a step-wise manner, namely time (year), sex, marital status, region, sector, occupation, class of work, tenure, and urbanity:

$$ln(wage)_{it} = \alpha_{it} + \beta_1 S_{it} + \gamma_1 T_{it} + \gamma_2 T_{it}^2 + X\beta + e_{it} \tag{2.9}$$

where β_1 is the return to each year of schooling. Including control variables is expected to correct for omitted variable bias in returns to schooling as shown by Griliches (1977). For example, if urban areas have higher wages and more schooling relative to rural areas, omitting urbanity would overestimate the returns to schooling, and including this variable reduces returns to schooling. Similarly, if wages and schooling are higher in the national capital region, omitting the variable region would bias returns to schooling upward while including it would lower the returns.

I then estimate returns to schooling by year, sex, marital status, region, sector, occupation, class of work, tenure, and urbanity by interacting the human capital earnings function (schooling, experience and experience squared) with dummies for each characteristic (x) while controlling for other factors (X):

$$ln(wage)_{it} = x'_{itK}\alpha_{itK} + S'_{it}x'_{itK}\beta_K + T'_{it}x'_{itK}\gamma_{1K} + {T'_{itK}}^2 x'_{it}\gamma_{2K} + X\beta + e_{it} \tag{2.10}$$

where $x_{it} = (1\ x_{it2}\ x_{it3}\ ...\ x_{itK})'$ is a variable with K categories and $\beta_K = (\beta_1\ \beta_2\ ...\ \beta_k)'$. For example, for the variable sex, $K = 2$ (male and female). With a dummy variable for male, β_1 is the return to schooling for females and $\beta_1 + \beta_2$ is the return for males.

We then fit an extended human capital earnings function (Psacharopoulos, 1995) relating log wage to primary, secondary, and college and post-graduate education attainment, experience and experience squared:

$$\begin{aligned} ln(wage)_{it} = \alpha_{it} + \beta_1 Pri_{it} + \beta_2 Sec_{it} + \beta_3 Col_{it} + \beta_4 PGr_{it} \\ + \gamma_{1t} Exp_{it} + \gamma_{2t} Exp^2_{it} + e_{it} \end{aligned} \tag{2.11}$$

where returns to primary, secondary, college and post-graduate education are as follows:

$$r_p = \frac{\beta_1}{S_p}; r_s = \frac{\beta_2 - \beta_1}{S_s}; r_c = \frac{\beta_3 - \beta_2}{S_c}; r_g = \frac{\beta_4 - \beta_3}{S_g} \tag{2.12}$$

2.3.1 Accounting for education quality

To account for education quality, the basic model is interacted with a dummy variable for the test cohort and augmented with a measure of education quality (NEAT and NSAT scores) .

$$\begin{aligned} ln(wage)_{it} = \alpha_1 + \alpha_2 Cohort_{it} + \beta_1 Schooling_{it} + \beta_2 Cohort_{it} \cdot Schooling_{it} \\ + \gamma_1 Exp_{it} + \gamma_2 Cohort_{it} \cdot Exp_{it} + \gamma_3 Exp^2_{it} + \gamma_4 Cohort_{it} \cdot Exp^2_{it} \\ + Division'_{it}\delta + \pi Quality_{i,q} + X'_{it}\beta_{it} + e_{it} \end{aligned} \tag{2.13}$$

where $Cohort_{it}$ is a dummy for the test cohort, $Division_{it}$ is a dummy variable for the division (province or key city), the lowest level at which the test scores are available, and $Quality_{iq}$ is the overall mean percentage score (MPS) in NEAT or mean raw score (MRS) in NSAT for the division at time q, i.e. 1993-1999 for primary and 1997-1999 for secondary. β_1 is the return to quantity of schooling for the non-cohort and $\beta_1 + \beta_2$ is the return for the test cohort. π is the return to quality of primary or secondary education. Accounting for education quality is expected to reduce returns to education as education quality is positively related to wages ($\pi > 0$) and years of schooling. To account for education quality by subject, the overall scores in NEAT/NSAT are then replaced with subject-specific average test scores.

2.3.2 Accounting for ability

Controlling for observed heterogeneity in demographic and labor characteristics as well as education quality is pretty straightforward as data are available. It is a different matter to control for unobserved heterogeneity. For instance, it is suspected that higher returns to education in urban areas are driven by the higher ability of migrants from rural areas where the less able are left behind. However, the unavailability of internal migration data especially at the individual level hinders the testing of this hypothesis. This study is therefore significant as it accounts for ability in returns to education at the national level as well as between urban and rural areas, across regions and across demographic and labor characteristics.

To account for unobserved heterogeneity (e.g. omitted ability), I use sibling fixed-effects estimation. This is done by performing the regression in deviations from the mean ($\ddot{z_{hi}}$) obtained by taking the sibling average for each variable ($\bar{z}_h$) for each household h and subtracting this from the values (z_{hi}) for different individuals i:

$$\begin{aligned} ln(wage)_{hi} - \ln(\bar{wage})_h &= \alpha_{hi} - \bar{\alpha}_h + \beta_1 \left(Sch_{hi} - \bar{Sch}_h\right) + \gamma_1 \left(Exp_{hi} - \bar{Exp}_h\right) \\ &+ \gamma_2 (Exp^2_{hi} - \bar{Exp}^2_h) + \left(X'_{hi} - \bar{X}'_h\right)\beta + (e_{hi} - \bar{e}_h) \end{aligned}$$

$$ln(\ddot{wage})_{hi} = \beta_1 \ddot{Sch}_{it} + \gamma_1 \ddot{Exp}_{it} + \gamma_2 \ddot{Exp}^2_{it} + \ddot{X}_{it}\beta + \ddot{e}_i \tag{2.14}$$

Assuming that unobserved individual characteristics α_i are the same within households (siblings have very similar unobserved ability), $\alpha_{hi} = \bar{\alpha_h}$, we eliminate the unobserved fixed-effects such as ability that would otherwise bias returns to education upward. The fixed-effects estimates are compared to the benchmark Pooled OLS estimates where the individual effect is assumed to be identical across individuals: $\alpha_i = \alpha$. Fixed-effects estimates of returns to education are expected to be lower than OLS estimates as unobserved heterogeneity / ability bias would be driving OLS estimates upward as in earlier studies. The difference in the OLS and fixed-effects estimates for returns to schooling is considered as the returns to ability. On the other hand, fixed effects estimation is thought to increase the downward-bias due to measurement error:

$$E(b) = \beta(1 - \frac{\sigma_v^2}{(\sigma_v^2 + \sigma_S^2)(1 - \rho_s)})$$

To mitigate measurement error due to the correlation of the schooling of siblings, I employ fixed effects instrumental variable estimation. I use the predicted schooling between siblings from a regression of schooling on age and sex as an instrument for own schooling. This is based on the assumption that siblings have the same optimal level of schooling when controlling for individual level characteristics and that this is unrelated to the deviation in individual schooling.

An alternative to the fixed-effects model is the random effects model. The random effects model assumes strict exogeneity (i.e. independence between α_i and X_i) and considers the individual effect as part of the error term: $v_i = \alpha_i + e_i$. In this case, ability is not the same between siblings but randomly distributed across the population. In choosing between the within or fixed-effects and random-effects results, I use the Hausman test to determine whether α_i and X_i are correlated.

$$H = (\hat{\beta}_W - \hat{\beta}_{RE})' \left(AVar\left(\hat{\beta}_W\right) - AVar\left(\hat{\beta}_{RE}\right)\right)^{-1} (\hat{\beta}_W - \hat{\beta}_{RE})$$

Under the null hypothesis of strict exogeneity, the fixed-effects estimate, $\hat{\beta}_W$, is consistent and the random effects estimate, $\hat{\beta}_{RE}$, is efficient, and the test statistic H will be relatively small. Under the alternative hypothesis, $\hat{\beta}_W$ is consistent but $\hat{\beta}_{RE}$ is inconsistent, and the test statistic H will be significantly different from zero.

2.4 Data and Measurement

2.4.1 Labor Force Survey

The principal data source is the quarterly Labor Force Survey (LFS). Primarily designed to provide statistics on employment, unemployment, and underemployment at the national, regional, provincial and key city levels, the Labor Force Survey also provides data on work hours and daily wage, highest grade completed, age, sex, urbanity, region, sector, occupation, class of work, and tenure. It is the primary source for wage data at the individual level.

The LFS sample is drawn from a population that covers all households and their members, related or otherwise, except those in the "least accessible barangays". Since July 2003, the LFS has 17 domains corresponding to the administrative regions. The domains are further stratified by province, highly urbanized / independent component cities, by housing type, farming intensity, and average municipal income. The primary sampling unit (PSU) is the village or a combination of villages having no less than 500 households, whose probability of selection is proportional to its size. There are 2,835 PSUs, 330 of which are certain to be selected. The master sample is divided into four sub-samples or independent replicates, each comprising a quarter of the PSUs. Enumeration areas (EAs), each of about 150 households, are then selected within the sample PSUs. Finally, housing units are selected where up to three households are interviewed.

This study uses the July rounds of the LFS for 2001-2010. In pooling the data, I first rename variables to make them consistent across years to allow pooling. Second, I reclassify the 2001 and/or 2002 regions to match the classification for 2003-2010. This entails breaking up Region IV into IV-A and IV-B according to province and moving Aurora to Region III. It also entails moving Lanao del Norte to Region X; South Cotabato and Saranggani to Region XII; Basilan to Region XV except Isabela City which is retained in Region IX. The problem is that the labor force survey public use files (PUFs) for 2001-2006 do not have unique household IDs; only those for 2007-2010 have unique household IDs. I generate unique household IDs for 2001-2002 by grouping the observations by region, province, stratum, PSU, household control number. For 2003-2004, I group the observations by region, stratum, PSU, enumeration area, sample housing serial number, and household control number. Finally, for 2005-2006, the observations are grouped by PSU, municipality, barangay, enumeration area, sample housing serial number, and household control number. To merge the education quality data, we need information on province and municipality. The labor force survey public use files for 2001-2002 have data on provinces but not municipalities while the PUFs for 2005-2006 have both data, but those for 2003-2004 and 2007-2010 do not have data on provinces and municipalities. I extract data on provinces from the PSU for 2003-2004 and 2007-2010. I extract data on municipalities from the PSU for 2001-2004. Education quality data can be merged at the provincial and city levels for 2001-2006 but only at the provincial level for 2007-2010. Using provincial scores for cities may underestimate education quality in cities.

The pooled data set contains a total of 2,041,826 observations. However, we are only concerned with the employed and those less than 65 years old composed of 749,129 individuals. The sample distributions by employment status are given in Table 2.5 for the entire sample, for males, and for females. The proportion of employed decreased from 2002 to 2004 and appears to have increased substantially in 2005. However, the latter is due to a change in the definition of employment. The proportion of employed is higher among males than among females. Among the employed, only 44 percent have positive wages. This might exclude the self-employed, employers in family-owned farm or business, and those who work without pay in family-owned businesses. Table 2.6 shows the sample distribution by class of work. Over three-tenths (31.3 percent) are self-employed, 13.4 percent work without pay in family-owned farm or business, and4.4 percent are employers in family-owned farm or business. Over a third (36.9 percent) of the sample work in private establishments, 8.5 percent work in government / government corporation, and 5.1 percent work in private households, and 0.4 percent work with pay in family-owned farm or business.

Earnings are measured in terms of hourly wage, as annual or weekly wage would yield returns to education that include the effect of time spent at work. *Hourly wage* is computed as basic pay per day divided by the normal number of hours worked per day. Summary statistics are given in Table 2.7. The average wage rate grew by an average of 10 percent per year over the decade. In most years, while the standard deviation of the wage rate rose, it was generally below the mean except in 2006 and 2007 when the dispersion of the wage rate rose by three-fold and four-fold, respectively, before normalizing in 2008.

The education system of the Philippines that applies to the data comprised six years of elementary education starting around age 6, four years of secondary education starting around age 12, and tertiary education starting around age 16. The Philippine Constitution promotes the right to education and provides a system of free public education at the primary and secondary levels, and mandates primary education as compulsory. Starting in 2012, the Department of Education has implemented the K-12 program, a new system with Kindergarten, six years of primary education, four years of junior high school, and two years of senior high school.

The Labor Force Survey includes data on highest educational attainment but not on years of schooling. Years of schooling can be inferred from highest grade completed where No Grade is assigned 0, Incomplete Elementary = 3, Elementary Graduate = 6, Incomplete High School = 8, High School Graduate = 10, College Undergraduate = 12, College Graduate =14, and Completed Post-Graduate = 16.[10] The assignment of years of schooling given the educational attainment may be sub-

[10]Post-graduate includes completion of a Masters degree and PhD. Returns to post-graduate degrees can be sensitive to the number of years assumed.

ject to measurement error especially for those with incomplete elementary, high school or college education. For instance, incomplete elementary can mean at least one year and at most five years of schooling. Returns to incomplete elementary can be sensitive to the number of years assumed. Even assigning the median of three years of schooling may bias estimates of returns to schooling if the distribution of schooling is skewed. Measurement error is particularly a concern for those workers who no longer attend school. However, it can be mitigated for those who attended school during the reference period. For those with incomplete education currently studying, years of schooling can be estimated as age minus six. To address measurement error, I use fixed-effects instrumental variable estimation as discussed in the model.

The sample distribution by highest grade completed for 2001-2010 is given in Table 2.8. As of 2010, less than 15 percent have at least college education, with this share of workers increasing only slightly during the decade. Nevertheless, this shows Over 85 percent have less than complete college education distributed as follows: 13 percent have incomplete college education, 25 percent have complete secondary education, 14 percent have incomplete secondary education, 16 percent have complete primary education, 15 percent have incomplete primary education, and 2 percent have no schooling.

Consistent with the literature, *work experience* is used rather than age, as using age leads to omitted variable bias that would underestimate return to schooling. Work experience is computed as age minus years of schooling minus six (6), the normal age before the start of schooling. This assumes continuous work experience after schooling and does not account for periods of unemployment and unpaid work.

Sex is recoded as a dummy variable where Male = 1 and Female = 0. Table 2.9 shows the sample distribution by sex. Over 6 out of 10 of those employed and under 65 years old are males while almost 4 out of 10 are females. *urban* dummy is created where Urban = 1 and Rural = 0. A variable *Sector* is created by combining subsectors into major sectors.

The variable *region* is recoded to make the National Capital Region the reference. Table 2.10 shows the sample distribution by region from 2001 to 2010. Over half of the sample live in Luzon: 10.3 percent in the National Capital Region, 9.7 percent in CaLaBaRZon, 8.1 percent in Central Luzon, 5.6 percent in Bicol, 5.3 percent in Ilocos, 4.9 in Cagayan Valley, 4.4 percent in MiMaRoPa, and 4.2 percent in Cordillera. Less than one-fifth reside in Visayas: 7 percent in Western Visayas, 6.6 percent in Central Visayas, and 5.3 percent in Eastern Visayas. Almost three-tenths live in Mindanao: 5.9 percent in Northern Mindanao, 5.2 percent in Davao, 5.2 percent in SoCCSKarGen, 4.3 percent in Caraga, 4.2 percent in ARMM, and 4.1 percent in Zamboanga.

Table 2.11 shows the sample distribution by sector for 2001-2010. Over one-third of the sample work in agriculture; 33 percent in agriculture and hunting and 4.5 percent in fishing. Almost 15 percent are engaged in industry: 8.5 percent in manufacturing, 5.3 percent construction, 0.5 percent in mining and quarrying, and 0.4 percent in electricity, gas and water. Almost half are engaged in services: 18.4 percent in wholesale and retail trade, 7.3 percent in transport, storage and communications, 5 percent in public administration, defense, and social security, 4.8 percent in private households, 3.3 percent in education, 2.4 percent each in hotel and restaurant and other social and personal services, 2.2 percent in real estate and renting, 1.1 percent in health and social work, and 1 percent in financial intermediation.

A variable *occupation* is created by combining various occupations into major occupations. Table 2.12 shows the sample distribution by occupation from 2001 to 2010. Laborers and unskilled workers are the largest group comprising one third of the sample, followed by farmers, fishermen, and forestry workers who make up almost one-fifth. Officials, executives, managers and supervisors make up 12 percent followed by service and sales workers (9.3 percent), and trades and related work (8.4 percent). Plant and machine operators and assemblers make up 6.9 percent, clerks and professional each make up 4.5 percent, technicians and associate professionals constitute 2.53 percent and those in special occupations comprise 0.4 percent.

Table 2.13 shows the sample distribution by tenure / nature of employment. Over three-fourths of the workers in the sample have permanent job / business / unpaid family work. Almost one-fifth are engaged in short-term /seasonal / casual job / business / unpaid family work. 3 percent worked for different employer on day to day or week to week basis.

Table 2.14 shows the sample distribution by urbanity. Over half of the sample live in rural areas while a little less than half reside in urban areas.

To account for sibling fixed-effects, I use the complete July round of the 2007-2010 Labor Force Survey. I extract the sons and daughters from the sample, drop households with less than two siblings, and rank the siblings by age. This yields a pooled sample of 338,088 individuals over four years, 36,725 of whom have wages. To allow fixed-effects estimation, I use the household ID and year to generate the panel variable and the sibling rank as the time variable.

Table 2.5: Sample Distribution by Employment Status

Employment Status (%)	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Total											
Employed	50.04	49.95	50.41	44.52	60.46	60.17	59.51	60.26	60.12	59.84	54.78
Unemployed	3.96	4.01	3.92	3.27	4.53	4.79	4.48	4.23	4.41	4.01	4.11
Not in the labor force	46	46.04	45.67	52.22	35.02	35.05	36	35.51	35.47	36.15	41.1
Males											
Employed	60.98	60.57	63	54.81	74.35	73.03	72.51	73.53	72.76	73.11	66.99
Unemployed	4.78	4.95	4.45	4.02	5.5	5.95	5.61	5.27	5.41	5.06	5.03
Not in the labor force	34.24	34.49	32.55	41.17	20.15	21.03	21.89	21.2	21.83	21.83	27.98
Females											
Employed	39.11	39.45	37.65	33.98	46.5	47.25	46.35	46.94	47.53	46.45	42.51
Unemployed	3.14	3.09	3.38	2.49	3.54	3.62	3.35	3.18	3.41	2.95	3.19
Not in the labor force	57.75	57.45	58.96	63.52	49.95	49.13	50.3	49.88	49.05	50.6	54.3

Table 2.6: Sample Distribution by Class of Work, by Year (Frequency / Column Percentage)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Private household	4,017	3,967	4,803	3,406	3,281	3,742	3,659	3,724	4,240	3,580	38,419
	5.41	5.47	5.92	4.33	4.27	4.99	5.14	5.16	5.75	4.87	5.13
Private establishment	25,549	25,689	29,648	29,625	27,588	27,793	26,522	27,040	28,965	27,748	276,167
	34.39	35.4	36.53	37.63	35.89	37.09	37.26	37.46	39.28	37.77	36.87
Gov't/gov't corporatiion	6,985	6,757	6,427	6,166	6,077	5,961	6,071	6,184	6,438	6,539	63,605
	9.4	9.31	7.92	7.83	7.9	7.95	8.53	8.57	8.73	8.9	8.49
Self employed	23,505	21,649	24,873	24,217	25,721	24,025	22,625	22,882	21,932	22,974	234,403
	31.64	29.83	30.64	30.76	33.46	32.06	31.79	31.7	29.74	31.27	31.29
Employer in family farm/business	3,091	3,259	3,982	3,467	3,426	3,714	3,000	2,965	3,163	2,750	32,817
	4.16	4.49	4.91	4.4	4.46	4.96	4.21	4.11	4.29	3.74	4.38
With pay in family farm/business	352	293	583	282	272	315	393	188	220	182	3,080
	0.47	0.4	0.72	0.36	0.35	0.42	0.55	0.26	0.3	0.25	0.41
Without pay in family farm/business	10,795	10,962	10,851	11,554	10,511	9,393	8,905	9,192	8,782	9,693	100,638
	14.53	15.1	13.37	14.68	13.67	12.53	12.51	12.74	11.91	13.19	13.43
Total	74,294	72,576	81,167	78,717	76,876	74,943	71,175	72,175	73,740	73,466	749,129
	100	100	100	100	100	100	100	100	100	100	100

Table 2.7: Wage mean and standard deviation by year

Year	Mean	Std.Dev.
2001	29.2	24.3
2002	30	25.8
2003	28.4	26.1
2004	29.4	26.1
2005	30.5	25.6
2006	32.9	76.3
2007	34.4	106.1
2008	35	32.1
2009	36.4	35
2010	38.9	33.5

Table 2.8: Sample Distribution by Educational Attainment by Year (Frequency / Column Percentage)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
No Schooling	1,710	1,569	1,918	2,046	1,895	1,490	1,540	1,523	1,472	1,439	16,602
	2.3	2.16	2.36	2.6	2.47	1.99	2.16	2.11	2	1.96	2.22
Incomplete Elementary	12,222	11,514	15,559	15,344	12,921	12,763	11,934	11,583	11,869	11,253	126,962
	16.45	15.86	19.17	19.49	16.81	17.03	16.77	16.05	16.1	15.32	16.95
Complete Elementary	13,492	13,162	14,646	13,981	14,004	12,541	11,640	11,983	11,765	11,461	128,675
	18.16	18.14	18.04	17.76	18.22	16.73	16.35	16.6	15.95	15.6	17.18
Incomplete Secondary	10,182	10,431	11,648	11,221	10,902	11,045	10,257	10,171	10,448	10,091	106,396
	13.71	14.37	14.35	14.25	14.18	14.74	14.41	14.09	14.17	13.74	14.2
Complete Secondary	16,734	16,152	17,586	17,331	17,562	17,542	16,785	18,091	18,369	18,603	174,755
	22.52	22.26	21.67	22.02	22.84	23.41	23.58	25.07	24.91	25.32	23.33
Incomplete College	9,413	8,917	9,786	8,824	9,391	9,029	9,116	8,874	9,401	9,766	92,517
	12.67	12.29	12.06	11.21	12.22	12.05	12.81	12.3	12.75	13.29	12.35
Complete College	10,323	10,607	9,892	9,800	10,057	10,394	9,791	9,801	10,246	10,716	101,627
	13.89	14.62	12.19	12.45	13.08	13.87	13.76	13.58	13.89	14.59	13.57
Complete Master/PhD	218	224	132	170	144	139	112	149	170	137	1,595
	0.29	0.31	0.16	0.22	0.19	0.19	0.16	0.21	0.23	0.19	0.21
Total	74,294	72,576	81,167	78,717	76,876	74,943	71,175	72,175	73,740	73,466	749,129
	100	100	100	100	100	100	100	100	100	100	100

Table 2.9: Sample distribution by Sex, by year (Frequency / Column Percentage)

MALE	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Female	28,896	28,755	29,756	30,011	29,231	28,623	27,378	27,836	28,956	28,116	287,558
	38.89	39.62	36.66	38.13	38.02	38.19	38.47	38.57	39.27	38.27	38.39
Male	45,398	43,821	51,411	48,706	47,645	46,320	43,797	44,339	44,784	45,350	461,571
	61.11	60.38	63.34	61.87	61.98	61.81	61.53	61.43	60.73	61.73	61.61
Total	74,294	72,576	81,167	78,717	76,876	74,943	71,175	72,175	73,740	73,466	749,129
	100	100	100	100	100	100	100	100	100	100	100

Table 2.10: Sample Distribution by Region, by Year (Frequency / Column Percentage)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
National Capital	10.12	9.83	9.78	9.55	10.06	10.33	10.63	10.64	11.14	11.05	10.3
Ilocos	4.78	4.6	5.43	5.35	5.63	5.72	5.32	5.48	5.43	5.25	5.3
Cagayan Valley	4.15	4.16	4.96	5.28	4.89	4.95	5.09	5.03	5.04	4.9	4.85
Central Luzon	10.17	10.09	7.77	7.56	7.68	7.49	7.55	7.99	7.54	7.53	8.13
Bicol	5.06	5.07	5.79	5.76	6.06	5.69	5.58	5.83	5.58	5.35	5.58
Western Visayas	7.49	7.91	6.83	7.03	6.81	7.12	6.82	6.66	6.55	6.76	7
Central Visayas	5.57	5.67	6.29	6.58	7.16	7.09	6.7	6.87	6.68	6.99	6.56
Eastern Visayas	5.24	5.18	5.73	5.7	5.24	5.47	5.21	5.06	5.04	5.23	5.32
Zamboanga	3.34	3.91	4.46	4.26	4.04	4.13	4.06	4.24	4.48	4.14	4.11
Northern Mindanao	8.27	8.25	5.76	5.85	5.24	4.84	5.21	5.26	5.11	4.71	5.85
Davao	3.89	3.78	5.26	5.28	5.43	5.31	5.59	5.66	5.77	5.79	5.18
SoCCSKSarGen	4.76	3.95	5.39	5	5.14	5.07	5.37	5.16	5.17	5.31	5.04
Cordillera	3.98	3.95	4.07	4.11	4.28	4.12	4.51	4.27	4.44	4.65	4.23
ARMM	4.73	4.93	4.32	3.97	3.7	4.04	4.07	4.07	4.1	3.93	4.18
Caraga	3.77	3.62	4.45	4.82	4.39	4.26	4.33	4.3	4.2	4.46	4.27
CaLaBaRZon	10.63	10.69	9.44	9.22	9.75	9.85	9.55	9.15	9.35	9.5	9.71
MiMaRoPa	4.07	4.39	4.27	4.69	4.49	4.49	4.39	4.34	4.38	4.44	4.4

Table 2.11: Sample Distribution by Sector, by Year (Frequency / Column Percentage)

INDUSTRY	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Agriculture, hunting	29.45	28.71	35.18	35.21	35.23	33.88	32.86	33.26	31.62	31.94	32.79
Fishing	4.35	4.18	4.86	4.7	4.78	4.53	4.38	4.28	4.4	4.39	4.49
Mining and quarrying	0.33	0.33	0.43	0.58	0.41	0.5	0.51	0.58	0.63	0.7	0.5
Manufacturing	9.81	9.73	8.8	8.52	8.61	8.47	8.25	7.71	7.58	7.54	8.51
Electricity, gas and water	0.45	0.39	0.32	0.33	0.34	0.33	0.42	0.43	0.4	0.38	0.38
Construction	5.48	5.4	5.33	4.94	5.02	4.85	5.33	5.23	5.52	5.53	5.26
Wholesale and retail	19.61	19.98	16.87	17.86	17.89	18.86	18.32	18.34	18.14	18.55	18.42
Hotels and restaurant	2.34	2.4	2.27	2.23	2.39	2.36	2.43	2.62	2.78	2.66	2.44
Transport, storage and comm.	7.51	7.75	7.23	7.19	7.1	7.06	7.69	7.08	7.32	7.19	7.31
Financial intermediation	1.03	1.11	0.9	0.96	0.98	0.94	1	0.98	0.99	1.07	0.99
Real estate, renting	1.75	1.89	1.97	1.84	1.9	2.18	2.26	2.45	2.72	2.82	2.17
Public admin., defense	5.5	5.58	4.55	4.47	4.7	4.75	4.93	5.31	5.27	5.37	5.03
Education	3.75	3.7	2.95	3.29	3.15	3.05	3.34	3.21	3.39	3.51	3.33
Health and social work	1.2	1.18	1.11	1.08	1.1	1.02	1.01	1.05	1.16	1.22	1.11
Other social services	3.06	3.12	2.5	2.2	2.03	2.3	2.3	2.3	2.33	2.24	2.44
Private households	4.39	4.53	4.72	4.59	4.36	4.94	4.98	5.16	5.75	4.87	4.82
Extra-territorial org.	0.01	0.01	0	0	0.01	0	0	0	0.01	0	0

Table 2.12: Sample Distribution by Occupation, by Year (Frequency / Column Percentage)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Officials, executives, managers	7,670	8,169	7,973	8,480	8,600	9,274	8,273	9,124	9,731	9,670	86,964
	10.32	11.26	9.82	10.77	11.19	12.37	11.62	12.64	13.2	13.16	11.61
Professionals	3,856	3,759	3,309	3,441	3,318	3,093	3,085	3,157	3,324	3,458	33,800
	5.19	5.18	4.08	4.37	4.32	4.13	4.33	4.37	4.51	4.71	4.51
Technicians and Assoc. Professionals	1,985	2,194	2,129	2,004	1,814	1,936	1,869	1,789	1,871	1,862	19,453
	2.67	3.02	2.62	2.55	2.36	2.58	2.63	2.48	2.54	2.53	2.6
Clerks	3,500	3,451	3,552	3,073	3,193	3,138	3,292	3,304	3,525	3,861	33,889
	4.71	4.76	4.38	3.9	4.15	4.19	4.63	4.58	4.78	5.26	4.52
Service and Sales Workers	7,106	7,025	7,184	6,695	6,618	6,671	6,652	6,908	7,334	7,258	69,451
	9.56	9.68	8.85	8.51	8.61	8.9	9.35	9.57	9.95	9.88	9.27
Farmers, Fishermen, F	14,694	13,070	18,167	15,038	15,504	14,718	13,468	13,216	12,423	12,847	143,145
	19.78	18.01	22.38	19.1	20.17	19.64	18.92	18.31	16.85	17.49	19.11
Trades and Related Workers	7,602	7,045	7,247	6,412	6,257	5,861	5,838	5,529	5,526	5,566	62,883
	10.23	9.71	8.93	8.15	8.14	7.82	8.2	7.66	7.49	7.58	8.39
Plant & machine Operators	5,860	5,563	5,899	5,472	5,563	5,238	5,096	4,461	4,337	4,367	51,856
	7.89	7.67	7.27	6.95	7.24	6.99	7.16	6.18	5.88	5.94	6.92
Laborers and Unskilled workers	21,640	21,985	25,320	27,786	25,687	24,692	23,311	24,337	25,346	24,297	244,401
	29.13	30.29	31.19	35.3	33.41	32.95	32.75	33.72	34.37	33.07	32.62
Special Occupation	381	315	387	316	322	322	291	350	323	280	3,287
	0.51	0.43	0.48	0.4	0.42	0.43	0.41	0.48	0.44	0.38	0.44
Total	74,294	72,576	81,167	78,717	76,876	74,943	71,175	72,175	73,740	73,466	749,129
	100	100	100	100	100	100	100	100	100	100	100

Table 2.13: Sample Distribution by Tenure, by Year (Frequency / Column Percentage)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Permanent	58,296	56,778	57,063	61,415	62,376	56,427	54,176	57,019	57,433	59,197	580,180
	78.47	78.23	70.3	78.02	81.14	75.29	76.12	79	77.89	80.58	77.45
Short-term	13,501	13,456	20,613	14,806	12,242	15,784	14,573	13,030	14,083	12,651	144,739
	18.17	18.54	25.4	18.81	15.92	21.06	20.47	18.05	19.1	17.22	19.32
Different Employer	2,497	2,342	3,491	2,496	2,258	2,732	2,426	2,126	2,224	1,618	24,210
	3.36	3.23	4.3	3.17	2.94	3.65	3.41	2.95	3.02	2.2	3.23
Total	74,294	72,576	81,167	78,717	76,876	74,943	71,175	72,175	73,740	73,466	749,129
	100	100	100	100	100	100	100	100	100	100	100

Table 2.14: Sample Distribution by Urbanity, by Year (Frequency / Column Percentage)

URBAN	2001	2002	2007	2008	2009	2010	Total
Rural	30,581	30,704	40,084	40,648	40,757	40,788	223,562
	41.16	42.31	56.32	56.32	55.27	55.52	51.11
Urban	43,713	41,872	31,091	31,527	32,983	32,678	213,864
	58.84	57.69	43.68	43.68	44.73	44.48	48.89
Total	74,294	72,576	71,175	72,175	73,740	73,466	437,426
	100	100	100	100	100	100	100

2.4.2 NEAT 1993–2000, NSAT 1997–1999

Education quality is measured in terms of student achievement test scores. Student achievement test scores include the National Elementary Achievement Test (NEAT) and the National Secondary Achievement Test (NSAT). The NEAT is "designed to assess abilities and skills of Grade VI pupils in all public and private elementary schools in five (5) subject areas: English, Filipino, Science, HEKASI (Geography, History and Arts) and Mathematics." The NSAT "aims to assess the abilities and skills of fourth year students to determine their knowledge and capabilities in five (5) subject areas: English, Filipino, Science, Mathematics and Araling Panlipunan (Social Studies)." National and division (province and key city) level NEAT mean percentage scores are available for 1993-2000. National and regional level NSAT mean percentage scores are available for 1994-1999 while division level data are only available in mean raw scores for 1997 and 1999.

Average performance in the National Elementary Achievement Test (NEAT) across education divisions for 1993-2000 is shown in Table 2.15. Overall performance shows a general improvement over time, but with notable declines in 1996 and 1998-1999. Performance in Math rose sharply between 1994 and 1998 but fell more abruptly in 1999 before recovering in 2000. Progress in Science follows the overall trend but is more pronounced and is generally higher than the overall performance. Performance in English also follows the overall trend but is lower throughout the period. Progress in Geography, History and Arts largely trails the overall trend but became counter-cyclical to the overall trend in 1998-2000.

Average performance in the National Secondary Achievement Test (NSAT) across regions for 1994-1999 is shown in Table 2.16. Again, there is an over-all improvement over time but with a notable decline in 1998 during the Asian crisis suggesting that an economic crunch adversely affects education outcomes. Performance in Math closely resembles the overall trend but fell below the overall trend in 1998-1999. Progress in Science follows the overall trend but is lower throughout the period. Performance in English is counter-cyclical to the overall trend in 1994-1997 and pro-cyclical in 1998-1999. Progress in Filipino is the highest throughout the period and follows the overall trend in 1994-1997 but moved opposite the overall trend in 1998-1999. Average division level performance in NSAT for 1997 and 1999 is shown in Table 2.17. Overall performance improved from 1997 to 1999. This improvement is solely due to progress in Filipino. Unlike the regional averages, average division level scores in Math, Science, and English decreased between 1997 and 1999.

Table 2.15: National Elementary Achievement Test: Summary Statistics, Overall and by Subject, by Year

Variable	Obs	Mean	Std. Dev.	Min	Max
Overall 1993	138	42.0	4.4	33.4	54.4
Overall 1994	152	44.4	5.7	33.9	71.0
Overall 1995	152	47.6	5.5	35.5	63.6
Overall 1996	153	45.9	5.6	34.4	64.8
Overall 1997	153	51.1	7.3	38.6	73.9
Overall 1998	153	50.8	7.5	35.5	72.0
Overall 1999	153	49.6	7.1	36.9	74.8
Overall 2000	153	51.3	8.2	35.9	74.9
Math 1993	138	41.7	4.2	32.6	56.3
Math 1994	152	41.7	5.4	33.1	69.0
Math 1995	152	45.7	5.2	35.5	65.0
Math 1996	153	48.8	6.2	36.2	74.3
Math 1997	153	51.9	8.0	39.1	79.3
Math 1998	153	53.1	7.6	38.2	74.5
Math 1999	153	46.0	9.5	32.7	77.8
Math 2000	153	49.2	11.0	31.6	78.2
Science 1993	138	40.9	4.5	32.2	55.1
Science 1994	152	47.0	6.0	35.0	74.0
Science 1995	152	51.4	6.2	36.8	67.2
Science 1996	153	47.6	5.9	35.1	63.3
Science 1997	153	53.1	6.9	40.5	72.6
Science 1998	153	50.9	7.9	33.2	72.2
Science 1999	153	49.3	6.9	37.3	73.1
Science 2000	153	49.7	7.3	36.2	70.8
English 1993	138	39.5	5.2	30.4	56.2
English 1994	152	42.8	6.4	31.5	75.8
English 1995	152	45.0	6.3	31.9	68.0
English 1996	153	44.3	6.4	31.9	63.9
English 1997	153	49.6	8.0	35.8	75.2
English 1998	153	47.6	8.3	33.5	73.0
English 1999	153	47.1	8.1	33.2	75.6
English 2000	153	47.5	8.4	32.2	73.1
Geog., Hist, Arts 1993	138	45.9	5.1	35.4	58.8
Geog., Hist, Arts 1994	152	46.0	6.0	35.4	65.3
Geog., Hist, Arts 1995	152	48.4	5.4	36.7	62.7
Geog., Hist, Arts 1996	153	43.1	4.9	33.0	66.3
Geog., Hist, Arts 1997	153	49.7	6.9	37.0	73.2
Geog., Hist, Arts 1998	153	51.5	6.7	34.2	70.5
Geog., Hist, Arts 1999	153	55.3	6.8	42.0	75.2
Geog., Hist, Arts 2000	153	53.4	8.3	38.1	76.0
Filipino 1999	153	50.4	6.2	38.7	72.3
Filipino 2000	153	56.9	6.9	41.3	76.2

Table 2.16: National Secondary Achievement Test, Regional-level Summary Statistics, Overall/Total and by Subject

Variable	Obs	Mean	Std. Dev.	Min	Max
Total 1994	16	38.4	2.8	34.7	43.4
Total 1995	16	44.5	2.8	40.7	49.3
Total 1996	16	45.2	3.1	40.9	50.5
Total 1997	16	48.2	3.1	42.3	53.2
Total 1998	16	45.3	3.5	38.7	51.5
Total 1999	16	53.9	3.5	48.6	62.7
Math 1994	16	38.4	3.8	33.2	49.5
Math 1995	16	45.8	3.5	39.4	53.2
Math 1996	16	45.8	3.6	39.8	54.4
Math 1997	16	49.8	3.7	42.9	55.7
Math 1998	16	43.9	4.1	35.8	49.6
Math 1999	16	50.7	4.5	44.5	63.1
Science 1994	16	34.7	2.1	32.0	38.4
Science 1995	16	39.9	2.6	36.3	45.6
Science 1996	16	40.2	2.5	36.0	44.8
Science 1997	16	45.4	3.2	40.0	50.4
Science 1998	16	42.3	3.0	37.5	48.0
Science 1999	16	46.6	3.4	42.0	56.1
English 1994	16	40.4	2.9	36.5	45.3
English 1995	16	43.1	3.4	38.5	50.7
English 1996	16	47.6	3.4	42.1	53.8
English 1997	16	46.7	3.1	41.0	52.4
English 1998	16	43.9	3.6	37.2	49.7
English 1999	16	50.5	3.7	44.8	60.0
Filipino 1994	16	43.4	5.2	37.2	54.1
Filipino 1995	16	57.2	4.2	51.7	64.6
Filipino 1996	16	51.0	3.9	46.2	59.7
Filipino 1997	16	54.9	5.0	48.0	65.1
Filipino 1998	16	59.2	5.4	48.6	69.4
Filipino 1999	16	64.2	4.6	55.2	72.8
Social Studies 1999	16	57.5	4.1	51.4	65.1

Table 2.17: National Secondary Achievement Test, Division-level Summary Statistics, Overall/Total and by Subject

Variable	Obs	Mean	Std. Dev.	Min	Max
Overall 1997	152	122.9	13.6	92.2	174.7
Overall 1999	152	129.1	14.1	99.8	172.4
Math 1997	152	37.9	4.9	27.7	55.1
Math 1999	152	30.6	4.5	23.2	45.4
Science 1997	152	34.6	4.1	24.6	51.2
Science 1999	152	28.3	3.8	21.5	42.4
English 1997	152	33.3	3.8	26.3	47.1
English 1999	152	30.7	3.9	23.7	43.0
Filipino 1997	152	17.0	1.9	12.4	22.9
Filipino 1999	152	39.5	3.4	28.6	46.2
Vocational 1997	152	34.7	3.3	23.3	42.1
Social Studies 1999	152	35.2	3.4	25.1	42.8

To match the education quality data with labor outcomes, I merge the division level test scores and the individual level labor data. To identify the test cohort in the labor force survey, I deduct the test year from the survey year and add 12 years (the expected age at grade 6 when NEAT is taken, plus or minus one). So for LFS 2010, for example, the relevant age cohort for the 1993 NEAT is 28-30 [=(2010-1993+ 12)+/-1]. Only those who completed at least elementary school are included in the test cohort. NSAT data are available for 1997 and 1999. The examinees are graduating high school students whose expected age is 16 years (plus or minus one). So for LFS 2010, for example, the relevant age cohort for the 1997 NSAT is 30-32 [=(2010-1997+16)+/-1]. Only those who completed at least high school are included in the test cohort. The NEAT and NSAT test cohorts are generally younger than the non-cohort. Since the data on test scores are at the division level of the Department of Educations administrative system, I merge it with the LFS data at the corresponding province and city levels. While the assignment of education quality data is subject to measurement error as the actual age when the tests are taken may be different from the expected age, allowing for some deviation around the expected age should identify most of the relevant test cohorts, if not all, from the non-cohorts. However, this does not preclude measurement error arising from the assignment of test scores to workers who migrated from different provinces or cities.

2.5 Regression Analysis

Table 2.18 and Figure 2.10 show the age-earnings profile for the Philippines for 2001-2010.[11] Table 2.19 shows returns to education by level using various methods. Using the short-cut method, returns to education are 4.8 percent at the primary level, 9 percent at the secondary level, 28.2 percent at college level, and 16 to 32 percent at post-graduate level (depending on whether 2 or 1 year(s) of post-graduate cycle is assumed). Using the full-discounting method, returns to education decreases in all levels, to 2.7 for primary education, 6 percent for secondary education, 27.8 percent for college, and 14 to 28 percent for post-graduate. An extended human capital earnings function using age puts returns to primary education at 4.6 percent, secondary education at 6.6 percent, college education at 19.9 percent and post-graduate education at 20.5 percent. As expected, using age underestimates returns to education. Using experience increases returns to primary education to 4.3 percent, to secondary education to 7.7 percent, to college education to 21.2 percent, although decreasing returns to graduate education to 19.9 percent.

The basic Mincerian yields a high rate of return to schooling. Table 2.20 shows the regression results of the human capital earnings function with various controls. Controlling only for time (year), return to schooling stands at 11.8 percent, with the model explaining only a little over a third of the variation in earnings. The relatively high rate of return is comparable with earlier estimates (e.g. Hossain and Psacharopoulos (1994)) and consistent with the global pattern of diminishing returns to income: returns to education decrease as a country's per capita income increases (Psacharopoulos and Patrinos, 2002). Given the Philippines' low per capita income ($1411 in 2011), it is not surprising that its rate of return is high relative to the average for high income countries (7.4 percent). It is even higher than the average for low income countries (10.9 percent). However, the higher returns for developing countries may be capturing greater heterogeneity in education quality. These are grossly overestimated by the omission of important variables.

Much of the returns to schooling is capturing the effects of other variables. It is underestimated by the omission of the variable sex, but overestimated by the omission of marital status, region, sector, occupation, class, tenure, and urbanity. Omitting sex underestimates return to schooling because while males have higher wages than females, males have less schooling. Omitting marital status somewhat overestimates return to schooling as married, widowed, and separted individuals

[11] This is derived by regressing wage on age dummies controlling for year dummies (to account for inflation, effectively putting wages at 2001 prices).

Table 2.18: Age-Earnings Profiles, 2001-2010 (Pesos/Hour)

Age	NoSch	Primary	Secondary	College	PostGrad
6	12.2				
7	9.6				
8	41.3				
9	15.7				
10	12.6				
11	15.9				
12	12.8	17.9			
13	12.1	17.1			
14	9.2	14.2			
15	17.3	11.5			
16	10.7	13.4	10.9		
17	12.7	12.9	12		
18	11.3	13	14.2		
19	12.3	13.6	16.1	25.1	
20	11.7	14.8	17.4	27.9	
21	14.1	16.3	18.7	30.3	41.8
22	13.3	16.3	19.5	32.7	5.9
23	14.4	16.9	21	37	36.7
24	13.1	17.4	21.6	36.1	39
25	14.5	17.9	22.3	37.1	37.8
26	13	18.7	23	38.4	51.5
27	16.5	18.9	23.7	42.8	52
28	15.3	19.6	24.3	41.5	66
29	14.7	19	25.5	43	63.6
30	15.2	19.8	24.7	46.6	76.4
31	13.1	19.4	25.2	45.3	56.7
32	13.6	19.5	26	48.8	69.8
33	15.6	19.5	25.4	49.3	63.8
34	14.9	20.7	26.4	50.6	56.5
35	14.2	20	26.1	51.5	53.9
36	17	20.2	25.9	53.4	77.5
37	15.5	20.1	26.3	54.7	78
38	13.8	21.1	26.8	54.7	73.7
39	17.2	20.7	26.5	54.7	68.9
40	14.8	20.5	26.7	55.3	76
41	14.3	21.3	27.8	57.2	99.3
42	16.8	20.6	27.1	57.4	85.6
43	14.9	20.7	27.8	60	87.7
44	14.7	21.1	27.5	61.9	77.8
45	13.7	20.4	27.5	60.1	81.5
46	17	25.5	28.4	60.8	71
47	14.5	20	28.7	61.7	86.9
48	14.8	21.5	29.3	63	81.4
49	15.5	21.6	30.9	64.7	86.4
50	13.2	21.7	28.9	66.3	71.2
51	17.5	21.6	32	75.6	84.6
52	14.5	20.3	28.2	67.3	95.3
53	15.3	21	29.4	70.8	85.4
54	15.1	21.8	35.3	65.1	89.4
55	15	22.2	31.3	61.8	84.6
56	15.9	21.2	31.8	67.9	78.9
57	28.7	22.3	29.1	69.9	89.8
58	16.4	21.1	33	68	75.5
59	13.9	22.4	31.6	69.2	93.5
60	11.9	20.9	30.7	73	112.4
61	16.4	21.9	31.1	70.2	123.3
62	13.6	19.7	30.6	74.6	88.8
63	18.1	20	35.6	72.3	72.2
64	15.3	20.4	32.2	74.9	109.9
65	13	20.6	30.3	75	61.7

Figure 2.10: Age-Earnings Profiles, 2001-2010

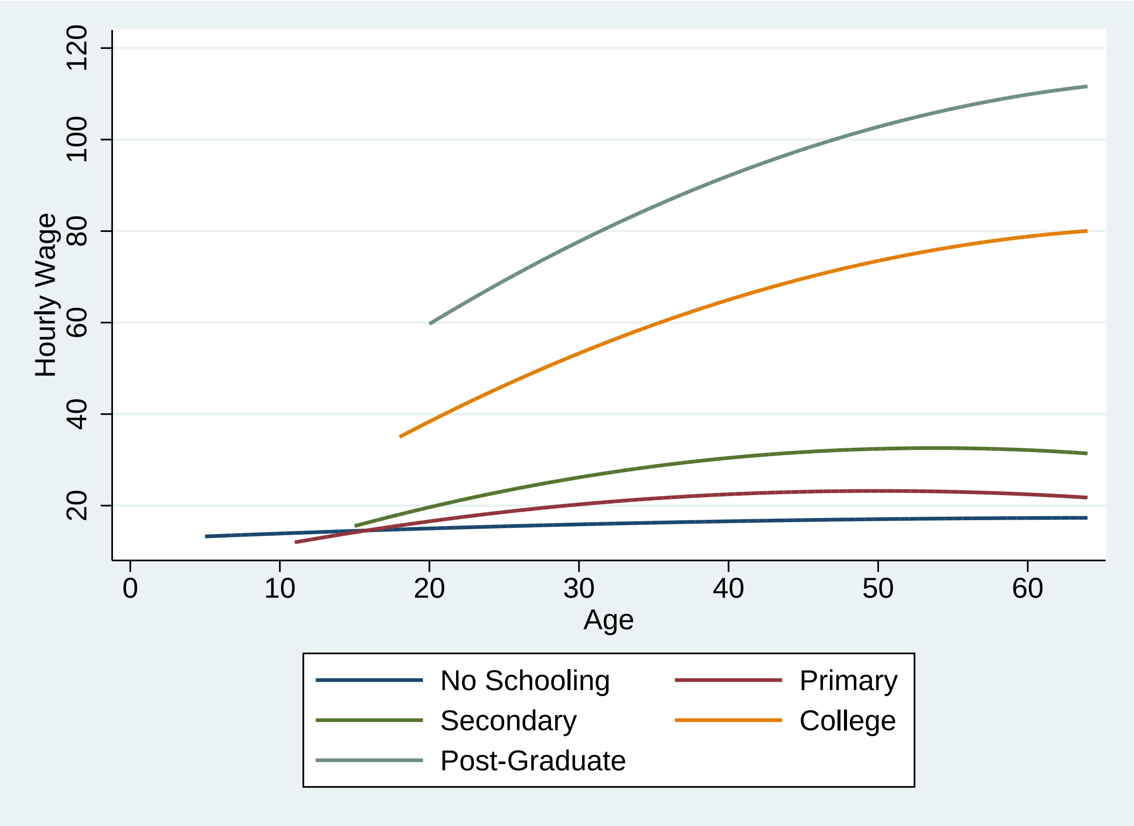


Table 2.19: Returns to Education, 2001-2010 (various methods)

			Extended Human Capital Earnings Function			
Level	Short-cut	Elaborate	Using Age	Using Experience	Incomplete	Complete
Elementary	4.8%	2.7%	4.2%	4.3%	3.5%	5.9%
Secondary	9.0%	6.0%	6.3%	7.7%	5.6%	9.8%
College	28.2%	27.8%	19.6%	21.2%	15.1%	27.3%
Post-graduate	16.0%	14.0%	22.3%	19.9%		19.9%

generally have more schooling and earn more than the reference single individuals. Omitting region overestimates return to education as most regions have lower wages and less schooling than the national capital region. Omitting sector overestimates return to education as most sectors have higher wages and more schooling relative to agriculture, hunting and forestry. Omitting occupation overestimates returns to education as most occupations have lower wages and less schooling than the reference occupation: officials of government and special interest organizations, corporate executives, managers, managing proprietors and supervisors. Omitting class of work somewhat overestimates return to education as it is driven by higher wages among workers in private establishments, government agencies and corporations, and paid workers in family-owned businesses relative to those working in private households. Omitting tenure overestimates return to education as short-term and workers with various employers earn less and have less schooling than permanent workers. Omitting urbanity overestimates return to education as urban workers earn more wages and have more schooling relative to their rural counterparts.

Accounting for sex, marital status, household position, region, sector, occupation, class of work, tenure, and urbanity raises the explanatory power of the model from about a third to over half the variation in earnings. Including sex (Table 2.20 column 2) raises the return to schooling by 0.6 percentage points and explanatory power of the model by 2 percentage points. Including marital status (column 3) reduces return to schooling by 0.23 percentage points and raises the explanatory power of the model by 0.4 percentage points. Including region (column 4) reduces return to schooling by 0.7 percentage points and raises the explanatory power of the model by 3.9 percentage points. Including sector (column 5) reduces return to schooling by 4.1 percentage points and increases the explanatory power of the model by almost 10 percentage points. Including occupation (column 6) reduces return to schooling by 2.6 percentage points and increases the explanatory power of the model by 5.4 percentage points. Including class (column 7) reduces return to schooling by 0.1 percentage point and raises the explanatory power of the model by 0.2 percentage points.

Returns to schooling was unchanged in the early part of the decade and rose only in the middle to latter part of the decade. Table 2.21 shows the human capital earnings function by year (2001 as reference). It shows that returns to schooling stood at 4.4 percent in 2001 and remained at this level until 2004. It rose by over 0.6 percentage points in 2005 and 2006, by over 0.2 percentage points in 2007 and 2008, and by over 0.5 percentage points in 2009 and 2010. The general upward trend is associated with the rising human capital composition of labor mentioned in section 2.4.

Returns to schooling are higher for females and lower for males. Table 2.22 shows the human capital earnings function by sex (female as reference). It shows an average return to schooling for females of 5.4 percent. Returns to schooling for males are 1.1 percentage points lower.

Returns to schooling are higher for singles and lower for married, widowed, divorced or separated individuals. Table 2.23 shows the human capital earnings function by marital status (single as reference). The return to schooling for single individuals is 4.8 percent. Returns to schooling for married, widowed, divorced or separated individuals are lower than that for singles.

Returns to schooling are highest in economic centers across the three main islands of the country. This may be capturing the higher ability of migrants from other regions. The rates of return to education are highest in the National Capital Region, Central Visayas and Northern Mindanao. Table 2.24 shows the human capital earnings function by region (national capital region as reference). It shows that wages are lower in most regions compared to the national capital, controlling for schooling. Only the wages in Central Luzon and CaLaBaRZon are not significantly different from that in the capital. Returns to schooling are also lower in most regions relative to the capital, except Central Visayas. The return to schooling in the national capital region is 5.9 percent while those in other regions are between 0.5 to 2.6 percentage points lower. Within Luzon, returns are highest in the national capital region. In Visayas, returns are highest in Central Visayas; while in Mindanao, returns are highest in Northern Mindanao. The foregoing regions are economic centers in their respective islands suggesting that the returns to education may be capturing higher ability among migrants from other regions.

Returns to schooling are highest in services, followed by industry and lowest in agriculture. Table 2.25 shows the human capital earnings function by sector (agriculture, hunting and forestry as reference). Relative to the reference, returns to schooling are higher in most other sectors except fishing where returns are the same, and construction and private households where returns are lower. Within the services sector, returns are highest (over 8 percent) in financial intermediation; public administration, defense and social security; extra-territorial organizations and hotel and restaurants. Returns are lowest (under 4 percent) in private households and other social and personal services. Within industry, returns are highest in electricity, gas and water, followed by manufacturing and mining and quarrying; returns are lowest in construction. In agriculture, returns are equally low in agriculture, hunting and forestry and in fishing.

Table 2.26 shows the regression results of the human capital earnings function by occupation. Returns to schooling are highest for officials in government, executives and managers at 13.6 percent, followed by special occupations (11 percent). Returns are also relatively high for technicians and associate professionals (9.6 percent), clerks (9.3 percent) and service and sales workers (9.1 percent). Returns to schooling are lowest for farmers, fishermen and forestry workers (1.9 percent), followed by laborers and unskilled workers (2.4 percent). Returns are also comparatively low for trades and related workers 3.4 percent), plant and machine operators and assemblers(4.5 percent), and ironically professionals (5 percent).

Across classes of work, returns are highest for employers in family farm or business and lowest among workers in private households. Table 2.27 shows the results by class. Return to schooling for workers in private households is only 1.8 percent while that for employers in family farm or business is 114 percent. Returns are also relatively high for the self-employed (17.9 percent) and workers in government or government corporations (8.9 percent). Returns are relatively low for workers with pay in family farm or business (3.6 percent) and private establishments (4.6 percent).

Permanent workers have higher returns to schooling than short-term workers and workers with various employers. Table 2.28 shows returns to schooling by tenure of employment. The return to schooling for permanent workers is 5.5 percent while those for short-term workers and workers with various employers only have half as much.

Returns to schooling in urban areas are higher than in rural areas. Table 2.29 shows returns to schooling by urbanity. The return to schooling for workers in urban areas is 5.2 percent while that for workers in rural areas is only 3.9 percent.

Table 2.20: Human Capital Earnings Function, with Controls

	(1) Coef./S.E	(2) Coef./S.E	(3) Coef./S.E	(4) Coef./S.E	(5) Coef./S.E	(6) Coef./S.E	(7) Coef./S.E	(8) Coef./S.E	(9) Coef./S.E
Schooling	0.1180***	0.1237***	0.1214***	0.1143***	0.0733***	0.0474***	0.0467***	0.0465***	0.0462***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Experience	0.0359***	0.0328***	0.0260***	0.0258***	0.0189***	0.0160***	0.0155***	0.0149***	0.0149***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Experience^2	-0.0005***	-0.0004***	-0.0003***	-0.0003***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	1.5520***	1.3834***	1.4203***	1.7240***	2.1427***	3.0138***	2.9421***	2.9519***	2.8909***
	(0.0052)	(0.0055)	(0.0056)	(0.0062)	(0.0061)	(0.0092)	(0.0128)	(0.0129)	(0.0171)
Controls:									
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sex		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region				Yes	Yes	Yes	Yes	Yes	Yes
Sector					Yes	Yes	Yes	Yes	Yes
Occupation						Yes	Yes	Yes	Yes
Class							Yes	Yes	Yes
Tenure								Yes	Yes
Urban									Yes
Adjusted R^2	0.3412	0.3613	0.3649	0.4036	0.5015	0.5558	0.5573	0.5578	0.5579
Observations	346616	346616	346510	346510	346510	346510	346510	346510	204871

Robust Standard Error in parenthesis. Legend: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.21: Human Capital Earnings Function, by Year

	Coef.	Robust S.E.
Constant	3.0109***	0.0162
2002	-0.0045	0.0155
2003	0.0447**	0.0153
2004	0.0515***	0.0152
2005	-0.0596***	0.0154
2006	-0.0399*	0.0162
2007	0.0719***	0.0163
2008	0.1370***	0.0159
2009	0.1076***	0.0158
2010	0.1997***	0.0158
Schooling	0.0439***	0.0008
2002 × Schooling	0.0009	0.0011
2003 × Schooling	-0.0018	0.0011
2004 × Schooling	0.0005	0.0010
2005 × Schooling	0.0064***	0.0011
2006 × Schooling	0.0061***	0.0011
2007 × Schooling	0.0027*	0.0011
2008 × Schooling	0.0023*	0.0011
2009 × Schooling	0.0056***	0.0011
2010 × Schooling	0.0051***	0.0011
Experience	0.0115***	0.0007
2002 × Experience	0.0012	0.0010
2003 × Experience	0.0004	0.0010
2004 × Experience	-0.0001	0.0010
2005 × Experience	0.0068***	0.0010
2006 × Experience	0.0073***	0.0011
2007 × Experience	0.0049***	0.0011
2008 × Experience	0.0046***	0.0011
2009 × Experience	0.0068***	0.0011
2010 × Experience	0.0036***	0.0011
Experience^2	-0.0001***	0.0000
2002 × Experience^2	-0.0000	0.0000
2003 × Experience^2	-0.0000	0.0000
2004 × Experience^2	0.0000	0.0000
2005 × Experience^2	-0.0001***	0.0000
2006 × Experience^2	-0.0001***	0.0000
2007 × Experience^2	-0.0001***	0.0000
2008 × Experience^2	-0.0001***	0.0000
2009 × Experience^2	-0.0001***	0.0000
2010 × Experience^2	-0.0001*	0.0000
Adjusted R^2	0.5582	
Observations	346510	

Controls: Sex, Marital Status, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.22: Human Capital Earnings Function, by Sex

	Coef.	Robust S.E.
Constant	2.8529***	0.0143
Male	0.2944***	0.0085
Schooling	0.0544***	0.0006
Male × Schooling	-0.0114***	0.0006
Experience	0.0144***	0.0004
Male × Experience	0.0000	0.0005
Experience^2	-0.0001***	0.0000
Male × Experience^2	-0.0001***	0.0000
Adjusted R^2	0.5585	
Observations	346510	

Controls: Year, Marital Status, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.23: Human Capital Earnings Function, by Marital Status

	Coef.	Robust S.E.
Constant	2.9207***	0.0137
Married	0.1414***	0.0087
Widowed	0.1212**	0.0443
Divorce/Separate	0.1345***	0.0403
Schooling	0.0481***	0.0005
Married × Schooling	-0.0021***	0.0006
Widowed × Schooling	-0.0056***	0.0016
Divorce/Separate × Schooling	-0.0004	0.0021
Experience	0.0180***	0.0005
Married × Experience	-0.0037***	0.0006
Widowed × Experience	-0.0056*	0.0026
Divorce/Separate × Experience	-0.0080**	0.0028
Experience^2	-0.0003***	0.0000
Married × Experience^2	0.0001***	0.0000
Widowed × Experience^2	0.0002***	0.0000
Divorce/Separate × Experience^2	0.0002**	0.0001
Adjusted R^2	0.5579	
Observations	346510	

Controls: Sex, Year, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.24: Human Capital Earnings Function, by Region

	Coefficient	Robust S.E.
Constant	2.8654***	0.0177
Ilocos	-0.1720***	0.0197
Cagayan Valley	-0.2819***	0.0180
Central Luzon	-0.0320	0.0166
Bicol	-0.3426***	0.0212
Western Visayas	-0.4512***	0.0178
Central Visayas	-0.4156***	0.0189
Eastern Visayas	-0.3124***	0.0213
Zamboanga	-0.2037***	0.0210
Northern Mindanao	-0.4228***	0.0192
Davao	-0.3436***	0.0203
SoCCSKSarGen	-0.3525***	0.0210
Cordillera	-0.1562***	0.0227
ARMM	-0.2747***	0.0367
Caraga	-0.3243***	0.0227
CaLaBaRZon	-0.0248	0.0171
MiMaRoPa	-0.1724***	0.0210
Schooling	0.0585***	0.0009
Ilocos × Schooling	-0.0192***	0.0015
Cagayan Valley × Schooling	-0.0150***	0.0013
Central Luzon × Schooling	-0.0189***	0.0012
Bicol × Schooling	-0.0124***	0.0015
Western Visayas × Schooling	-0.0078***	0.0013
Central Visayas × Schooling	-0.0011	0.0013
Eastern Visayas × Schooling	-0.0167***	0.0014
Zamboanga × Schooling	-0.0167***	0.0014
Northern Mindanao × Schooling	-0.0045**	0.0014
Davao × Schooling	-0.0121***	0.0014
SoCCSKSarGen × Schooling	-0.0132***	0.0015
Cordillera × Schooling	-0.0134***	0.0016
ARMM × Schooling	-0.0172***	0.0022
Caraga × Schooling	-0.0251***	0.0015
CaLaBaRZon × Schooling	-0.0134***	0.0012
MiMaRoPa × Schooling	-0.0257***	0.0015
Adjusted R^2	0.5594	
Observations	346510	

Results for interactions of region and experience and experience squared omitted.
Controls: Sex, Year, Marital Status, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.25: Human Capital Earnings Function, by Sector

	Coefficient	Robust S.E.
Constant	3.1648***	0.0136
Fishing	-0.0885**	0.0343
Mining and quarrying	-0.0245	0.0524
Manufacturing	-0.1886***	0.0143
Electricity, gas and water	-0.4918***	0.0536
Construction	0.2774***	0.0105
Wholesale and retail trade	-0.5063***	0.0163
Hotels and restaurants	-0.5347***	0.0284
Transport, storage and communications	-0.2809***	0.0196
Financial intermediation	-0.8098***	0.0595
Real estate, renting and business	-0.3321***	0.0315
Public admin., defence; social security	-0.7797***	0.0238
Education	-0.4252***	0.0400
Health and social work	-0.4204***	0.0559
Other social and personal services	0.0343	0.0338
Private households	-0.4687***	0.0183
Extra-territorial organizations	-0.5702	0.5473
Schooling	0.0254***	0.0006
Fishing × Schooling	0.0008	0.0028
Mining and quarrying × Schooling	0.0141***	0.0034
Manufacturing × Schooling	0.0310***	0.0011
Electricity, gas and water × Schooling	0.0506***	0.0036
Construction × Schooling	-0.0063***	0.0009
Wholesale and retail trade × Schooling	0.0425***	0.0013
Hotels and restaurants × Schooling	0.0561***	0.0022
Transport, storage and communications × Schooling	0.0400***	0.0014
Financial intermediation × Schooling	0.0817***	0.0042
Real estate, renting and business × Schooling	0.0458***	0.0022
Public admin., defence; social security × Schooling	0.0729***	0.0017
Education × Schooling	0.0408***	0.0029
Health and social work × Schooling	0.0345***	0.0040
Other social and personal services × Schooling	0.0095***	0.0023
Private households × Schooling	-0.0060***	0.0015
Extra-territorial organizations × Schooling	0.0666*	0.0335
Adjusted R^2	0.5703	
Observations	346510	

Controls: Sex, Year, Marital Status, Region, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.26: Human Capital Earnings Function, by Occupation

	Coefficient	Robust S.E.
Constant	1.7167***	0.0444
Professionals	1.1800***	0.0948
Technicians and Associate Professionals	0.3604***	0.0611
Clerks	0.2728***	0.0488
Service and Sales Workers	-0.0059	0.0457
Farmers, Fishermen, Forestry	0.7539***	0.0561
Trades and Related Workers	0.7292***	0.0446
Plant & machine Operators & Assemblers	0.7971***	0.0457
Laborers and Unskilled Workers	0.6616***	0.0438
Special Occupation	0.0368	0.0848
Schooling	0.1361***	0.0029
Professionals × Schooling	-0.0860***	0.0067
Technicians and Associate Professionals × Schooling	-0.0397***	0.0043
Clerks × Schooling	-0.0435***	0.0034
Service and Sales Workers × Schooling	-0.0454***	0.0032
Farmers, Fishermen, Forestry × Schooling	-0.1171***	0.0040
Trades and Related Workers × Schooling	-0.1017***	0.0030
Plant & machine Operators & Assemblers × Schooling	-0.0915***	0.0032
Laborers and Unskilled Workers × Schooling	-0.1124***	0.0030
Special Occupation × Schooling	-0.0263***	0.0059
Experience	0.0189***	0.0019
Professionals × Experience	0.0019	0.0021
Technicians and Associate Professionals × Experience	-0.0101***	0.0026
Clerks × Experience	-0.0103***	0.0021
Service and Sales Workers × Experience	0.0026	0.0021
Farmers, Fishermen, Forestry × Experience	-0.0103***	0.0031
Trades and Related Workers × Experience	-0.0050*	0.0020
Plant & machine Operators & Assemblers × Experience	-0.0148***	0.0021
Laborers and Unskilled Workers × Experience	-0.0055**	0.0019
Special Occupation × Experience	0.0104*	0.0048
Experience^2	-0.0002***	0.0000
Professionals × Experience^2	-0.0000	0.0000
Technicians and Associate Professionals × Experience^2	0.0002***	0.0001
Clerks × Experience^2	0.0002***	0.0000
Service and Sales Workers × Experience^2	-0.0001	0.0000
Farmers, Fishermen, Forestry × Experience^2	0.0001	0.0001
Trades and Related Workers × Experience^2	0.0000	0.0000
Plant & machine Operators & Assemblers × Experience^2	0.0002***	0.0000
Laborers and Unskilled Workers × Experience^2	0.0001	0.0000
Special Occupation × Experience^2	-0.0002	0.0001
Adjusted R^2	0.5702	
Observations	346510	

Controls: Sex, Year, Marital Status, Region, Sector, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.27: Human Capital Earnings Function, by Class

	Coefficient	Robust S.E.
Constant	2.9996***	0.0180
Private establishment	0.0895***	0.0169
Gov't/gov't corporation	-0.3974***	0.0238
Self employed	3.9139	3.0350
Employer in family farm or business	-11.4907***	0.0472
With pay in family farm or business	0.0056	0.0520
Without pay in family farm or business	0.2629***	0.0119
Schooling	0.0180***	0.0013
Private establishment × Schooling	0.0279***	0.0013
Gov't/gov't corporation × Schooling	0.0710***	0.0018
Self employed × Schooling	0.1607***	0.0255
Employer in family farm or business × Schooling	1.1189***	0.0040
With pay in family farm or business × Schooling	0.0182***	0.0038
Without pay in family farm or business × Schooling	0.0000	.
Experience	0.0239***	0.0008
Private establishment × Experience	-0.0125***	0.0009
Gov't/gov't corporation × Experience	-0.0053***	0.0012
Self employed × Experience	-0.4958	0.2965
Employer in family farm or business × Experience	0.0136***	0.0006
With pay in family farm or business × Experience	-0.0047	0.0036
Without pay in family farm or business × Experience	0.0000	.
Experience^2	-0.0003***	0.0000
Private establishment × Experience^2	0.0001***	0.0000
Gov't/gov't corporation × Experience^2	0.0000	0.0000
Self employed × Experience^2	0.0110	0.0065
Employer in family farm or business × Experience^2	0.0000	.
With pay in family farm or business × Experience^2	-0.0000	0.0001
Without pay in family farm or business × Experience^2	0.0000	.
Adjusted R^2	0.5647	
Observations	346510	

Controls: Sex, Year, Marital Status, Region, Sector, Occupation, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.28: Human Capital Earnings Function, by Tenure

	Coefficient	Robust S.E.
Constant	2.8057***	0.0134
Short-term	0.3261***	0.0094
Different Employer	0.3014***	0.0133
Schooling	0.0552***	0.0005
Short-term × Schooling	-0.0278***	0.0007
Different Employer × Schooling	-0.0286***	0.0012
Experience	0.0175***	0.0003
Short-term × Experience	-0.0110***	0.0006
Different Employer × Experience	-0.0062***	0.0009
Experience^2	-0.0002***	0.0000
Short-term × Experience^2	0.0001***	0.0000
Different Employer × Experience^2	0.0001***	0.0000
Adjusted R^2	0.5607	
Observations	346510	

Controls: Sex, Year, Marital Status, Region, Sector, Occupation, Class.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.29: Human Capital Earnings Function, by Urbanity

	Coefficient	Robust S.E.
Constant	2.9322***	0.0176
Urban	-0.0343***	0.0100
Schooling	0.0389***	0.0006
Urban × Schooling	0.0134***	0.0007
Experience	0.0155***	0.0005
Urban × Experience	-0.0014*	0.0006
Experience^2	-0.0002***	0.0000
Urban × Experience^2	0.0001***	0.0000
Adjusted R^2	0.5587	
Observations	204871	

Controls: Sex, Year, Marital Status, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 2.30: Human Capital Earnings Function with Primary Education Quality

	(1)		(2)		(3)	
	Coefficient	Robust S.E.	Coefficient	Robust S.E.	Coefficient	Robust S.E.
Schooling	0.0456***	0.0004	0.0443***	0.0004	0.0443***	0.0013
Experience	0.0148***	0.0003	0.0151***	0.0004	0.0151***	0.0007
Experience^2	-0.0002***	0.0000	-0.0002***	0.0000	-0.0002***	0.0000
NEAT Cohort			-0.1891***	0.0125	-0.1891***	0.0377
NEAT Cohort × Schooling			0.0167***	0.0009	0.0167***	0.0028
NEAT Cohort × Experience			0.0018	0.0018	0.0018	0.0029
NEAT Cohort × Experience^2			0.0002	0.0001	0.0002	0.0002
NEAT Score					0.0003	0.0022
Constant	2.6829***	0.0164	2.6985***	0.0166	2.6851***	0.1336
Adjusted R^2	0.5630		0.5635		0.5635	
Observations	346510		346510		346510	

Controls: Sex, Year, Marital Status, Division, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Model 3 Robust Standard Errors adjusted for 85 clusters at the Division level.

Table 2.31: Human Capital Earnings Function with Secondary Education Quality

	(1)		(2)	
	Coefficient	Robust S.E.	Coefficient	Robust S.E.
NSAT Score			0.0011	0.0007
Schooling	0.0450***	0.0014	0.0450***	0.0014
Experience	0.0157***	0.0005	0.0157***	0.0005
Experience^2	-0.0002***	0.0000	-0.0002***	0.0000
NSAT Cohort	-0.3421***	0.0386	-0.3422***	0.0387
NSAT Cohort × Schooling	0.0292***	0.0024	0.0292***	0.0024
NSAT Cohort × Experience	0.0060	0.0049	0.0061	0.0049
NSAT Cohort × Experience^2	-0.0003	0.0004	-0.0003	0.0004
Constant	2.6787***	0.0330	2.4882***	0.1307
Adjusted R^2	0.5635		0.5635	
Observations	346510		346510	

Controls: Sex, Year, Marital Status, Division, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Model 2 Robust Standard Errors adjusted for 85 clusters at the Division level.

2.5.1 Accounting for Education Quality

Accounting for primary education quality does not affect returns to schooling. Table 2.30 shows the regression results of including the quality of primary education. The benchmark model (column 1) estimates the human capital earnings function controlling for division (province and key city) fixed effects, year, sex, marital status, sector, occupation, class and tenure (robust standard errors are clustered at the division level). Compared to the model including only regional fixed effects (Table 2.20, column 8), this model reduces returns to schooling further to 4.56 percent. Column 2 disaggregates the human capital earnings function by cohort and non-cohort and yields return to schooling for the test cohort 1.7 percentage points higher than the reference return of 4.4 percent for the non-cohort. The higher return to the test cohorts may simply be due to their being younger than the non-cohorts. This is confirmed by the low and insignificant returns to their experience while non-cohorts have higher and significant returns to experience. Including NEAT score (column 3) does not change return to schooling and this measure of primary education quality does not affect earnings either. Division level test scores have no effect on earnings and returns to schooling apart from that already accounted for by division level fixed effects. For robustness check, I replace the overall NEAT score with individual subject scores. Only Math scores are significant but returns to schooling are virtually unaffected.

Accounting for secondary education quality also does not affect returns to schooling. Table 2.31 shows the results of including the quality of secondary education. Disaggregating the human capital earnings function by NSAT cohort and non-cohort shows that returns to schooling are higher for NSAT cohorts by 2.9 percentage points, although wages are lower among cohorts. Including NSAT score (column 2) does not affect returns to schooling and the quality of secondary education is also insignificant to earnings. For robustness check, I replace the overall NSAT score with individual subject scores. Only English and Filipino scores are significant but returns to schooling are also unchanged.

2.5.2 Accounting for Ability

Accounting for ability substantially reduces returns to schooling. Table 2.32 shows estimates of returns to schooling for 2007-2010 using OLS, fixed-effects and fixed effects instrumental variable estimation, controlling for year, sex, marital status, division, sector, occupation, class and tenure (fixed effects robust standard errors adjusted for clusters at the family level). The OLS estimate is 5.6 percent, higher than the estimate for the entire decade 2001-2010 (Table 2.30, column 1) due to increasing returns over time. On the other hand, fixed effects estimation substantially reduces returns to schooling to 3.1 percent. This indicates that almost half of what is hitherto known as returns to schooling is due to ability and other unobserved effects common between siblings. In other words, much of what employers pay for each additional year of schooling of their employees is due not so much for its productive content but for the ability it signals. This is much higher than that found in the US (25-30%, (Ashenfelter and Zimmerman, 1997; Ashenfelter and Rouse, 1998)) although less than that found in South Africa (76%, (Hertz, 2003)). It confirms the large unobserved heterogeneity I proferred earlier for developing countries.

However, as fixed effects estimation is argued to increase the bias due to measurement error, I also use fixed effects instrumental variable estimation using predicted schooling between siblings as an instrument for own schooling. The fixed effects instrumental variable estimated return to schooling is significant at 1 percent and only slightly higher than the fixed effects estimate, indicating negligible measurement error bias.

Accounting for ability increasingly reduces returns to schooling as the education level rises. Table 2.33 shows estimates by level of education. Least squares estimates show generally rising returns to education. Although returns decline from incomplete to complete elementary, they continually rise from 2 percent for com-

Table 2.32: Human Capital Earnings Function, Fixed Effects estimation

	Least Squares		Fixed Effects		FE IV	
	Coef.	R.S.E.	Coef.	R.S.E.	Coef.	R.S.E.
Schooling	0.0556***	0.0019	0.0314***	0.0047	0.0315***	0.0047
Experience	0.0239***	0.0016	0.0153***	0.0037	0.0154***	0.0036
Experience^2	-0.0005***	0.0001	-0.0003*	0.0001	-0.0003*	0.0001
Constant	2.5389***	0.2103	3.3760***	0.3244	3.3751***	0.3896
Adjusted R^2	0.5634		0.1973			
Observations	16501		16501		16501	

Controls: Sex, Year, Marital Status, Division, Sector, Occupation, Class, Tenure. Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

plete elementary to 24 percent for post-graduate. Random effects estimates are slightly less (i.e. by 2-6 percent) than least squares estimates for complete elementary until complete college and substantially less only for incomplete elementary (by 21 percent) and post-graduate (by 24 percent). Fixed effects estimates, on the other hand, are substantially lower than least squares estimates, and show no significant returns to primary education. Returns to incomplete secondary education are only significant at the 10 percent level, and compared to no schooling only stand at 0.3 percent. This suggests that those with primary education and incomplete secondary education are paid not for the productive content of their education but for the ability they signal. Nevertheless, returns to schooling remain positive, at 2.8 percent for complete secondary, 5.3 percent for incomplete college, 8.1 percent for college and 3.6 percent for post-graduate. This means that schooling has productive content only starting with secondary education completion. However, returns to schooling are substantially lower than the OLS estimates by 44 percent for complete secondary, 50 percent for incomplete college, by 34 percent for complete college, and by 85 percent for post-graduate. This means that much of the additional earnings normally attributed to schooling are due innate ability. While most of the income differential for college graduates is due to their education, most of those for college undergraduates and post-graduates can be attributed to their ability. In general, returns to ability increase as the education level increases. This is consistent with the signaling theory of education where higher education signals higher ability.

Accounting for ability reduces returns to schooling more for males than for females. Table 2.34 shows the human capital earnings function by sex. OLS estimation puts return to schooling for females at 7.8 percent while that for males is 5.1

percent lower. Random effects estimates are 3 percent lower for females and 2 percent lower for males. On the other hand, fixed effects estimates are 43 percent lower for females and 46 percent lower for males. While standard estimates of returns to schooling are higher for females than males, much more of these are due to ability for males.

Accounting for ability reduces returns to schooling across years by over half. Table 2.35 shows the human capital earnings function by year. OLS estimation puts return to schooling in 2007 at 5.9 percent with no significant change over the next three years. The random effects estimate for 2007 is 3 percent lower. On the other hand, the fixed effects estimate for 2007 is 55 percent lower with no significant change in the next three years.

Accounting for sibling fixed effects reduces returns to schooling across marital status by almost half. Table 2.36 shows the human capital earnings function by marital status. OLS estimation puts return to schooling for single individuals at 5.9 percent. The return to married workers are 10 percent lower while those for widowed and divorced/separated are not significantly different from those of singles. The random effects estimate of return to schooling for single individuals is 2 percent lower than the OLS estimate and returns to married, widowed, divorced/separated individuals are not significantly different to those of singles. The fixed effects estimate for singles is 48 percent lower than the OLS estimate and returns to married, widowed, divorced/separated individuals are not significantly different to those of singles.

Table 2.37 shows the human capital earnings function by region. OLS estimates of return to schooling are highest in regions considered as economic hubs, particularly the National Capital Region (NCR) (7.2 percent), Central Visayas (8.4 percent), Central Luzon (6.6 percent), CaLaBaRZon (6.6 percent), and Northern Mindanao (6.3 percent). Least squares estimates of returns to schooling are lowest for peripheral regions, namely MiMaRoPa (3.4 percent), Caraga (3.6 percent), ARMM (4.1 percent), Eastern Visayas (4.1 percent), Cagayan Valley (4.5 percent), and Ilocos (4.8 percent). Moderate returns to schooling accrue to intermediate regions, namely Western Visayas and Northern Mindanao (6.2 percent), SoCCSKSarGen (5.4 percent), Bicol (5.1 percent) and Zamboanga (4.9 percent). Random effects estimates are up to 5 percent lower than least squares estimates for most regions but higher for Zamboanga, Eastern Visayas, CaLaBaRZon, Davao, and Northern Mindanao.

Accounting for unobserved heterogeneity reduces returns to schooling across regions by almost four-tenths on average. The absolute reductions for regions considered as economic hubs (National Capital Region, Central Luzon, CaLaBaRZon, Central Visayas, and Davao), considered as returns to ability, average 2.6 percent while for the rest of the regions, the reduction averages only 1.8 percent. These indicate that the higher standard estimates of return to schooling in economic centers is driven by higher ability. As many of the workers in the capital are migrants from the other regions, this confirms the hypothesis that the high returns to education in cities / the capital is driven by the higher ability of migrants.

Fixed effects estimates of returns to schooling for most peripheral regions are lower than OLS estimates by 44–66 percent and lower than fixed effects estimates for economic centers. Returns to schooling are lowest for peripheral regions, between 1.5 to 2.2 percent. However, returns to ability are higher than returns to schooling.

Table 2.38 shows the returns to schooling by sector. OLS estimates show returns to schooling are lowest in agriculture, only 2.6 percent. Returns to schooling in sector vary from 2.6 percent in construction, 4.9 percent in mining and quarrying, 7.4 percent in manufacturing, to 9 percent in electricity, gas and water. Returns to schooling in most services are high, from 8.5 percent in wholesale and retail trade, 8.9 percent in transport, storage and communications, 9 percent in real estate, renting and business, 9.1 percent in public administration, defense and social security, 9.8 percent in financial intermediation, to 10 percent in hotels and restaurants. Returns to schooling are lowest in private households (5.2 percent) and health and social work (5.6 percent), followed by other social and personal services (6.4 percent) and education (7.5 percent). Random effects estimates are generally slightly lower than OLS estimates.

Accounting for ability reduces returns to schooling across sectors by over half on average. Fixed effects estimates are between 21 and 88 percent lower than OLS estimates. Returns to schooling remain lowest in agriculture and construction (both at 1.2 percent), are not significantly different in health and social work, other social and personal services, and even in education and financial intermediation. Returns to schooling remain higher in electricity, gas and water; public administration, defense and social security, hotel and restaurants; real estate, renting and business; wholesale and retail trade; and transport, storage and communications. Sectors with lowest returns to schooling have the highest relative reduction in returns to schooling (from OLS to fixed effects estimates). This means that returns to ability are relatively higher than returns to education in these sectors. On the other hand, returns to ability are lower than returns to schooling when return to schooling is high.

Table 2.39 shows returns to schooling by occupation. OLS estimates show highest returns to officials, CEOs, managers and supervisors at 16.6 percent, followed by service and sales workers, clerks, technicians and associate professionals, and workers in special occupations. Returns are lowest for farmers, fishermen and forestry workers (1.7 percent), and ironically, professionals (2.9 percent). In the middle are returns to trades and related workers (5.7 percent), plant and machine operators (6 percent) and assemblers and laborers and unskilled workers (3.4 percent). Random effects estimates are generally slightly lower than OLS estimates, as usual.

Accounting for ability reduces returns to schooling across occupations by two-thirds on average. Fixed effects estimates of returns to schooling are lower by at least 22 percent. However, the relative sizes across occupations are generally the same. Returns remain highest for officials, CEOs, managers and supervisors at 11.4 percent. This followed by special occupations with 7.6 percent, service and sales workers (6 percent), clerks (5.7 percent) and technicians and associate professionals (5.1 percent). Returns to schooling are lowest for plant and machine operators and assemblers (1.4 percent) and laborers and unskilled workers (1.7 percent). The reduction in returns to schooling are highest for professionals and farmers, fishermen and forestry workers, indicating highest relative returns to ability. Returns to ability (the difference between OLS and fixed effects estimates) are lower than returns to schooling where the latter are relatively high. When returns to schooling are low, returns to ability are higher.

Table 2.40 shows returns to schooling by class. OLS estimates range from 3 percent for workers with pay in family farm or business, to 5.1 percent for workers in private households and in private establishments, to 8 percent for workers in government or government corporations. Random effects estimates are slightly lower for the first and slightly higher for the last three. Fixed effects estimates are 12 percent lower on average than least squares estimates. Returns to workers in private households and private establishments decreased by over one-fourth (27 percent) while returns to workers in government agencies and corporations dropped by 17 percent. On the other hand, returns to paid workers in family-owned farm or business increased by less than one-fourth (23 percent). This suggests negative selection: the less able siblings tend to family farm or business rather than pursue independent careers.

Accounting for ability reduces returns to schooling by tenure by 47 percent on average. Table 2.41 shows estimates by tenure / nature of employment. The fixed effects estimate of return to permanent workers is 44 percent lower than the least squares estimate. Return to short-term workers are 50 percent lower while that for workers with various employers are 48 percent lower.

Accounting for ability reduces returns to schooling by urbanity by an average of 46 percent. Table 2.42 shows returns to schooling estimates by urbanity. Fixed effects estimates for rural areas are 49 percent lower than least squares estimates while estimates for urban areas are 42 percent lower. Returns to schooling remain higher for urban areas at 3.7 percent compared to 2.6 percent in rural areas. While the relative reduction is higher for rural areas, the absolute reduction is higher for urban areas confirming the hypothesis that rural to urban migrants are positively selected.

Table 2.33: Fixed Effects estimation, by Education

	Least Squares		Random Effects		Fixed Effects	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
Incomplete Elementary	0.1390***	0.0339	0.0387	0.0449	0.1103***	0.0322
Complete Elementary	0.1999***	0.0342	0.0858	0.0475	0.1739***	0.0328
Incomplete Secondary	0.2618***	0.0341	0.1081*	0.0474	0.2318***	0.0327
Complete Secondary	0.3617***	0.0341	0.1643***	0.0482	0.3283***	0.0328
Incomplete College	0.5770***	0.0348	0.2710***	0.0499	0.5341***	0.0335
Complete College	0.8199***	0.0354	0.4325***	0.0519	0.7733***	0.0343
Complete Master/PhD	1.3015***	0.1176	0.5043***	0.1356	1.1398***	0.1135
Experience	0.0227***	0.0011	0.0239***	0.0019	0.0237***	0.0012
Experience^2	-0.0005***	0.0000	-0.0005***	0.0001	-0.0005***	0.0000
Constant	2.5217***	0.1393	2.3821***	0.2899	2.4498***	0.1576
Adjusted R^2	0.5714		0.2415			
Observations	36706		36706		36706	

Controls: Sex, Year, Marital Status, Division, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.34: Fixed Effects estimation, by Sex

	Least Squares		Random Effects		Fixed Effects	
	Coef.	R.S.E.	Coef.	R.S.E.	Coef.	R.S.E.
Male	0.4681***	0.0297	0.4350***	0.0295	0.2970***	0.0426
Schooling	0.0783***	0.0022	0.0758***	0.0023	0.0446***	0.0035
Experience	0.0312***	0.0020	0.0312***	0.0019	0.0279***	0.0030
Experience^2	-0.0006***	0.0001	-0.0006***	0.0001	-0.0006***	0.0001
Male × Schooling	-0.0276***	0.0022	-0.0259***	0.0022	-0.0181***	0.0032
Male × Experience	-0.0104***	0.0023	-0.0094***	0.0023	-0.0070*	0.0034
Male × Experience^2	0.0003***	0.0001	0.0002**	0.0001	0.0002	0.0001
Constant	2.6646***	0.1311	2.5869***	0.1535	2.1397***	0.2932
Adjusted R^2	0.5546				0.2383	
Observations	36706		36706		36706	

Controls: Year, Marital Status, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.35: Fixed Effects estimation, by Year

	Least Squares		Random Effects		Fixed Effects	
	Coef.	R.S.E.	Coef.	R.S.E.	Coef.	R.S.E.
Constant (2007)	2.9344***	0.1349	2.8459***	0.1580	2.3215***	0.2982
2008	0.0936**	0.0318	0.0848*	0.0341	0.0000	.
2009	0.0746*	0.0321	0.0630	0.0343	0.0000	.
2010	0.1456***	0.0317	0.1317***	0.0342	0.0000	.
Schooling	0.0586***	0.0019	0.0567***	0.0020	0.0263***	0.0043
2008 × Schooling	-0.0023	0.0022	-0.0015	0.0024	0.0070	0.0063
2009 × Schooling	-0.0012	0.0023	-0.0004	0.0025	0.0025	0.0061
2010 × Schooling	-0.0012	0.0022	0.0004	0.0025	0.0081	0.0060
Experience	0.0232***	0.0024	0.0236***	0.0024	0.0179***	0.0036
2008 × Experience	0.0004	0.0032	0.0003	0.0033	0.0051	0.0053
2009 × Experience	0.0036	0.0032	0.0045	0.0033	0.0106*	0.0053
2010 × Experience	0.0047	0.0031	0.0045	0.0031	0.0085	0.0049
Experience^2	-0.0004***	0.0001	-0.0004***	0.0001	-0.0003**	0.0001
2008 × Experience^2	-0.0000	0.0001	-0.0000	0.0001	-0.0001	0.0002
2009 × Experience^2	-0.0001	0.0001	-0.0001	0.0001	-0.0004*	0.0002
2010 × Experience^2	-0.0002	0.0001	-0.0002	0.0001	-0.0003	0.0002
Adjusted R^2	0.5521				0.2356	
Observations	36706		36706		36706	

Controls: Sex, Marital Status, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.36: Fixed Effects estimation, by Marital Status

	Least Squares		Random Effects		Fixed Effects	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
Constant	2.9227***	0.1336	2.8273***	0.1562	2.3228***	0.2960
Married	0.1752***	0.0421	0.1382***	0.0407	0.0169	0.0622
Widowed	0.0297	0.2643	0.0469	0.2690	-0.4044	0.4258
Divorce/Separate	0.2667*	0.1103	0.2207*	0.1064	0.0868	0.1481
Schooling	0.0585***	0.0013	0.0571***	0.0013	0.0305***	0.0023
Married × Schooling	-0.0060*	0.0026	-0.0046	0.0025	0.0003	0.0039
Widowed × Schooling	-0.0024	0.0134	0.0021	0.0143	0.0379	0.0245
Divorce/Separate × Schooling	-0.0123	0.0074	-0.0094	0.0072	-0.0013	0.0097
Experience	0.0272***	0.0013	0.0273***	0.0013	0.0241***	0.0020
Married × Experience	-0.0096*	0.0039	-0.0070	0.0038	0.0013	0.0055
Widowed × Experience	-0.0067	0.0164	-0.0075	0.0155	0.0134	0.0208
Divorce/Separate × Experience	-0.0163*	0.0072	-0.0179**	0.0067	-0.0202*	0.0092
Experience^2	-0.0005***	0.0000	-0.0005***	0.0000	-0.0005***	0.0001
Married × Experience^2	0.0002	0.0001	0.0001	0.0001	-0.0000	0.0002
Widowed × Experience^2	0.0002	0.0003	0.0001	0.0003	-0.0004	0.0004
Divorce/Separate × Experience^2	0.0004*	0.0002	0.0004**	0.0002	0.0005**	0.0002
Adjusted R^2	0.5523				0.2362	
Observations	36706		36706		36706	

Controls: Sex, Year, Region, Sector, Occupation, Class, Tenure.

Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.37: Fixed Effects estimation, by Region

	Least Squares		Random Effects		Fixed Effects	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
Constant	2.8145***	0.1407	2.7144***	0.1626	2.3005***	0.2997
Schooling (NCR)	0.0723***	0.0032	0.0712***	0.0034	0.0442***	0.0075
Ilocos × Schooling	-0.0244***	0.0047	-0.0257***	0.0049	-0.0279**	0.0096
Cagayan Valley × Schooling	-0.0269***	0.0046	-0.0275***	0.0049	-0.0225*	0.0103
Central Luzon × Schooling	-0.0061	0.0039	-0.0084*	0.0043	-0.0146	0.0096
Bicol × Schooling	-0.0217***	0.0048	-0.0204***	0.0050	-0.0127	0.0129
Western Visayas × Schooling	-0.0107**	0.0041	-0.0114*	0.0045	-0.0197	0.0107
Central Visayas × Schooling	0.0120**	0.0043	0.0104*	0.0047	0.0030	0.0120
Eastern Visayas × Schooling	-0.0314***	0.0048	-0.0292***	0.0052	0.0031	0.0151
Zamboanga × Schooling	-0.0233***	0.0045	-0.0217***	0.0048	-0.0156	0.0110
Northern Mindanao × Schooling	-0.0107*	0.0047	-0.0087	0.0051	-0.0066	0.0133
Davao × Schooling	-0.0093*	0.0047	-0.0081	0.0049	-0.0059	0.0117
SoCCSKSarGen × Schooling	-0.0188***	0.0050	-0.0194***	0.0054	-0.0258*	0.0120
Cordillera × Schooling	-0.0232***	0.0056	-0.0236***	0.0059	-0.0208	0.0124
ARMM × Schooling	-0.0315***	0.0083	-0.0318***	0.0088	-0.0262*	0.0131
Caraga × Schooling	-0.0368***	0.0050	-0.0366***	0.0054	-0.0295*	0.0150
CaLaBaRZon × Schooling	-0.0062	0.0040	-0.0052	0.0043	-0.0036	0.0103
MiMaRoPa × Schooling	-0.0380***	0.0058	-0.0383***	0.0063	-0.0251*	0.0124
Adjusted R^2	0.5568				0.2401	
Observations	36706		36706		36706	

Controls: Experience and Experience Squared by Region, Sex, Year, Marital Status, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.38: Fixed Effects estimation, by Sector

	Least Squares		Random Effects		Fixed Effects	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
Schooling (Agriculture, hunting and forestry)	0.0263***	0.0019	0.0256***	0.0020	0.0115***	0.0032
Fishing × Schooling	0.0005	0.0086	0.0025	0.0090	0.0111	0.0158
Mining and quarrying × Schooling	0.0225**	0.0082	0.0188*	0.0085	-0.0188	0.0153
Manufacturing × Schooling	0.0472***	0.0036	0.0453***	0.0038	0.0291***	0.0064
Electricity, gas and water × Schooling	0.0637***	0.0120	0.0674***	0.0134	0.0592*	0.0259
Construction × Schooling	-0.0025	0.0027	-0.0003	0.0029	-0.0006	0.0055
Wholesale and retail trade × Schooling	0.0591***	0.0035	0.0570***	0.0036	0.0358***	0.0060
Hotels and restaurants × Schooling	0.0734***	0.0056	0.0701***	0.0057	0.0521***	0.0086
Transport, storage and communications × Schooling	0.0623***	0.0047	0.0585***	0.0048	0.0314***	0.0084
Financial intermediation × Schooling	0.0716***	0.0116	0.0629***	0.0120	0.0281	0.0228
Real estate, renting and business × Schooling	0.0637***	0.0074	0.0608***	0.0074	0.0383**	0.0118
Public admin., defence; social security × Schooling	0.0648***	0.0070	0.0656***	0.0073	0.0599***	0.0125
Education × Schooling	0.0483***	0.0117	0.0480***	0.0128	0.0389	0.0210
Health and social work × Schooling	0.0294**	0.0107	0.0298**	0.0112	0.0226	0.0227
Other social and personal services × Schooling	0.0375***	0.0092	0.0329***	0.0092	0.0026	0.0135
Private households × Schooling	0.0261***	0.0056	0.0278***	0.0058	0.0262**	0.0090
Extra-territorial organizations × Schooling	0.0000	.	0.0000	.	0.0000	.
Constant	3.1836***	0.1387	3.0917***	0.1627	2.5325***	0.3086
Adjusted R^2	0.5632				0.2489	
Observations	36706		36706		36706	

Controls: Experience and experience squared by Sector, Sex, Year, Marital Status, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.39: Fixed Effects estimation, by Occupation

	Least Squares		Random Effects		Fixed Effects	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
Constant (Gov't officials, executives and managers)	1.4969***	0.2947	1.4789***	0.2994	1.0944*	0.4454
Professionals	1.7306***	0.4454	1.6584***	0.4282	1.8431**	0.6248
Technicians and Associate Professionals	0.7196*	0.2990	0.6652*	0.2897	0.8347*	0.3747
Clerks	0.5635*	0.2712	0.5717*	0.2619	0.7249*	0.3358
Service and Sales Workers	0.1716	0.2651	0.1996	0.2568	0.4606	0.3317
Farmers, Fishermen, Forestry	0.9595**	0.3093	0.9373**	0.2993	1.1703**	0.4250
Trades and Related Workers	0.8036**	0.2655	0.8012**	0.2579	0.8778**	0.3356
Plant & machine Operators & Assemblers	0.9793***	0.2706	0.9831***	0.2637	1.2648***	0.3471
Laborers and Unskilled Workers	0.9562***	0.2626	0.9445***	0.2543	1.0223**	0.3285
Special Occupation	0.9247*	0.3904	0.7821*	0.3837	0.4776	0.4885
Schooling	0.1663***	0.0186	0.1594***	0.0180	0.1139***	0.0227
Professionals × Schooling	-0.1376***	0.0318	-0.1292***	0.0305	-0.1279**	0.0443
Technicians and Associate Professionals × Schooling	-0.0689**	0.0212	-0.0635**	0.0205	-0.0629*	0.0261
Clerks × Schooling	-0.0641***	0.0193	-0.0619***	0.0186	-0.0569*	0.0234
Service and Sales Workers × Schooling	-0.0614**	0.0189	-0.0595**	0.0182	-0.0539*	0.0231
Farmers, Fishermen, Forestry × Schooling	-0.1489***	0.0220	-0.1388***	0.0217	-0.1235***	0.0317
Trades and Related Workers × Schooling	-0.1097***	0.0189	-0.1053***	0.0183	-0.0859***	0.0235
Plant & machine Operators & Assemblers × Schooling	-0.1060***	0.0194	-0.1026***	0.0188	-0.1001***	0.0243
Laborers and Unskilled Workers × Schooling	-0.1326***	0.0187	-0.1260***	0.0181	-0.0966***	0.0229
Special Occupation × Schooling	-0.0699**	0.0269	-0.0612*	0.0265	-0.0384	0.0346
Adjusted R^2	0.5647				0.2481	
Observations	36706		36706		36706	

Controls: Experience and experience squared by Occupation, Sex, Year, Marital Status, Region, Sector, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.40: Fixed Effects estimation, by Class

	Least Squares		Random Effects		Fixed Effects	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
Constant (Private households)	2.8583***	0.1446	2.7326***	0.1667	2.1317***	0.3107
Private establishment	0.4454**	0.1428	0.5549***	0.1650	0.9843**	0.3087
Gov't/gov't corporation	0.2842	0.1573	0.3646*	0.1783	0.6046	0.3311
With pay in family farm or business	0.8630***	0.1915	0.9294***	0.2120	0.7632	0.4081
Schooling	0.0507***	0.0052	0.0522***	0.0053	0.0372***	0.0083
Private establishment × Schooling	0.0069	0.0053	0.0037	0.0055	-0.0086	0.0085
Gov't/gov't corporation × Schooling	0.0291***	0.0071	0.0291***	0.0072	0.0292*	0.0118
With pay in family farm or business × Schooling	-0.0204*	0.0100	-0.0244*	0.0105	-0.0145	0.0202
Experience	0.0433***	0.0052	0.0439***	0.0052	0.0406***	0.0076
Private establishment × Experience	-0.0196***	0.0053	-0.0197***	0.0053	-0.0192*	0.0077
Gov't/gov't corporation × Experience	-0.0145*	0.0067	-0.0147*	0.0066	-0.0066	0.0103
With pay in family farm or business × Experience	-0.0498***	0.0119	-0.0457***	0.0117	-0.0213	0.0168
Experience^2	-0.0009***	0.0002	-0.0008***	0.0002	-0.0008***	0.0002
Private establishment × Experience^2	0.0004*	0.0002	0.0004*	0.0002	0.0003	0.0002
Gov't/gov't corporation × Experience^2	0.0002	0.0002	0.0002	0.0002	0.0001	0.0003
With pay in family farm or business × Experience^2	0.0010***	0.0003	0.0010***	0.0003	0.0006	0.0005
Adjusted R^2	0.5534				0.2388	
Observations	36706		36706		36706	

Controls: Sex, Year, Marital Status, Region, Sector, Occupation, Tenure.

Legend: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.41: Fixed Effects estimation, by Tenure

	Least Squares		Random Effects		Fixed Effects	
	Coef.	Robust S.E.	Coef.	Robust S.E.	Coef.	Robust S.E.
Constant (Permanent)	2.7786***	0.1363	2.6838***	0.1597	2.2156***	0.3031
Short-term	0.2606***	0.0262	0.2536***	0.0277	0.1910***	0.0524
Different Employer	0.3979***	0.0418	0.4031***	0.0431	0.3641***	0.0829
Schooling	0.0682***	0.0014	0.0668***	0.0015	0.0380***	0.0027
Short-term × Schooling	-0.0252***	0.0019	-0.0243***	0.0020	-0.0166***	0.0038
Different Employer × Schooling	-0.0388***	0.0035	-0.0376***	0.0037	-0.0226***	0.0065
Experience	0.0282***	0.0015	0.0289***	0.0015	0.0276***	0.0024
Short-term × Experience	-0.0090***	0.0024	-0.0084***	0.0024	-0.0081*	0.0039
Different Employer × Experience	-0.0134***	0.0038	-0.0144***	0.0038	-0.0137*	0.0057
Experience^2	-0.0005***	0.0001	-0.0006***	0.0001	-0.0006***	0.0001
Short-term × Experience^2	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001
Different Employer × Experience^2	0.0003**	0.0001	0.0004***	0.0001	0.0004*	0.0002
Adjusted R^2	0.5551				0.2377	
Observations	36706		36706		36706	

Controls: Sex, Year, Marital Status, Region, Sector, Occupation, Class.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

Table 2.42: Fixed Effects estimation, by Urbanity

	Least Squares		Random Effects		Fixed Effects	
	Coef.	R.S.E.	Coef.	R.S.E.	Coef.	R.S.E.
Constant	2.8633***	0.1335	2.7673***	0.1567	2.2977***	0.3009
Urban	0.0152	0.0246	0.0099	0.0262	0.0000	.
Schooling	0.0505***	0.0014	0.0489***	0.0015	0.0259***	0.0029
Urban × Schooling	0.0139***	0.0018	0.0147***	0.0019	0.0112*	0.0045
Experience	0.0294***	0.0017	0.0292***	0.0017	0.0235***	0.0027
Urban × Experience	-0.0092***	0.0022	-0.0078***	0.0022	-0.0001	0.0037
Experience^2	-0.0006***	0.0001	-0.0006***	0.0001	-0.0005***	0.0001
Urban × Experience^2	0.0002**	0.0001	0.0002*	0.0001	-0.0001	0.0001
Adjusted R^2	0.5568				0.2363	
Observations	36706		36706		36706	

Controls: Sex, Year, Marital Status, Region, Sector, Occupation, Class, Tenure.
Legend: *** p<0.01, ** p<0.05, * p<0.1. Fixed-Effects Robust Standard Errors adjusted for clusters at the family level.

2.6 Summary

Previous estimates of returns to schooling in the Philippines have been high as expected for a low-income country without justification for this stylized diminishing returns to income. These high returns actually overestimate returns to education due to the omission of important variables. They are capturing the heterogeneity in returns across sex, marital status, region, sector, occupation, class, tenure and urbanity. Controlling for these factors reduces returns to schooling by three-fifths and raises the explanatory power of the model from a third to over half of the variation in earnings with sector, occupation, and region accounting for most of the variation.

Notwithstanding these corrections, the average returns conceal large variations across demographic and labor characteristics. Returns are higher for females than males, and higher for singles than married, widowed, divorced or separated individuals. Across regions, returns are higher in economic centers as these may be capturing higher ability of migrant labor. Similarly, returns are higher in urban areas than in rural areas. Across sectors, returns are highest in services, followed by industry, and lowest in agriculture. Across occupations, returns are highest for officials in government, executives and managers and lowest for farmers, fishermen and forestry workers. Across classes of work, returns are highest for employers in family-owned farm or business and lowest for workers in private households. Returns by employment tenure are higher for permanent workers than short-term workers and workers with various employers.

Controlling for education division (province and city) fixed effects reduces average returns a bit more and raises the explanatory power of the model further. However, education quality as measured by provincial and city level average primary and secondary achievement test scores is insignificant to earnings and does not affect returns to quantity of education.

Accounting for sibling fixed-effects further reduces returns to schooling by almost half, suggesting that most of what were hitherto known as returns to education are actually returns to ability. This confirms the idea of wage premiums for ability on top of returns to education. Moreover, there are no significant returns to primary education and barely significant returns to incomplete secondary education. Standard estimates for returns to primary and incomplete secondary education turn out to be returns to ability. This means that workers with only basic education are paid not so much for the productive content of their education but for the innate ability that allowed them to pursue primary or secondary education. This suggests that basic education plays a signaling rather than a productivity enhancing role. Truly significant returns to education accrue only starting from secondary education completion, through college, up to post-graduate education. Moreover, returns to ability generally rise as education level increases, consistent with the signaling theory of education where higher education signals higher ability.

Accounting for ability reduces returns to schooling across years by over half. It also reduces returns to schooling across sexes by almost half but more for males. Accounting for sibling fixed effects reduces returns to schooling across marital status, equalizing returns to singles, married, widowed, divorce or separated individuals. The greater reduction for singles suggest higher ability for younger cohorts. Accounting for ability reduces returns to schooling across regions by almost four-tenths on average. The reductions are highest in economic centers confirming the hypothesis that standard estimates of returns to schooling are driven by higher ability of migrant labor. Moreover, returns to schooling by urbanity decreased by 46 percent on average, with the higher absolute reduction in urban areas confirming positive selection. In light of the foregoing, we can conclude that migration is driven by higher returns to schooling in urban and economic centers and that migrants comprise the more able workers. As international migration is considered an alternative to internal migration, we can infer that higher returns to schooling are likewise driving overseas Filipino employment and that international migrants have greater ability than non-migrants. Returns to migration and education of overseas Filipino workers will be subject of the third study in this thesis.

Accounting for ability reduces returns to schooling across sectors by over half on average; the higher the least squares estimate, the higher the reduction confirming that ability is driving standard returns to schooling. Accounting for ability reduces returns to schooling across occupations by two-thirds on average. The reductions are highest for professionals and farmers, fishermen and forestry workers, indicating highest relative returns to ability. Returns to schooling by class are 12 percent lower on average, decreasing for workers in private households, private establishments and government agencies and corporations. However, returns to workers in family-owned farm or business increased suggesting negative selection. Returns to schooling by tenure decreased by 47 percent on average, decreasing for permanent and short-term workers as well as workers with various employers.

Chapter 3

Bricks without Straw: Determinants of Permanent and Temporary Migration of Filipinos

> "Therefore, say to the Israelites: 'I am the Lord, and I will bring you out from under the yoke of the Egyptians, I will free you from being slaves to them, and I will redeem you with an outstretched arm and with mighty acts of judgement...'" - Exodus 6:6

This study develops a demand and supply model of migration to estimate the impacts of proximate and underlying factors on both permanent and temporary migration from the Philippines using a Vector Auto-Regressive model. Results show that permanent migration is positively related to destination wages but also to domestic wages and employment indicating that they are positively selected from the local labor force. Permanent migration is negatively related to local demand for labor proxied by GDP per capita but also to local labor supply; positively related to destination demand for labor and negatively related to destination labor supply (both lagged two periods). Temporary migration is also positively related to destination and Philippine wages, negatively related to local labor demand and supply, and positively related to destination labor demand. However, temporary migration is also positively related to destination labor supply indicating that they are negatively selected in the destination labor force.

3.1 Context and Objectives

3.1.1 Stock of Filipino Migrants

The Philippines is among the top emigration countries. The United Nations defines migrants broadly as persons who changed their country of residence (Ozden et al., 2011). Various criteria are applied across destination countries in defining migrants, but mainly whether a person is 'foreign-born' or a 'foreign citizen'. The Philippines ranks ninth among the top source countries of international migrants [Table 3.1]. The World Bank's Bilateral Migration Matrix 2010 shows that the migrant stock from the Philippines totaled 4.3 million in 2010, comprising 2 percent of migrants world-wide. The Philippines is also the fourth largest remittance-receiving country in 2010, with USD 21.3 Billion in remittances (World Bank, 2011). In 2009, remittances amounted to 12 percent of GDP.

Table 3.1: Top 10 Sources of Migrants Worldwide

Source Country	Migrant Stock	Share (%)
Mexico	11,859,236	5.5
India	11,360,823	5.3
Russian Federation	11,034,681	5.1
China	8,344,726	3.9
Ukraine	6,525,145	3.0
Bangladesh	5,384,875	2.5
Pakistan	4,678,730	2.2
United Kingdom	4,666,172	2.2
Philippines	4,275,612	2.0
Turkey	4,261,786	2.0
World Total	215,763,573	

Source: World Bank Bilateral Migration Matrix 2010

The stock of Filipino migrants grew 30-fold in the past 50 years.Table 3.2 shows the stock of Filipino migrants over time. In 1960, the stock of migrants from the Philippines was only 155,651. This grew by over 2.5 times to 400,889 in 1970 and again by almost 2.5 times to 980,831 in 1980. It further doubled to over 2 million in 1990 and rose by 1.5 times more to over 3 million in 2000. The Filipino migrant stock grew by almost 20 times between 1960 and 2000 while the global migrant stock grew by only 1.8 times. By 2010, there were 4.3 million Filipino migrants worldwide. The migrant stock also grew relative to the population from 0.6 percent in 1960 to 4.6 percent in 2010. The emigration rate increased from 6 per thousand people in

1960 to 11 per thousand in 1970. It continued to rise to 20 per thousand in 1980 and to 32 per thousand in 1990. It further rose to 38 per thousand in 2000 and stood at 44 per thousand in 2010.

Table 3.2: Filipino Migrant Stock, 1960-2010

	Migrant Stock	Annual Growth (%)	Emigration Rate
1960	155,651	-	5.9
1970	400,889	25.8	11.1
1980	980,831	24.5	20.3
1990	2,048,870	20.9	32.0
2000	3,083,240	15.0	38.2
2010	4,275,612	13.9	43.8

Source: World Bank Bilateral Migration Database 1960-2000, Bilateral Migration Matrix 2010

The recent growth of migrant stock remains high. The Philippine government's stock estimate of overseas Filipinos is over twice as much as the World Bank data. The Commission on Filipinos Overseas puts the stock of overseas Filipinos at 9.45 million in 2010, almost 2.2 times that of the World Bank. The discrepancy lies in the fact that while the World Bank data only count the Philippine-born or Filipino citizens, the Commission counts all those of Filipino ancestry (International Organization for Migration, 2013). The Philippine government includes in its definition of overseas Filipino workers (migrant workers), their dependents abroad and other Filipino nationals.[1]

Table 3.3 gives the stock estimates of overseas Filipinos from the Philippine government for 1997-2011. The annual stock of overseas Filipinos grew from almost 7 million in 1997 to about 7.8 million in 2003 with an annual average growth rate of 1.9 percent. The stock fell by 8 percent in 2004 and further by 2.3 percent back to 7 million in 2005. However, it has since rebounded growing by an average of 5.7 percent to 8.6 million in 2009. It further grew by 10.4 percent per year to 10.5 million in 2011. While emigration rate has decreased from 88 per thousand in 1998 to 86 per thousand in 2003 and further to 75 per thousand in 2005, it has rebounded since, reaching 85 per thousand in 2009, and rising steeply to 99 in 2011. These trends beg the question why has emigration fallen in the earlier period and sharply in the mid-2000s? And, what caused the resurgence in emigration in recent years?

[1] RA 8042: Migrant Workers and Overseas Filipinos Act of 1995 as amended by RA 10022

Table 3.3: Stock of Overseas Filipinos, 1997-2011

YEAR	PERMANENT			TEMPORARY			IRREGULAR			TOTAL		Emig.
	Stock	Share	Growth	Stock	Share	Growth	Stock	Share	Growth	Stock	Growth	Rate
1997	2,153,967	30.9		2,940,082	42.2		1,880,016	27.0		6,974,065		87.4
1998	2,333,843	32.4	8.4	2,961,254	41.1	0.7	1,913,941	26.5	1.8	7,209,038	3.4	88.3
1999	2,482,470	34.0	6.4	2,981,529	40.9	0.7	1,828,990	25.1	-4.4	7,292,989	1.2	87.5
2000	2,551,549	34.6	2.8	2,991,125	40.5	0.3	1,840,448	24.9	0.6	7,383,122	1.2	86.8
2001	2,736,528	36.9	7.2	3,049,622	41.1	2.0	1,625,936	21.9	-11.7	7,412,086	0.4	85.5
2002	2,807,356	37.0	2.6	3,167,978	41.8	3.9	1,607,170	21.2	-1.2	7,582,504	2.3	85.6
2003	2,865,412	36.9	2.1	3,385,001	43.6	6.9	1,512,765	19.5	-5.9	7,763,178	2.4	85.9
2004	3,204,326	44.9	11.8	2,899,620	40.6	-14.3	1,039,191	14.5	-31.3	7,143,137	-8.0	78.2
2005	3,407,967	48.8	6.4	2,943,151	42.2	1.5	626,389	9.0	-39.7	6,977,507	-2.3	75.2
2006	3,568,388	49.0	4.7	3,093,921	42.5	5.1	621,713	8.5	-0.7	7,284,022	4.4	77.0
2007	3,693,015	47.6	3.5	3,413,079	44.0	10.3	648,169	8.4	4.3	7,754,263	6.5	80.2
2008	3,907,842	47.7	5.8	3,626,259	44.3	6.2	653,609	8.0	0.8	8,187,710	5.6	83.1
2009	4,056,940	47.3	3.8	3,864,068	45.0	6.6	658,370	7.7	0.7	8,579,378	4.8	85.4
2010	4,423,680	46.8	9.0	4,324,388	45.7	11.9	704,916	7.5	7.1	9,452,984	10.2	91.9
2011	4,867,645	46.6	10.0	4,513,171	43.2	4.4	1,074,972	10.3	52.5	10,455,788	10.6	99.1

Source: Commission on Filipinos Overseas

3.1.2 Shares of Filipino Migrant Stock

Permanent migrants have the largest share. Table 3.3 also shows the shares of Filipino migrant stock. In 1997, the largest proportion (42.2 percent) of overseas Filipinos were temporary, followed by permanent migrants (30.9 percent); irregular migrants comprised 27 percent.[2] While the share of temporary migrants has not changed much (43.2 percent in 2011), the share of permanent migrants steadily rose in 1997-2001 before rising abruptly in the mid-2000s to 49 percent. While it has declined since, it stood at 46.6 percent in 2011. This share may be lower if foreign-born and foreign citizens with Filipino ancestry are excluded. Corollary to this, the share of irregular migrants steadily decreased in 1997-2003, and more sharply in 2004-2005 to 9 percent, and continued its descent through to 2010 to 7.5 percent, before rising to 10.3 percent in 2011.

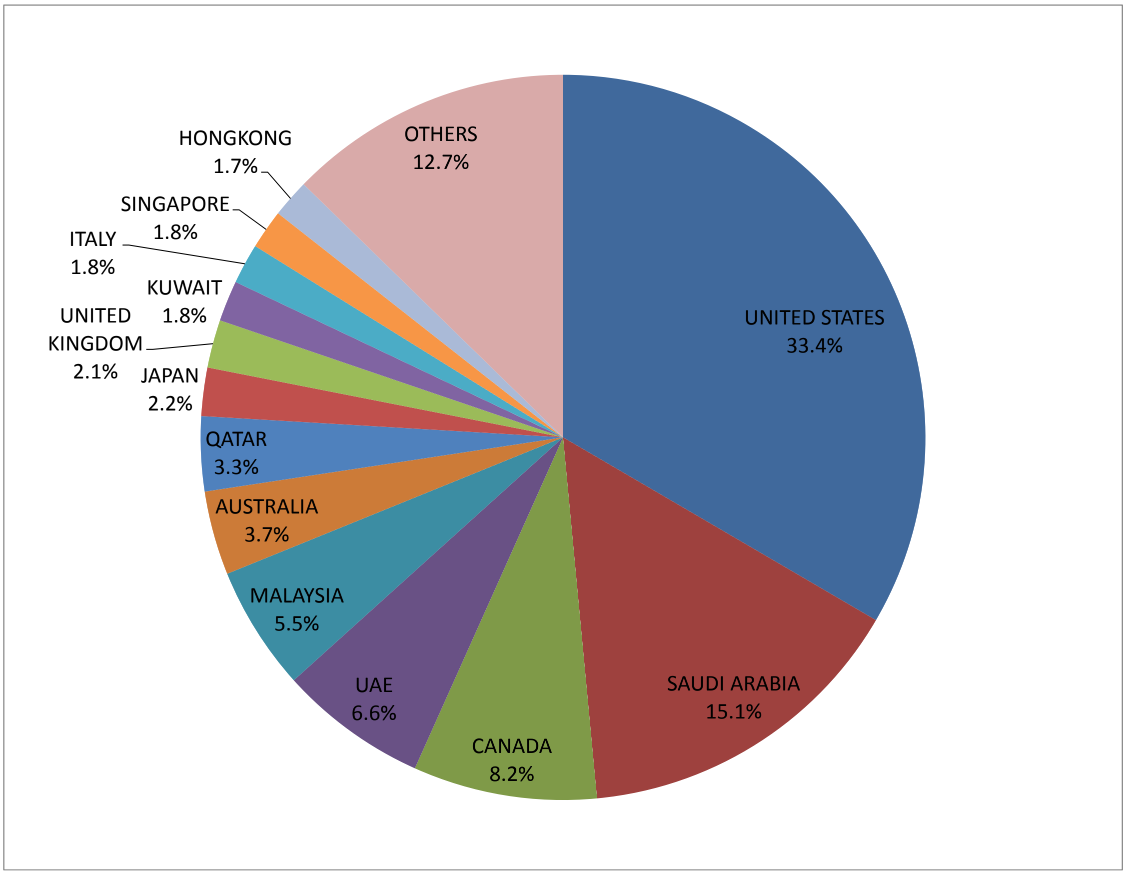
As of 2011, ten destination countries accounted for 87.5 percent of Filipino migrants (Figure 3.1). The United States alone is host to a third (33.4 percent) of all Filipino migrants, followed by Saudi Arabia (15.1 percent), Canada (8.2 percent), and UAE (6.6 percent). Malaysia hosts 5.5 percent of Filipino migrants, Australia 3.7 percent, and Qatar 3.3 percent. Japan is host to 2.2 percent, United Kingdom 2.1 percent, Italy, Singapore and Kuwait 1.8 percent each, and finally Hong Kong 1.7 percent.

The shares of migrants by status in each of the 10 major destination countries are shown in Figure 3.2. Most of the Filipinos in the United States (89 percent), Canada (87 percent), Australia (85 percent), United Kingdom (73 percent), and Japan (70 percent) are permanent migrants. On the other hand, most of the Filipinos in Saudi Arabia (99 percent), UAE (97 percent), Kuwait and Qatar (96 percent each), and Hong Kong (90 percent) are temporary migrants. Most Filipinos in Malaysia (79 percent) are irregular migrants.

There are no long-term data on migrant shares by country, but based on the dominant shares of top destinations in 2010 and the growth of migration in these countries over time, it can be inferred that while the share of permanent migrants dominated in the 1960s-1980s, this has decreased. With the growing shares of the Middle-East, the share of temporary migrants grew from the 1960s to 1990. While this has decreased in the 1990s to 2000, it has risen again in the 2000s. While the

[2] "Permanent: Immigrants or legal permanent residents abroad whose stay does not depend on work contracts. Temporary: persons whose stay overseas is employment related, and who are expected to return at the end of their work contracts. Irregular: those not properly documented or without valid residence or work permits, or who are overstaying in a foreign country." (Commission on Filipinos Overseas)

Figure 3.1: Share of Filipino Migrants by Destination Country, 2011



Source: Philippine Overseas Employment Administration

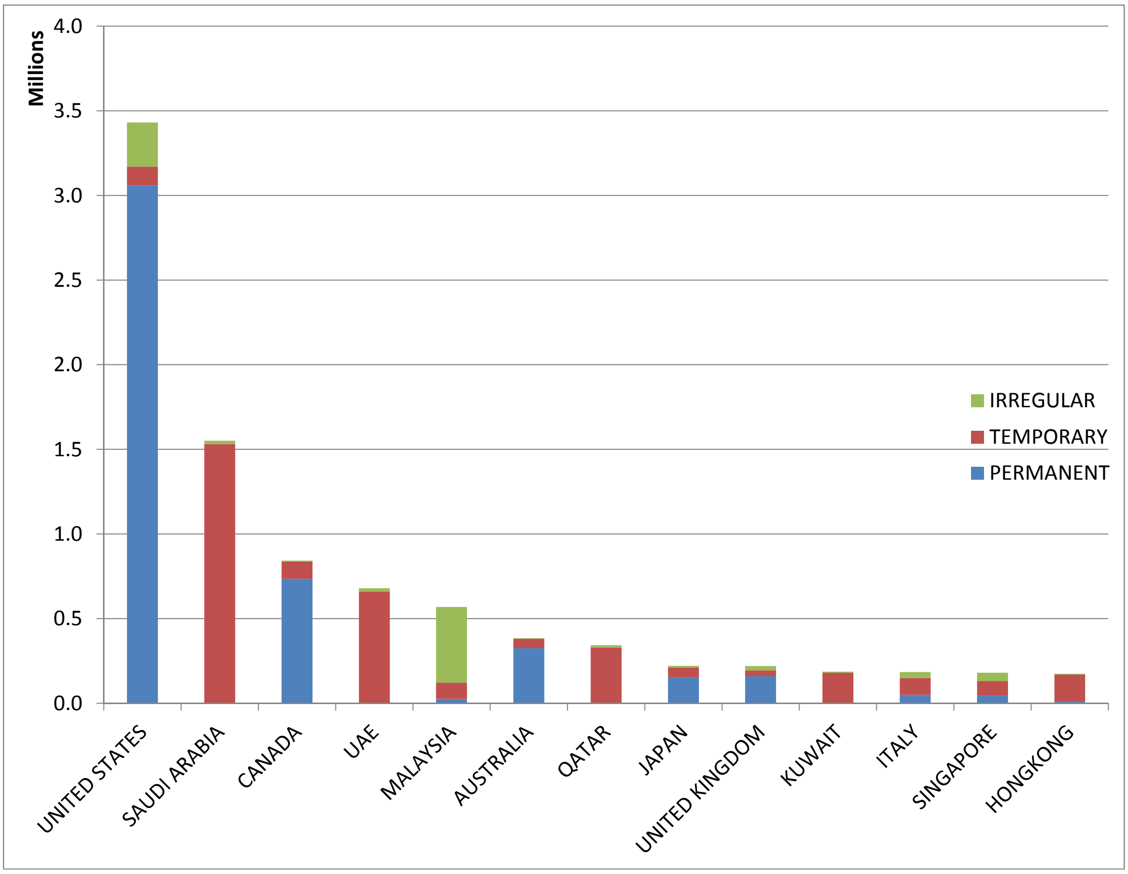
share of irregular migrants, mostly to Malaysia, has increased in the 1960s to 1980s, it has declined in the 1990s but picked up slightly in the 2000s.

3.1.3 Permanent Migrants

The Commission on Filipinos Overseas documents Filipino emigrants through its Pre-Departure Registration and Orientation Seminars. From 1981 to 2012, the total number of registered migrants was over 1.9 million with annual departures averaging over 60 thousand [Table 3.4]. Almost two-thirds (64%) moved to the United States.[3] Two-fifths were males while three-fifths were females. 51 percent were single, 45 percent were married, the rest were either widowed, separated or divorced. About 4 out of 5 were in the labor force/economically active. However,

[3] The Philippines-US is among the top emigration corridors in 2010, with 1.7 million migrants (World Bank, 2011). This corridor ranks 11th with the former Soviet Union included and 7th without.

Figure 3.2: Migrants by Status, Top 10 Destination Countries



Source: Commission on Filipinos Overseas

only 28.5 percent of emigrants were employed prior to migration. A quarter were students, a fifth were housewives, 8 percent were minors (below 8 years old) and 4 percent were retirees. In 1988, only 31.4 had completed college; 47.5 percent of emigrants had at least some college education. In 2012, 34.8 percent had completed college; 53 percent had at least some college education.

Table 3.4: Registered Filipino Emigrants by Major Country of Destination: 1981-2012

YEAR	USA	Canada	Japan	Australia	Italy	New Zealand	Germany	UK	South Korea	Spain	Others	Total
1981	40,307	5,226	254	2,752	4	12	45	88	14	8	157	48,867
1982	44,438	4,898	310	2,931	8	25	263	682	7	35	356	53,953
1983	34,794	3,946	140	2,608	11	41	282	346	2	18	293	42,481
1984	34,682	2,463	137	2,915	19	55	346	364	6	57	507	41,551
1985	38,653	2,097	126	3,458	10	52	213	276	6	34	344	45,269
1986	40,650	3,206	53	4,374	4	37	88	658		11	257	49,338
1987	40,813	5,757	6	8,983	9	45	58	436		28	215	56,350
1988	41,378	6,602	62	9,319	32	11	83	256	1	56	220	58,020
1989	39,524	8,040	1,271	5,943	109	55	135	248	4	120	296	55,745
1990	43,781	8,400	3,569	5,847	160	50	334	291	4	94	619	63,149
1991	43,824	7,211	3,946	5,715	130	91	522	286	14	57	668	62,464
1992	46,691	7,454	4,048	4,104	105	128	593	205	14	77	735	64,154
1993	44,903	11,627	4,527	3,083	123	237	780	159	25	108	818	66,390
1994	40,515	14,302	4,225	3,224	99	287	784	174	18	86	817	64,531
1995	34,614	11,288	4,883	2,966	71	579	661	151	31	68	930	56,242
1996	41,312	10,050	4,510	2,002	72	1,005	542	150	237	40	993	60,913
1997	37,002	8,215	4,171	2,124	50	405	566	195	277	25	1,029	54,059
1998	24,886	5,651	3,810	2,189	96	253	560	193	256	39	1,076	39,009
1999	24,123	6,712	4,219	2,597	125	186	550	225	422	345	1,003	40,507
2000	31,324	8,245	6,468	2,298	371	261	552	174	110	336	892	51,031
2001	31,287	9,737	6,021	1,965	823	284	507	176	62	411	781	52,054
2002	36,557	8,795	5,734	2,603	982	624	518	271	55	451	1,130	57,720
2003	33,916	9,521	5,929	2,223	662	382	445	225	77	586	1,171	55,137
2004	42,350	10,108	5,993	2,647	859	131	393	309	289	579	1,266	64,924
2005	40,280	13,598	7,062	3,027	1,250	394	367	478	480	685	1,407	69,028
2006	49,522	13,230	9,742	3,735	954	1,973	457	556	281	898	1,619	82,967
2007	46,420	14,572	8,806	3,467	1,490	1,639	424	654	576	933	1,618	80,599
2008	34,201	16,443	7,682	3,657	2,405	1,252	489	552	1,482	907	1,730	70,800
2009	40,598	19,967	5,278	3,850	2,734	1,725	518	646	1,458	970	1,974	79,718
2010	42,007	27,302	3,766	3,062	3,319	1,114	510	817	1,565	693	1,920	86,075
2011	38,463	26,203	3,965	3,957	3,632	1,185	590	749	1,618	871	2,177	83,410
2012	39,124	24,354	4,759	4,259	3,818	1,170	553	881	1,632	808	2,282	83,640
Total	1,242,939	335,220	125,472	117,884	24,536	15,688	13,728	11,871	11,023	10,434	31,300	1,940,095
Share (%)	64.07	17.28	6.47	6.08	1.26	0.81	0.71	0.61	0.57	0.54	1.61	100

Source: Commission on Filipinos Overseas

Permanent migration is becoming more difficult. Filipino migrants to the OECD, particularly in the U.S., Canada, and Australia are positively selected in terms of education. The share of Filipino migrants with higher educational attainment in key OECD destination countries (U.S.A., U.K., Australia, Canada, France, and Germany) have increased over time [Table 3.5]. The proportion of highly educated migrants (i.e. those with tertiary education) has risen from 51.5 percent in 1975 to 72.2 percent in 2000. In the U.S., the proportion of highly educated migrants rose from 51 percent in 1975 to 73 percent in 2000. In Canada, the proportion of Filipino migrants with high education rose from 71 percent in 1975 to over 81 percent in 2000. In Australia, most (86 percent) Filipino migrants in 1975 had low education (i.e. had only primary education). However, since 1980, most migrants had high education although this dropped from 84 percent in 1980 to 66 percent in 2000.

This follows policy changes in the destination countries that focus on skills. Mayda and Patel (2004) reviewed policy changes in OECD countries. They noted that US immigration policy is skill-based, although it also accommodates family reunification. Canada's immigration policy is also focused "towards admitting skilled workers". Australia's immigration policy has also shifted

> from encouraging foreign immigration for manufacturing to that based on family migration for relatives, skill-based migration driven by sector-specific demand, and humanitarian and refugee admission. Migration policy during the 1980s focused on building a knowledge-based economy to meet the challenges of globalization. As a result, immigration policies have been designed to encourage immigration of highly skilled workers in order to develop high value-added sectors such as banking and insurance, as well as on building a knowledge-based economy

(Mayda and Patel, 2004, p. 2).

Some Filipinos migrate as spouses or partners of foreign nationals. Between 1989 and 2012, there were 434,137 marriage migrants. This is equivalent to 28 percent of registered emigrants for the same period. However, it is not clear whether these are included among the registered migrants. This proportion increased in the 1990s but decreased in the 2000s. The U.S. is also the most popular destination among marriage migrants hosting 42 percent, followed by Japan (27%), Australia (8%), Canada (4%) and Germany (3%). In 1991, only 50 percent of marriage migrants have at least some college education. By 2012, 64 percent had at least some college education.

3.1.4 Temporary Migrants: Overseas Filipino Workers

Most of the growth in migration is due to temporary migration. 55 percent of the change in total migration is due to temporary migration. A third (32.5%) of the growth is due to permanent migration while the remainder (11.4%) is due to irregular migration. Interestingly, temporary migration is counter-cyclical (negatively related) to permanent migration. As the growth of permanent migration decreased in the early 2000s, the growth of temporary migration increased. With the surge in permanent migration in 2004 came a drop in temporary migration. As growth in permanent migration again decreased from the mid-2000s, there was a resurgence in temporary migration. On the other hand, while irregular migration is not significantly related to permanent migration, it does move pro-cyclically (positively) with temporary migration.

In policy, "the State does not promote overseas employment as a means to sustain economic growth and achieve national development."[4] However, it encourages the deployment of Filipino workers overseas to countries where their rights are protected. In this regard, the Philippine Overseas Employment Administration is mandated to regulate the recruitment and deployment of overseas workers (temporary migrants).

Rehired OFW are the largest and fastest growing. Table 3.6 shows the deployment of overseas Filipino workers (OFWs)[5] by type from 1984-2012. From just 350,982 in 1984, the number of overseas Filipino workers rose to 1.8 million in 2012. In relation to the labor force, the share of deployed overseas Filipino workers has grown from 1.7 percent in 1984 to 3.8 percent in 2010. In 1984, 85.6 percent of the overseas workers were land based while 14.4 percent were sea based. The share of sea based workers grew sharply in the late 1980s, declined in the early 1990s, and rebounded in the mid-1990s. It has remained around 25 percent throughout the next decade until it decreased to 21 percent in 2008. While it rose subsequently, it fell again to 20.4 in 2012. While most of the land based workers were rehires (55.6 percent in 1984, rising to 68 percent in 2012), the number of new hires have grown from over 133 thousand in 1984 to almost 459 thousand in 2012. That is over 50,000 more than the growth in domestic employment of 408,000 from 2011 to

[4] RA 8042: Migrant Workers and Overseas Filipinos Act of 1995

[5] Overseas Filipino workers deployed are define as "recruited Filipino worker who has actually left for overseas job with the pre-condition that employment/travel documentation papers are processed by POEA and his/her departure is actually recorded at the Labor Assistance Center at Ninoy Aquino International Airport." (Bureau of Labor and Employment Statistics as cited in International Organization for Migration (2013)).

2012. Already, local job creation is below the annual target of 1 million new jobs in 2011-2016.[6] There are 14 times more temporary migrants leaving than permanent migrants, although close to half are rehires. Nevertheless, there are over four times more newly hired temporary workers leaving than permanent migrants.

3.1.5 Research Questions and Objectives

The Philippines remains in the growth phase of its migration life cycle. What is driving these rising emigration rates? Is population growth making people face local resource scarcities that drive them to live elsewhere? Is economic development resulting in structural transformation that is driving people off the farms into industry, services and abroad? Are migrant networks making it easier to migrate by lowering costs? What accounts for the rising importance of temporary migration? Is permanent migration becoming more difficult that workers settle for temporary migration? Are higher qualifications for permanent migration unachievable to increasing number of workers? I try to answer these questions in turn.

This paper aims to study the determinants of migration among Filipinos. It contains six sections including this introduction. Section 3.2 reviews the international literature on factors affecting migration. Section 3.3 develops a model based on the best variables identified in the literature. Section 3.4 describes the data sources and provides a descriptive analysis of the dependent vis-a-vis the independent variables. Section 3.5 discusses the regression results. The final section recaps the findings and provides a conclusion.

3.2 Literature Review

3.2.1 Wage differential

Migration is an investment in human capital (Sjaastad, 1962). Accordingly, the return on investment for migration is dependent on the additional earnings relative to the monetary and opportunity costs of migration. Migration is primarily a response to wage differences and a movement to areas with higher pay. Workers migrated from rural to urban areas if urban wages exceeded rural wages and the probability of urban employment is high (Harris and Todaro, 1970). Similarly, the emigration

[6] Department of Labor and Employment, 2011. The Philippine Labor and Employment Plan 2011-2016: Inclusive Growth through Decent and Productive Work

Table 3.5: Share of Filipino immigrants to OECD6 by Educational Attainment

	Low	**Medium**	**High**
1975	21.4	27.0	51.5
1980	19.4	19.9	60.7
1985	17.5	18.5	63.9
1990	13.2	18.3	68.2
1995	15.8	13.0	71.0
2000	9.4	18.3	72.2

Source of data: Schiff and Sjoblom (nd)

Table 3.6: Deployed Overseas Filipino Workers by Type: 1984 - 2012

Year	New Hires	Rehires	Land-based	Sea-based	Total
1984	133,494	166,884	300,378	50,604	350,982
1985	160,815	159,679	320,494	52,290	372,784
1986	170,705	152,812	323,517	54,697	378,214
1987	211,962	170,267	382,229	67,042	449,271
1988	182,142	202,975	385,117	85,913	471,030
1989	170,433	184,913	355,346	103,280	458,626
1990	217,942	116,941	334,883	111,212	446,095
1991	301,317	187,943	489,260	125,759	615,019
1992	291,219	258,436	549,655	136,806	686,461
1993	274,305	276,567	550,872	145,758	696,630
1994	268,711	296,515	565,226	154,376	719,602
1995	219,018	269,603	488,621	165,401	654,022
1996	206,731	277,922	484,653	175,469	660,122
1997	222,139	337,088	559,227	188,469	747,696
1998	223,589	414,754	638,343	193,300	831,643
1999	237,714	402,617	640,331	196,689	837,020
2000	253,418	389,886	643,304	198,324	841,628
2001	271,085	391,563	662,648	204,951	867,599
2002	288,677	393,638	682,315	209,593	891,908
2003	279,565	372,373	651,938	216,031	867,969
2004	284,912	419,674	704,586	229,002	933,588
2005	289,981	450,651	740,632	247,983	988,615
2006	317,680	470,390	788,070	274,497	1,062,567
2007	313,260	497,810	811,070	266,553	1,077,623
2008	376,973	597,426	974,399	261,614	1,236,013
2009	349,715	742,447	1,092,162	330,424	1,422,586
2010	341,966	781,710	1,123,676	347,150	1,470,826
2011	437,720	881,007	1,318,727	369,104	1,687,831
2012	458,575	976,591	1,435,166	366,865	1,802,031

Source: Philippine Overseas Employment Administration rate increases with earnings in the destination country, and decreases as earnings in the home country and migration costs increase (Borjas, 1987).

3.2.2 Population growth

Wages depend on population growth and labor supply. Malthus (1798) noted that while food production only grew arithmetically, population rose in geometric rates and unless regulated would bring about wide-spread poverty. Lewis (1954) observed that unlimited supplies of labor in agriculture kept rural wages at subsistence level. Development took place as excess labor moved to urban areas for industrial employment at wages higher than subsistence rates to cover the costs of moving, the difference in living costs and work experience. Easterlin (1961) analyzed the role of population growth in the context of European emigration before World War I. He used the rate of natural increase twenty years earlier as a proxy for the growth in working age population. The hypothesis is that earlier population growth especially with the decline in infant mortality would have increased the labor force which in turn would increase emigration. Easterlin found a positive correlation between the rank orders of emigration rates and population growth. However, the responsiveness of emigration to population growth was higher for Southern and Eastern Europe (excluding Russia) compared to Northern and Western Europe. He suggested that this may be due to the difference in incomes between these two groups, with Southern and Eastern Europe generally poorer. Moe (1970) argued that the use of the rate of natural increase as a proxy is mis-specified as it gives more weight to the older non-migrant population. He modelled migration from Norway to the U.S. in 1740-1940 as a function of the Norwegian population aged 20-25 in the previous year, controlling for the income ratio between the two countries over the past few years and the rates of unemployment in the two countries. With a significant cohort effect, he concluded that emigration was related to the long swings in demographic composition.

For many European countries, emigration rates between the mid-19th century to the mid-20th century increased before decreasing. Describing migration from Sweden to America in 1851-1960, Akerman (1976) depicted migration as having a "growth curve", where a small volume of emigration (introductory phase) was followed by a big upsurge (growth phase) and then levelled off (saturation phase) before decreasing (regression phase). He related this pattern to demographic conditions where a rare surge in birth rates translated to a considerable increase in subsequent labor force. He also described emigration as a process of innovation initiated by information agents, followed by highly selective streams of migrant families, neighbors and contingents. At its peak, emigration matched the size of internal migration with a less selective character. It then waned with economic convergence and improvements in transportation and communication. However, this characterization was more of a theoretical description and fell short of an empirical evidence.

Modeling emigration on a quadratic trend for nine European countries (Belgium, Denmark, France, Germany, Great Britain, Ireland, Netherlands, Norway, and Sweden) from 1890 to 1913, Hatton and Williamson (1994) and Hatton and Williamson (1998) found support for an "inverted U" emigration pattern for most countries over the period. Emigration rates for most of these countries rose earlier in the period, before declining in the latter part. However, the relationship appeared to be significant only for five countries (Denmark, France, Germany, Norway, and Sweden). The insignificance of an inverted U emigration pattern for Belgium, Great Britain, Ireland, and Netherlands was attributed to the fact that the different countries went through the emigration phases at different periods. Accounting for the peak emigration decade, Hatton and Williamson (1994) and Hatton and Williamson (1998) found a strong inverted U emigration pattern.

3.2.3 Economic conditions

Wages also depend on overall economic conditions relating to the demand for labor. Much of the early literature on migration focused on migration from Europe to the United States, and on the relative importance of economic conditions in the origin and destination countries, or 'push' and 'pull' factors of migration. Jerome (1926) argued that migration from Europe to the US between 1870 and 1913 was dominated by economic conditions in the U.S.. Migration was high when economic conditions were good in the U.S. and bad in the origin country, but also when economic conditions were equally good in both countries. On the other hand, when conditions were equally bad, migration was low. Using composite indices of economic activity from nine indicators for the United States (including wholesale prices, commercial failures, coal production, iron production, railway mileage, bank clearings, employment and imports), five for the United Kingdom (wholesale prices, exports, coal and iron production, and trade union unemployment), four for Germany (wholesale prices, exports, coal and iron production), and two for Italy (imports and exports), Jerome found the economic cycles for the United States, United Kingdom, Germany and Italy to behave similarly. With the co-movement of US and European economic cycles, and of immigration and the US economic cycle, he concluded that increases in emigration to the United States corresponded with economic growth in the European countries.

Pull factors or economic conditions in the United States were not always dominant. Earlier push factors in European countries led to pull factors in later periods in the U.S.. Thomas (1973) agreed that immigration lagged behind railway construction in 1870-1913 and coal production in 1886-1913. However, he argued that immigration preceded economic development in the U.S. in 1849-62, before the structural change in 1863-1870. Before the Civil War, immigration preceded railway construction. Railway expansion followed the flow of migration as rails would not have been built without the influx of labor. Various factors in the origin countries pushed migration, including the famine in Ireland and evictions by English landlords, crop failures in Germany, population pressures and innovations in trans-Atlantic travel. Capital exports from Britain also accompanied emigration, spurring investments in railway development in the U.S. Moreover, railway construction was supported by British exports especially of iron and steel. Building construction in the U.S. also corresponded with emigration. Emigration from Britain was inversely related to incomes, wages, and employment in Britain. After a structural change around 1970, British emigration, foreign investment, and exports lagged behind railway and building construction in the U.S.. Elsewhere, emigrations were driven by high birth rates as in Sweden, Ireland and Italy, and economic conditions as in Italy. These support the idea of emigration as a 'safety valve'.

3.2.4 Economic development and the migration hump

Contrary to the view that poverty in the origin drives migration, an alternative view considers economic development as the reason for rural-to-urban and international migration (Massey, 1988). Economic development entailed substitution of capital for labor and consolidation of agricultural land raising agricultural underemployment and compelling the export of labor to urban areas. Moreover, the concentration of capital in urban areas created rural-urban wage disparities driving migration from rural to urban areas. Some farmers and rural workers migrated to other countries, similarly motivated by wage differentials net of migration costs. Economic development also entailed a reduction in transportation and communication costs, promoting emigration, with the development of road networks and railway systems, postal services, telephone, radio, and television networks.

Emigration is also determined by the extent of economic linkages between origin and destination countries (Massey, 1988). Economic cycles of highly linked economies tend to be inversely related. The US recession in 1975-82 corresponded with Mexico's oil boom. Highly connected economies also have good transportation and communication links. Finally, closely linked economies allow active labor recruitment from the poorer to the richer economy. Economic development therefore reduces migration costs by linking origin and destination countries.

The growth curve has been attributed to origin country incomes, or more broadly economic development in origin countries. While emigration is expected to decrease with origin country income, it has been observed to first rise before declining with income. The common notion is that people migrate from poor countries to developed countries and that the only way to control this is to promote development in origin countries. Migration is thought to stop when standards of living are equalized among countries. Massey (1988) argued that while this may be true in the long run, development may increase rather than reduce migration in the short run as economic and social changes make emigration more possible. He cited the case of Europe in the nineteenth to early twentieth century when mass emigrations corresponded with industrialization. This spurred development in the U.S., linking their business cycles. Emigration rose with declining economic activity in Europe and with economic boom in the United States.

In the 19th century, migration from Europe mostly to the United States rose substantially (Hatton and Williamson, 1994). Early migrants were mostly farmers or rural workers and their families. With industrialization, migrants increasingly came from urban areas and non-farm occupations. Later migrants were generally young adults, mostly single males with neither the burden of dependents nor the skills for productive work. Nevertheless, they were able to adapt to the emerging working conditions and benefit from the move. Migrating alone kept costs low, aided further by the help of relatives and friends in the destination. The primary reason for moving was economic - most were escaping from poverty.

Similarly, emigration from Mexico to the United States was due not to Mexico's poor economic performance but its rapid growth (Massey, 1988). The first wave of substantial emigration from Mexico followed the consolidation of agricultural lands and mechanization in agriculture. It was also encouraged by development in Southwestern U.S., which created a need for Mexican workers. The railway system reduced transportation costs and allowed the recruitment of Mexican workers into the U.S. The second wave of migration was driven by declining agricultural productivity due to droughts and encouraged by labor demand in the U.S. following World War II, filled through the Bracero Program. The third wave was pushed by rapid mechanization in agriculture and fuelled by migrant networks that were established during the Bracero program. Emigration sped up again after 1982 with Mexico facing an economic crisis. To promote development in Mexico, Massey (1988) argued that it was better to allow Mexican migrants into the U.S. as Mexican emigration may have already peaked or was near its peak anyway.

While the United States Commission for the Study of International Migration and Cooperative Development (1990) believed that economic progress through free trade was the only way to mitigate unauthorized migration into the United States (paving the way for the North American Free Trade Area (NAFTA)), it cautioned that economic progress may stimulate migration in the short to medium term. Martin (1993) called this temporary rise in migration with economic progress a "migration 'hump'". He argued that NAFTA was likely to create a temporary migration hump but also less long-term immigration from Mexico. This assumed that short-term migration does not have a cumulative effect on subsequent migration, and a decrease in wage disparities that reduces long-term migration. The conclusion of a migration hump was based on the assumption that migration and trade are complementary in the short-term, but substitutes in the long-term, and that the length and size of the hump are small (Martin and Taylor, 1996). However, if migration and trade were substitutes in both the short run and the long run, there will be a "migration trough" instead, with migration decreasing throughout. On the other hand, if migration and trade were complements, it would be a "migration plateau" with a permanent increase in migration.

Asians did not migrate to the U.S. in the 19th to early 20th century as much as Europeans did, due to policy barriers and poverty constraint (Hatton and Williamson, 2009). Mass migrations happened only after 1965. Emigration from the third world showed the same life cycle, decreasing for Middle East and North Africa after 1980-84, for East Asia and South Asia after 1990-94, although rising again for the latter in 2000-04. Emigration from Sub-Saharan Africa was still rising. Between 1970 and 2004, emigration had an inverse U shape for 26 Latin American countries, and 36 Middle East and North African and Asian countries, and a positive linear trend for 38 Sub-Saharan African countries. The size of the population 0-14 years old 15 years before had a significant positive effect. The ratio of US-origin country GDP per capita had a positive effect. The ratio of US-origin country education had a negative effect. Origin country education had a positive effect, suggesting higher returns to education in the US. Poverty had a negative effect but this is offset by the size of the migrant stock, suggesting the"importance of family reunification in US immigration policy". In general, the rise in emigration was due to the increasing size of young adults, increasing education, and in Latin America and Africa, increasing wage gap. The eventual decline in Latin America and Asia was due to the declining size of young adults, slowing educational progress, and decreasing migrant stocks.

Some authors argue that migration is decreasing throughout instead of having a hump. Using cross-country data for 1995-2000, Lucas (2005) found a significant negative relationship between net out-migration and GDP per capita. Fitting a regression line by income groups, he found that among the poorest countries, emigration rates in fact decreased as income increases leading him to deny the existence of a migration hump. However, apart from the poorest countries, his graph shows a migration hump with net migration rising with income in the second quartile and then decreasing in the third and fourth quartile. Also, the scatterplot may well fit a quadratic on income.

Others observed that emigration continued to rise with development. While Turkey experienced rapid economic growth in the 1980s, substantial emigration pressure persisted after a decade due to limited employment opportunities and declining real incomes (Martin, 1993). Concerned that Turkey had not developed sufficiently to avoid a substantial migration hump, the European Community turned down Turkey's membership application. However, there may not have been a migration hump even if Turkey entered the European Community given the high unemployment rates in the EC by the 1980s and the tightened immigration policy. On the other hand, increasing unemployment and underemployment in Turkey would have pushed unskilled workers to create jobs for themselves in the Community.

3.2.5 Cost of Migration

While earlier studies focused on the relative importance of push and pull factors, more recent studies explore the importance of barriers to migration. These include monetary as well as opportunity costs of migration. Tomaske (1971) agreed with Easterlin (1961) on the importance of income but contradicted the notion that emigration was a vent for surplus labor. He found that while a simple regression of emigration rate on lagged population growth showed a positive effect of population growth, accounting for the ratio of home-to-U.S. income per capita and migrant stock made population growth insignificant. However, the ratio of home-to-U.S. income per capita, without accounting for migrant stock, was insignificant. This is due to the effects of the income ratio and migrant stock cancelling out. This underlines the importance of information on opportunities from relatives and friends who have migrated earlier. Otherwise, information costs would restrict migration. As Letouz et al. (2009) suggested, migration occurs only if origin income is sufficient to cover costs and if utility from destination income exceeds that from origin income and migration cost. However, as origin income increases, destination income must be even bigger to induce migration.

Reductions in migration costs promote migration in the face of decreasing income differentials. Emigration creates social and economic changes that further fuels migration, a process called "cumulative causation" (Massey, 1988). It depends on three mechanism: network formation, agrarian transformation, and income redistribution. Migrant networks of relatives, friends and community members in destination countries enhance the likelihood of migration as they reduce the costs of migration, including for travel and settlement, employment information, opportunity costs and psychological costs. Income from foreign employment can be used to purchase land at home, making land ownership and economic power more concentrated. Remittances to migrants' families can create a feeling of relative deprivation among those of non-migrants, motivating them to migrate as well.

The debate on the determinants of migration has shifted from push versus pull to income gain versus costs. For instance, Baines (1994) compared the relative income and the information hypotheses. The relative youth of emigrants has been considered as evidence in favor of the relative income hypothesis, as lifetime earnings differentials were higher among younger workers. Both the relative income and information hypotheses relied on assumptions about the effects of economic development. The relative income hypothesis assumed that migration fills excess labor demand in the destination country. The information hypothesis assumed that improvements in trade and communications facilitated migration. However, their long-run predictions were different. The relative income hypothesis argued that emigration rates will decline as the income gap decreases. The information hypothesis argued that emigration may not fall as information decreases the costs and risks of migration. While differences in income were falling between Europe and destination countries, they were still high in the face of migration. However, not many more people migrated from Europe between 1815 and 1930, perhaps due to high transactions costs. It may be that information was not readily available. On the other hand, decreasing transportation costs in the late 19th to early 20th century appears to have eased migration. This is suggested as the reason behind higher return migration rates among southern and eastern Europeans during this period than northern and western Europeans in any period. The decrease in transport costs may have created a new purpose for migration, of augmenting family income with remittances.

This has led to the "new economics of labor migration". The decision to migrate is made not only by the migrant but also his non-migrant family (Stark and Bloom, 1985). Migration costs and returns are shared among family members with an implicit agreement as to their distribution. Returns to migration for the family include remittances. Lucas and Stark (1985) presents three motivations of remittances. The first is 'pure altruism' where the migrant's utility is enhanced not only by his consumption but by that of his family in the home country. The second is 'pure self-interest' where the migrant sends remittance in view of gaining an inheritance, or to ensure that his business interests or property are cared for, or to promote his social standing upon his return. The third is 'tempered altruism or enlightened self-interest' where the migration of some members is a household strategy to spread risk. Remittances are a contractual obligation of the migrant to the sending household. It includes repayment of the household's investment on the migrant's education.

The ease of migration due to lower transportation costs have allowed workers to migrate only temporarily without having to bring the entire family and abdicate all property and interests in the origin country. However, it required migrants to send remittances to support their family and maintain their interests. Lower transport costs may well have raised migration, in part due to higher temporary migration which would have otherwise been impossible.

3.2.6 Temporary Migration

The relationship between migration and remittances creates a distinction between permanent migration and temporary migration. Microeconomic theories of migration can encompass both permanent and temporary migration (Budnik, 2011). For example, temporary migration might be chosen if experience in the destination country raises earnings and employment prospects at the origin country. Temporary migration is consistent with the social cost of migrating and the preference for the home country. Motivations for temporary migration are also consistent with the 'new economics of labor migration'. Relative deprivation drive individuals to migrate but they return when they have obtained enough wealth. Capital constraint induces migration but the accumulation of savings allows return to home country for entrepreneurial activity. Risk sharing motivates migration but insufficient compensation for risk induces return. Remittances are made to a migrant's family and in view of the his return.

While existing theories can subsume temporary migration, various studies indicate that the behavior of temporary migrants differ in several respects from those of permanent migrants (Budnik, 2011). For instance, temporary migrants save more and remit more of their savings. Their motivation to save also encourages them to participate more actively and successfully in the host country labor market. On the other hand, temporary migrants are less likely to invest in human capital specific to the host country.

Similarly, Dustmann and Gorlach (2015) review the literature on the determinants of return migration and cites preference for consumption in the origin country and greater purchasing power of destination currency in origin country. Temporary migration is also seen as a faster way of accumulating human capital while return migration provides higher returns in origin country to human capital obtained in the destination country. Return migration is also a means of addressing financial constraint and provides higher returns to self-employment in the origin country.

3.2.7 Distortions

Migration may not respond to economic growth if immigration is controlled. Wilkinson (1970) analyzed European emigration to the United States in 1870-1914 econometrically using the levels of output in the U.S. and the origin country and the difference in real wages as explanatory variables. Output was used over employment as the latter was considered to be endogenous. He augmented this basic model with labor supply variables namely lagged emigration rates, changes in the U.S. labor force, and U.S. immigration rates. He used autoregressive distributed lag models on top of the OLS. He found that U.S. output had a positive effect on emigration from Denmark, Sweden, Russia and Italy, but with a one-year lag for the first two, and no effect on emigration in Germany and the United Kingdom. However, controlling for labor supply variables, the effect of U.S. output disappeared except for Sweden. The absence of effect may be due to holding U.S. immigration rates fixed or to an inelastic labor supply. He concluded that pull factors seem to have little effect. On the other hand, origin country income had a significant negative effect on emigration for Denmark, Germany, Russia, Sweden and Italy even when controlling for labor supply variables. Where data were available, the wage differential had a significant positive effect on emigration. Lagged emigration rate had a significant, but surprisingly, negative effect on current emigration rates for Denmark, United Kingdom and Sweden.

Migration may also be constrained by minimum wages. Puzzled with the absence of either a pull or push effect for the UK in Wilkinson (1970), Gallaway and Vedder (1971) modelled migration from UK to US (in differences) on unemployment in the UK, economic conditions in the US as a proxy for unemployment, wages in the UK and US (in differences), emigrations to alternative destinations Australia, South Africa and Canada, and dummies for cyclical shocks. They found unemployment in the UK and economic conditions in the US to be significant, wages in the UK to be weakly significant, and wages in the US not to be significant. The insignificance of wages may be due to market distortions such as minimum wages. Emigrations to other destinations were not significant but economic shocks were significant. Considering only the significant variables in a step-wise regression, they found that US economic conditions had the strongest influence, followed by UK unemployment, UK wages and cyclical shocks. They argued that 'pull' factors were more important, accounting for 40 percent of the variation in emigration from the UK to the US, but that 'push' factors were significant as well.

Migration can decrease with greater labor supply in the origin country if employment increases. Modeling labor demands in the U.S. and origin countries (Sweden, United Kingdom, Denmark and Germany) as functions of their respective wages, output, and labor supplies (native labor force less (plus) net migration in the origin (destination) country), Williamson (1974) derived a reduced form equation relating migration on the labor force and outputs in the origin and destination countries. Interestingly, the reduced form equation did not include wage variables as including these apparently misspecified the model, especially when lagged population growth was included. Wage would be capturing the effect of lagged population growth on migration. A higher coefficient on U.S. output relative to that of the origin country meant stronger pull effects. This can be due to relatively lower wage elasticities in the U.S., higher output elasticities in the U.S. and higher capacity growth in the U.S.

The theoretical model was modified in the econometric estimation to account for immigration to the US from other countries and the effect of changes in employment conditions. The significance and direction of pull factors are consistent across four countries. Despite low explanatory power and significance, Williamson found that migration in all four countries was directly related to U.S. output and negatively related to U.S. labor force, as expected. The direction of push factors is less consistent. Migration was negatively related to outputs in Denmark and Sweden and positively related to labor force in these countries, also as expected. However, the coefficients for output and labor force in UK and Germany had the wrong signs. This can be explained by the fact that an increase in origin labor supply holding income fixed would increase employment, thereby decreasing migration. The underlying coefficients confirm a positive effect of U.S. output on U.S. labor demand and a positive effect of wage differentials on migration. However, contrary to expectation, labor demand was positively related to wages in the UK and Germany, and negatively related to output in Germany.

Minimum wages would decrease migration. McKenzie et al. (2014) found that Filipino migration to various destinations is significantly positively related to destination incomes. However, migrant wages are not significantly related to destination incomes. They attribute this to binding minimum wages as the Philippine government requires that overseas Filipino workers' contracts guarantee wages not lower than the minimum in the Philippines, host country or that set in bilateral agreements or international conventions. This has increased Filipino wages in destinations but decreased Filipino migration to low wage destinations. For domestic helpers, migration to destinations with minimum wages decreased by 55 percent compared to those with no minimum wages. Compared to other occupations, the migration of domestic helpers decreased by 57 percent.

Restrictive polices reduce the effects of push and pull factors. Mayda (2010) analyzed migration to 14 OECD countries and found emigration rate rose by 20 percent for every 10 percent increase in (log) GDP per worker in destination countries. However, the income level in the home country did not affect the emigration rate. Distance between the destination and origin countries was highly negatively related with emigration rate. On the other hand, having a common land border, a common language, and colonial link did not affect emigration rate. The share of the young in the population positively affected emigration rate. The average education in the origin country positively affected emigration rate, while that in the destination country negatively affected emigration rate. The foregoing push and pull factors were in turn affected by migration policies in destination countries. Less restrictive policies reinforced the expected effects of push and pull factors, making the income level in the home country significant. Moreover, Mayda (2010) found that a rise in the relative inequality between origin and destination countries increased emigration. On the other hand, unemployment rates in the destination and origin countries were insignificant.

3.2.8 Previous Studies on the Philippines

In the Philippines, Tan (2006) cited poor economic performance, persistent poverty and high unemployment; Filipinos' ability to respond to labor market opportunities and positive migration attitude among the factors affecting emigration. Agbola and Acupan (2010) analyzed migration for the Philippines for the period 1975-2005 using an error correction model. They found that the share of emigrants to the population was negatively related with per capita income, population density, adult literacy, and political instability in the country. On the other hand, the share of emigrants was positively related to the unemployment rate. The cost of migration proxied by one-way airfare, income inequality, and the inflation rate were insignificant. A problem with their model is its measure of human capital. Adult literacy is a poor measure of human capital; literacy is achieved with primary education, attained by most of the population, and does not say much about what it can do. Actual educational attainment or years of schooling would have been more appropriate. Also, the model includes push factors in the home country but not pull factors in the destination countries.

In summary, migration was initially seen as motivated by population growth, rising and then tapering off. The effect of population, however, is conditional on wage differentials, with migration motivated by economic gain. The emigration rate is positively related to average income in the destination country, and negatively related to average income in the home country and migration costs. Most early studies on migration focused on relative incomes or economic conditions in origin and destination countries, or push and pull factors. Arguments for push factors focus on poverty in the origin country due to unregulated population growth and unemployment, with workers moving to other countries with higher wages. An alternative view argues that economic development drives international migration, as it does internal migration, with capital substitution for labor, agricultural consolidation, and decreasing transportation and communication costs.

Arguments for pull factors focused on general economic conditions and employment opportunities in the United States. However, the dominance of pull factors were conditional on structural technological changes. Moreover, pull factors were dominant for some but not all countries, and their significance was sensitive to model specification. Nevertheless, some authors maintain the significance of pull factors, even more than push factors.

More recent studies explored the importance of barriers to migration, for instance by looking at how existing migrant stocks facilitate subsequent migration by reducing information costs. The importance of migration costs appears to explain the migration hump, with emigration rising despite rising origin incomes. Emigration from European countries in the 19th-20th century manifested migration humps although at different periods. These have been attributed to rising population growth, industrialization, and rising emigrant stocks. Emigrations from Asia and other regions were much less during this period due to policy barriers and poverty constraint. Mass migrations happened only after 1965, with the Middle East and North Africa, East Asia and South Asia having passed their migration humps. Emigration from Sub-Saharan Africa is still rising.

Previous studies generally find migration rising with incomes in developed destination countries and decreasing related to migration costs proxied by distance. Origin country incomes can be significant but sometimes only when controlling for policy restrictions. A previous study in the Philippines finds a negative effect of domestic income on emigration. However, migration costs proxied by airfare is insignificant. There is limited evidence on the determinants of Filipino migration to particular destinations such as the U.S. This study determines factors in the Philippines and the U.S. affecting Filipino migration to the U.S. It focuses on effects of the rising economic growth in the Philippines, the education and skills of Filipino migrants, the minimum wage policy of the Philippine government for overseas Filipino workers.

3.3 Model and Methodology

3.3.1 Model

Our model begins with an emigration equation similar to Borjas (1987):

$$M_t = \mu_0 + \mu_1 W_{1t} + \mu_2 W_{0t} + \mu_3 K_t + \varepsilon_t \tag{3.1}$$

where the emigration rate, M, depends positively on the average wage in the destination country, W_1 ($\mu_1 > 0$), and negatively on the average wage in the origin country, W_0 ($\mu_2 < 0$), and the cost of migration, K ($\mu_3 < 0$). A larger wage differential will motivate greater migration to the higher-wage country. In other words, migration increases with greater destination income holding origin income fixed, or with lower origin income controlling for destination income. Thus, even with equilibrium in the labor market in the origin country, the wage differential motivates migration but constraints render the status quo. Migration also depends on the cost of migration and related factors / proxies such as the previous stock of migrants or remittances. The previous stock of migrants would reduce information costs while remittances would cover transportation and settlement costs.

Since the decision to migrate depends not only on the wage differential but also on the probability of getting a job (Todaro, 1969; Harris and Todaro, 1970), the model can be modified by including employment rates in the origin and destination countries:

$$M_t = \mu_0 + \mu_1 E_{1t} + \mu_2 W_{1t} + \mu_3 E_{0t} + \mu_4 W_{0t} + \mu_3 K_t + \varepsilon_t \tag{3.2}$$

Emigration would be positively related to employment in the destination ($\mu_1 > 0$) and negatively related to employment at home ($\mu_3 < 0$). However, wages and employment are endogenously determined in the respective labor markets in both countries.

$$L^s_{0t} = \alpha_0 + \alpha_1 W_{0t} + \alpha_2 LF_{0t} + \varepsilon_{2t} \tag{3.3}$$

$$L^d_{0t} = \beta_0 + \beta_1 W_{0t} + \beta_2 Y_{0t} + \varepsilon_{3t} \tag{3.4}$$

$$L^s_{1t} = \delta_0 + \delta_1 W_{1t} + \delta_2 LF_{1t} + \varepsilon_{4t} \tag{3.5}$$

$$L^d_{1t} = \gamma_0 + \gamma_1 W_{1t} + \gamma_2 Y_{1t} + \varepsilon_{5t} \tag{3.6}$$

where L^s and L^d are labor supply and demand, respectively, and the subscripts 0 and 1 refer to the origin and destination countries, respectively. Labor supply depends on wages, W, and the size of the labor force, LF. The higher the wages, the more people are willing to work ($\alpha_1 > 0$, $\delta_1 > 0$). The larger the labor force, the bigger the labor supply ($\alpha_2 > 0$, $\delta_2 > 0$). The demand for labor depends on the wage rate and on the economy's output, Y. The higher the wage, the less workers firms are willing to employ ($\beta_1 < 0$, $\gamma_1 < 0$). The higher the output, the greater the demand for labor ($\beta_2 > 0$, $\gamma_2 > 0$).

These yield the reduced form equations:

$$L_{0t} = \pi_{10} + \pi_{11} LF_{0t} + \pi_{12} Y_{0t} + \upsilon_{1t} \tag{3.7}$$

$$W_{0t} = \pi_{20} + \pi_{21} LF_{0t} + \pi_{22} Y_{0t} + \upsilon_{2t} \tag{3.8}$$

$$L_{1t} = \pi_{30} + \pi_{31} LF_{1t} + \pi_{32} Y_{1t} + \upsilon_{3t} \tag{3.9}$$

$$W_{1t} = \pi_{40} + \pi_{41} LF_{1t} + \pi_{42} Y_{1t} + \upsilon_{4t} \tag{3.10}$$

where wages and employment in the origin destination countries depend on their respective labor force and output.[7] High population growth and a large labor supply relative to demand will keep wages low ($\pi_{21} < 0$) (Malthus, 1798; Lewis, 1954).

The endogeneity of wages and employment may lead to biased estimates in equations 3.1 and 3.2. To address this problem, migration can be related ultimately to the output and labor force underlying labor demand and supply, respectively, in these countries as in Williamson (1974). Substituting the wage equations into 3.1 yields:

$$M_t = \pi_{50} + \pi_{51} LF_{0t} + \pi_{52} Y_{0t} + \pi_{53} LF_{1t} + \pi_{54} Y_{1t} + \mu_3 K_t + \upsilon_{5t}{}^{8} \quad (3.11)$$

Based on the literature, there are two competing hypotheses on the effect of income on migration. Correspondingly, does poverty in the Philippines drive migration ($\pi_{52} < 0$) (Lewis, 1954; Harris and Todaro, 1970) or does economic growth facilitate migration ($\pi_{52} > 0$) (Massey, 1988)? Is economic growth reducing transportation and communication costs, thereby promoting migration? How are the economic cycles of the Philippines and destination countries related? To what extent does the Philippines' economic links with destination countries drive migration? To what extent does migration depend on economic conditions in destination countries? To what extent does the previous migrant stock affect current migration? How do destination migration policies affect migration? Do remittances promote inequality that motivate more migration or do they prevent more workers from having to work abroad?

Given the origin labor demand and supply, a higher destination wage would raise the quantity of labor supplied relative to the quantity of labor demanded. The resulting excess labor (unemployment) at corresponding destination wages would be the supply of migrants from the origin country. The supply of migrants is positively related to the destination wage, positively related to the origin labor supply, and negatively related to the origin labor demand.

$$M^s_{0t} = \sigma_0 + \sigma_1 W_{1t} + \sigma_2 LF_{0t} + \sigma_3 Y_{0t} + \varepsilon_{2t} \quad (3.12)$$

Rigidities or distortions in the labor market also affect migration. A higher than equilibrium origin wage creates domestic unemployment and a supply of migrants. Changes in labor demand and supply conditions in the origin country would shift

[7] where $\pi_{11} = -(\alpha_2\beta_1)/(\alpha_1 - \beta_1), \pi_{12} = \alpha_1\beta_2/(\alpha_1 - \beta_1), \pi_{21} = -\alpha_2/(\alpha_1 - \beta_1), \pi_{22} = \beta_2/(\alpha_1 - \beta_1), \pi_{31} = -\delta_{21}/(\delta_1 - \gamma_1), \pi_{32} = \delta_1\gamma_2/(\delta_1 - \gamma_1), \pi_{41} = -\delta_2/(\delta_1 - \gamma_1)$, and $\pi_{42} = \gamma_2/(\delta_1 - \gamma_1)$.

[8] where $\pi_{51} = -(\alpha_2\mu_2)/(\alpha_1 - \beta_1), \pi_{52} = (\beta_2\mu_2)/(\alpha_1 - \beta_1), \pi_{53} = -(\delta_2\mu_1)/(\delta_1 - \gamma_1)$, and $\pi_{54} = (\gamma_2\mu_1)/(\delta_1 - \gamma_1)$.

the supply of migrants. These include changes in output and in the labor force. The supply of migrants also depends on migration costs and related factors such as the stock of migrants and remittances. Migrant stock and remittances decrease migration costs, effectively raising domestic wages. Given the destination labor demand and supply, the lower wage in the origin raises the quantity of labor demanded relative to the quantity of labor supplied. The resulting excess demand at corresponding origin wages is the demand for migrants in the destination country. The demand for migrants is negatively related to the origin wage, positively related to the destination country labor demand, and negatively related to the destination country labor supply.

$$M_{1t}^{d} = \delta_0 + \delta_1 W_{0t} + \delta_2 LF_{1t} + \delta_3 Y_{1t} + \varepsilon_{2t} \tag{3.13}$$

Under free market conditions, the level of migration from origin to destination is the equilibrium level where the quantity of migrants supplied is equal to the quantity of migrants demanded. It depends on the origin and destination wages, labor supply and demand.

$$M_t^e = \mu_0 + \mu_1 W_{1t} + \mu_2 W_{0t} + \mu_3 LF_{0t} + \mu_4 Y_{0t} + \mu_5 LF_{1t} + \mu_6 Y_{1t} + \mu_7 K_t + \upsilon_{5t} \tag{3.14}$$

Migration may not be in equilibrium if there are market distortions. The quantity demanded of migrants may be subject to barriers such as quotas and qualification restrictions.

3.3.2 Methodology

With the objective of analyzing the behavior of migration over time, macroeconomic time series analysis is used. Time series analysis differs from cross-section analysis in several ways. Firstly, independent variables may be endogenous, that is, they may be correlated with the error term. Secondly, the variance may not be constant over time. Thirdly, error terms may be correlated over time. Modeling time series data depends on the stationarity of the data, that is, whether a process has the same unconditional mean, variance and covariances across time. There are various time series models. Independent variables may have a lagged effect on the dependent variable. Previous values of the dependent variable may also have an effect on its current value. The dependent variable may also depend on lagged values of the error term.

In modeling the variables, the Box-Jenkins methodology is used. First, each variable is plotted to determine whether it has an intercept, a deterministic trend and a stochastic trend. It is then checked for stochastic trend (unit root) using the Dickey-Fuller test. Non-stationary series are differenced (integrated) to make them stationary. Second, the inclusion of auto-regressive and moving average terms is determined using the auto-correlation and partial auto-correlation coefficients and the models that exhibit no auto-correlation are identified. Third, the best model with minimum information criteria (Schwarz information criterion) is chosen. For the multi-variate regressions, Auto-regressive Distributed Lag (ADL) models are used starting with one lag for all variables. Insignificant variables are then dropped in a step-wise manner to achieve adequate (i.e. has no autocorrelation) parsimonious models. In some instances, some insignificant variables of interest are retained. The ADL models are supplemented with Vector Auto-Regressive models relating all the variables. Finally, Granger Causality Test is used to determine which variables help predict permanent and temporary migration.

3.4 Data and Descriptives

The emigration data are from the Commission on Filipinos Overseas. The data pertain to registered emigrants for the period 1981-2012. The series is a trend stationary auto-regressive, AR(1), process with a growth trend of 1.9 percent per year, and growing at 74 percent its lag value (see Figure 3.3):

$$lnEmigration_t = 10.66 + 0.019 * T + 0.74 * lnEmigration_{t-1}$$

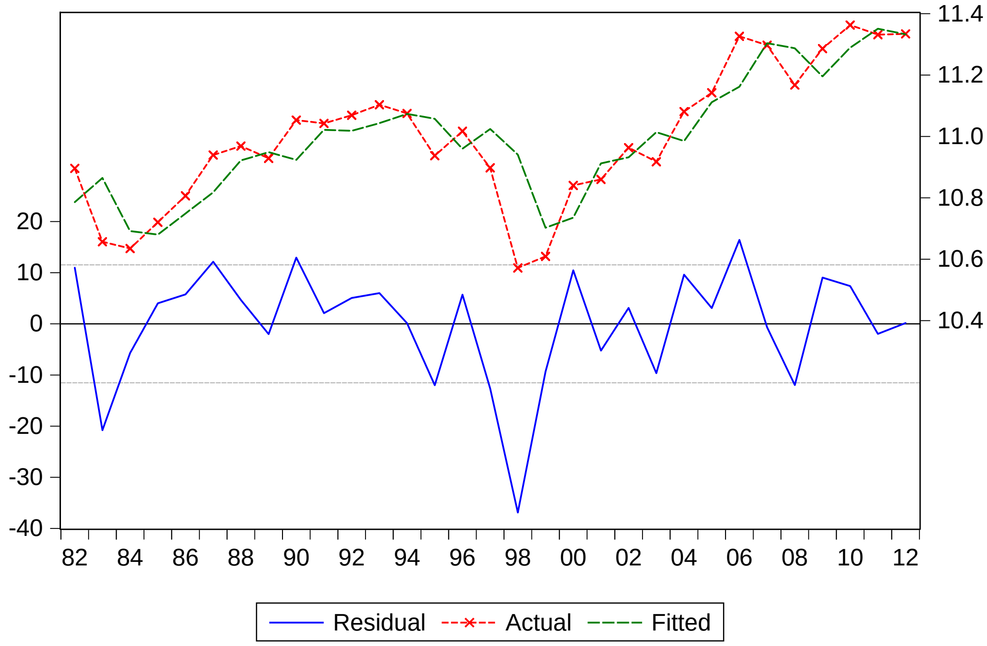
This confirms the process of cumulative causation whereby current migrants facilitate further migration as they help reduce the costs of migration.

Temporary migration data are from the Philippine Overseas Employment Administration. The data pertain to the deployment of overseas Filipino workers from 1980-2012. The series is a trend stationary auto-regressive, AR(1), process, growing at 5.2 percent per year (faster than permanent migration), and by 66 percent of its lag value (see Figure 3.4):

$$lnOFWDeployment_t = 12.63 + 0.052 * T + 0.66 * lnOFWDeployment_{t-1}$$

Domestic wage data are from the Bureau of Labor and Employment Statistics. The data represent to the Index of Compensation per Employee in Non-Agricultural Industries from 1980-2011. The series is a moving average process whose current value depends on its previous error term (see Figure 3.5). This makes wages unpre-

Figure 3.3: Logarithm of Registered Emigration, 1982–2012



dictable. In fact, as the results will show, wages do not conform to labor demand and supply:

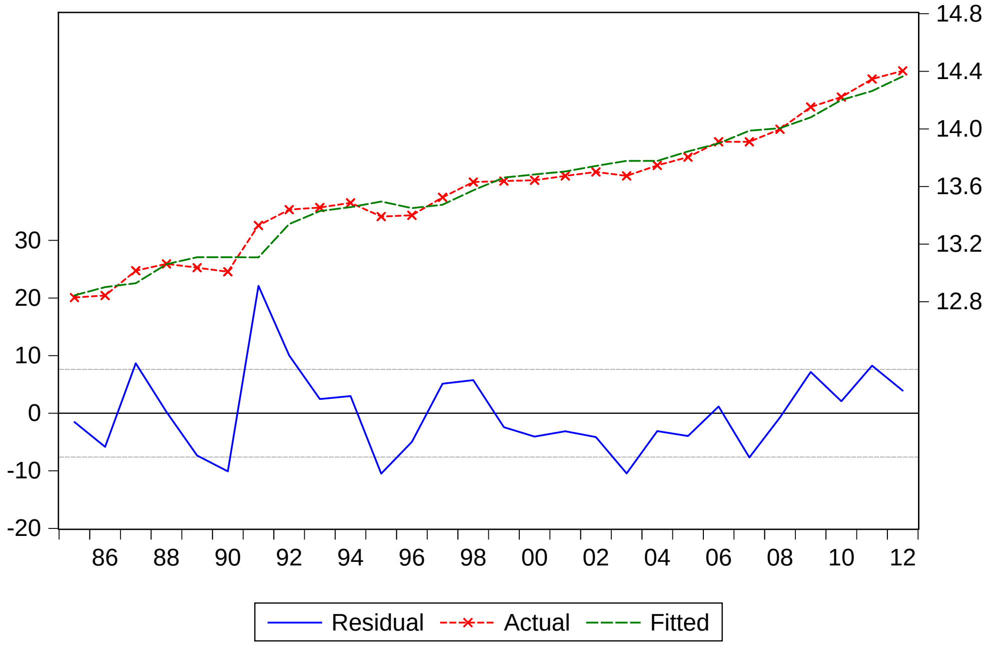
$$Wage = 111.59 + 0.99\varepsilon_{t-1}$$

For permanent migration, I use US wage for destination wage as the United States is the primary destination for permanent migrants. Data on US wages are from the US Bureau of Labor Statistics. The data pertain to the Employment Cost Index for 1981-2012. The series is a difference stationary moving average process of order one, MA(1) (see Figure 3.6):

$$D(USWage) = 2.55 + 0.95\varepsilon_{t-1}$$

For temporary migration, I use Saudi wage for destination wage as Saudi Arabia is the primary destination for temporary migrants. As there are no available wage (index) data for Saudi Arabia, the Consumer Price Index for Saudi Arabia from the IMF International Financial Statistics is used. The consumer price index measures the cost of consumption goods and services in a given year relative to a

Figure 3.4: Logarithm of OFW Deployment, 1985–2012

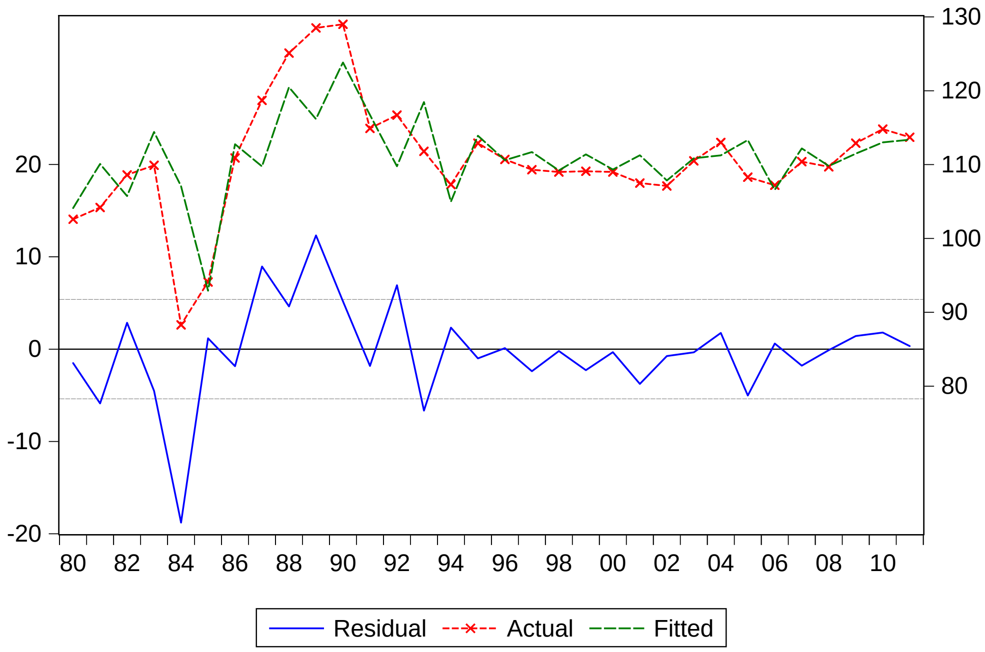


base year. Wages are assumed to follow the cost of living closely. This implies that wages are constant in real terms. Several macroeconomic theories indicate a positive relationship between wages and prices (see e.g. Mankiw (2003)). Classical theory states that nominal wages are directly proportional to prices and labor productivity. Business cycle theory posits that aggregate supply shocks directly affect prices. For example, as labor unions push for higher wages, unemployment and output decrease; as output decreases along the aggregate demand curve, the price level increases by exactly the shift in the aggregate supply. Therefore, the cost of labor is expected to move with the cost of living. This relationship has been empirically proven as early as Mehra (1977) who found that nominal wages and consumer prices are simultaneously determined and as recent as Josheski and Bardarova (2013) who found that CPI and average real wages are cointegrated. The CPI series is a trend stationary second order auto-regressive process, AR(2) (see Figure 3.7):

$$SACPI_t = 84.21 + 0.927T + 1.569SACPI_{t-1} - 0.791SACPI_{t-2}$$

An alternative to the consumer price index, oil prices is used as an instrument

Figure 3.5: Philippine Wage Index, 1980–2011



of Saudi Arabia's demand for foreign labor. I use WTI crude oil spot price from the U.S. Department of Energy. The oil price series is a difference stationary process growing at 3.9 percent annually, (see Figure 3.8):

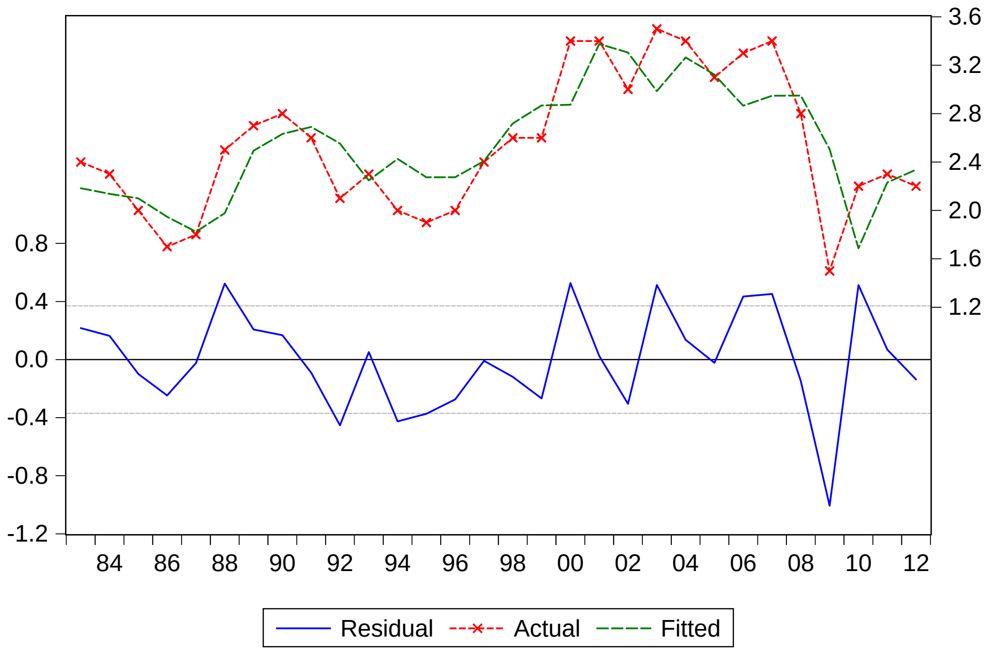
$$D(LNOilPrice) = 0.98 + 0.039T - 0.496LNOilPrice_{t-1}$$

Data on personal remittances received (current US dollars) are from the World Bank World Development Indicators. The series in a trend stationary first-order auto-regressive process, AR(1), growing at 12.5 percent per year and by 64 percent of its previous value (see Figure 3.9):

$$lnRemit_t = 20.12 + 0.125T + 0.64lnRemit_{t-1}$$

Domestic employment data are from the Bureau of Labor and Employment Statistics. The data pertain to the annual average number of employed persons 15 years old and over for 1980-2011. The log series is a trend stationary first-order auto-regressive process, AR(1), growing at an average of 2.4 percent per year (slower

Figure 3.6: Logarithm of US Wage Index, Trend and Cycle



than the growth of the labor force; this partly explains migration) and by 36 percent of its lag value (see Figure 3.10:

$$lnEmployed_t = 16.68 + 0.024T + 0.36lnEmployed_{t-1}$$

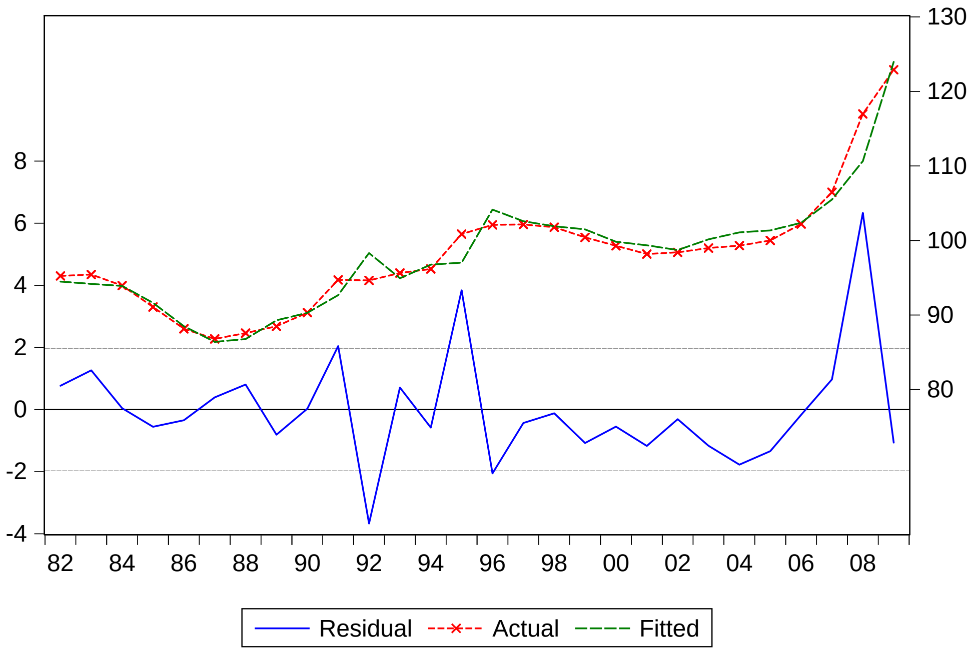
US employment data are from the US Bureau of Labor Statistics. The log series is a trend stationary second-order auto-regressive process, AR(2), growing at 0.12 percent per year (see Figure 3.11):

$$lnUSEmp_t = 18.75 + 0.0012T + 1.73lnUSEmp_{t-1} - 0.81lnUSEmp_{t-2}$$

Saudi Employment data are from the Penn World Table 8.0, defined as number of persons engaged (in millions). The log series is a trend stationary auto-regressive process of order two, AR(2), growing at 3.8 percent per year (see Figure 3.12 (faster than the labor force growth; this partly explains temporary immigration):

$$lnSAEmp_t = 1.12 + 0.038T + 1.75lnSAEmp_{t-1} - 0.86lnSAEmp_{t-2}$$

Figure 3.7: Logarithm of Saudi CPI



Data on GDP per capita in PPP (constant 2005 international dollars) are from the World Bank World Development Indicators. The log series is a difference stationary first-order moving average process, MA(1) (see Figure 3.13), growing at less than 0.1 percent per year:

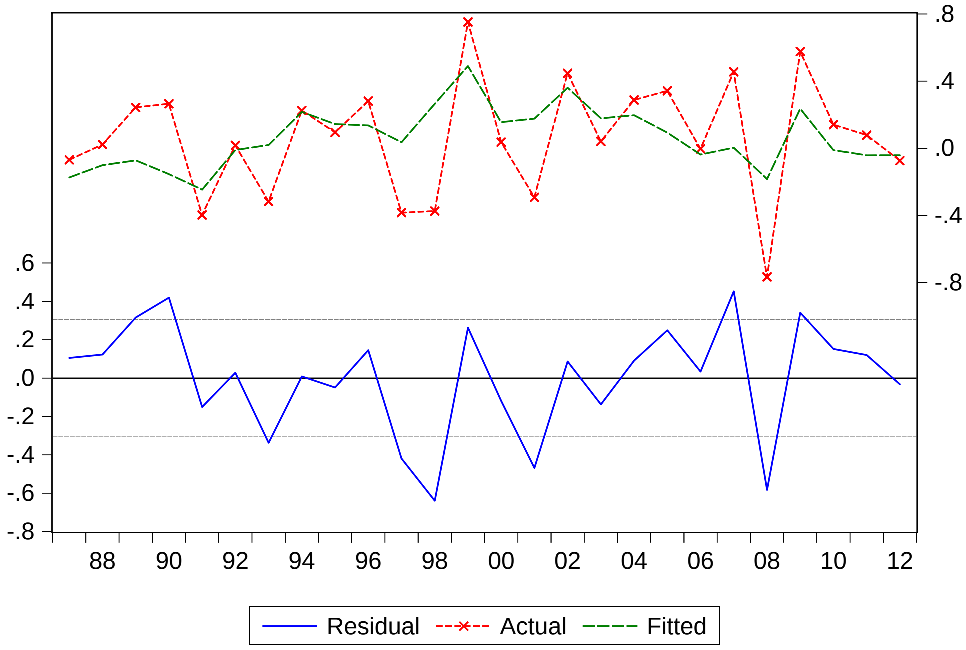
$$D(lnGDPpc_t) = 0.00098T + 0.58\varepsilon_{t-1}$$

Data on US GDP per capita (constant 2005 international dollars) are from the World Bank World Development Indicators. The log series is a trend stationary first-order auto-regressive moving average process, ARMA(1,1), growing at an average of 1.5 percent per year (see Figure 3.14) (faster than the growth of Philippine GDP per capita):

$$lnUSGDPpc_t = 10.35 + 0.015T + 0.82lnUSGDPpc_{t-1} + 0.49\varepsilon_{t-1}$$

Saudi GDP per capita data are from the Penn World Table 8.0. GDP per capita is derived by dividing expenditure-side real GDP at chained PPPs (in mil.

Figure 3.8: Logarithm of World Crude Oil Price



2005US$) by population (in millions). The log series is a trend stationary first-order auto-regressive process, AR(1), with a growth trend of 4.8 percent per year, and growing by 84 percent of its previous value (see Figure 3.15):

$$lnSAGDPpc_t = 8.6 + 0.048T + 0.84lnSAGDPpc_{t-1}$$

The robust growth reflects growing demand for Overseas Filipino Workers.

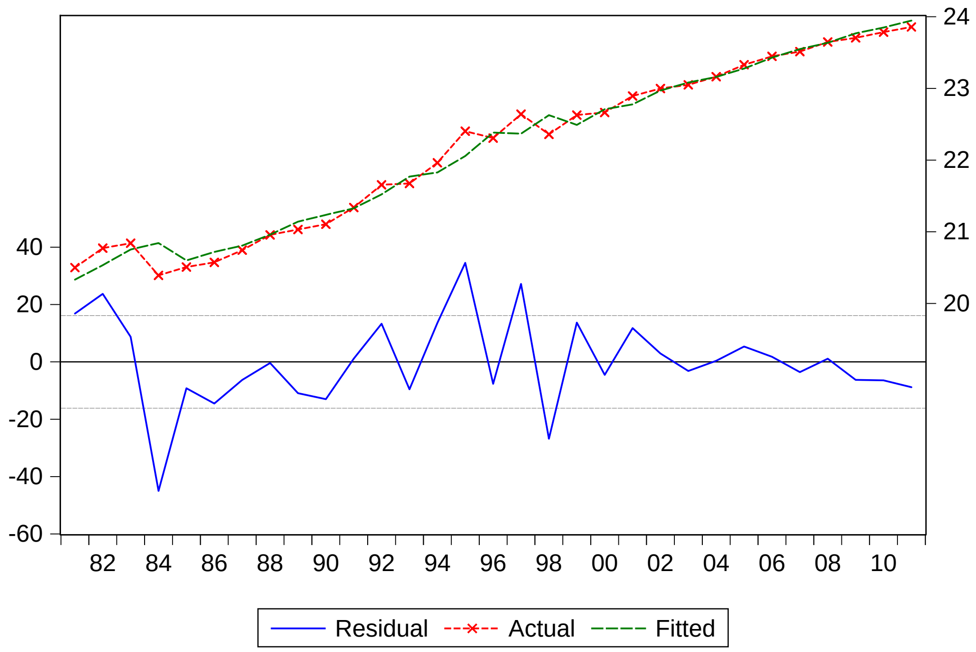
Philippine labor force data are from the Bureau of Labor and Employment Statistics. The labor force is defined as the population 15 years and over who are either employed or unemployed.[9] It excludes those not looking for work. The log series is difference stationary, growing at an average of 2.6 percent annually (see Figure 3.16):

$$D(lnLabor) = 0.026$$

US labor force data are from the US Bureau of Labor Statistics. The log series is difference stationary first-order auto-regressive process, AR(1), growing at

[9]Source: National Statistics Office

Figure 3.9: Logarithm of Remittances, Trend and Cycle



1.8 percent annually (see Figure 3.17):

$$D(lnUSLF_t) = 0.018 - 0.0004T + 0.18D(lnUSLF_{t-1})$$

Saudi labor force data are from the World Bank World Development Indicators. The labor force is derived by adding the proportions of the population ages 15-64 and 65 and above and multiplying to the total population. The log series is a trend stationary auto-regressive moving average process of orders 5 and 2, ARMA(5,2), growing at an average of 3.6 percent annually (see Figure 3.18:

$$\begin{aligned} lnSALF_t = 15.65 + 0.036T + 2.21lnSALF_{t-1} - 1.0lnSALF_{t-2} - 1.54lnSALF_{t-3} \\ + 1.99lnSALF_{t-4} - 0.71lnSALF_{t-5} + 1.84\varepsilon_{t-1} + 0.85\varepsilon_{t-2} \end{aligned}$$

Figure 3.10: Logarithm of Employment

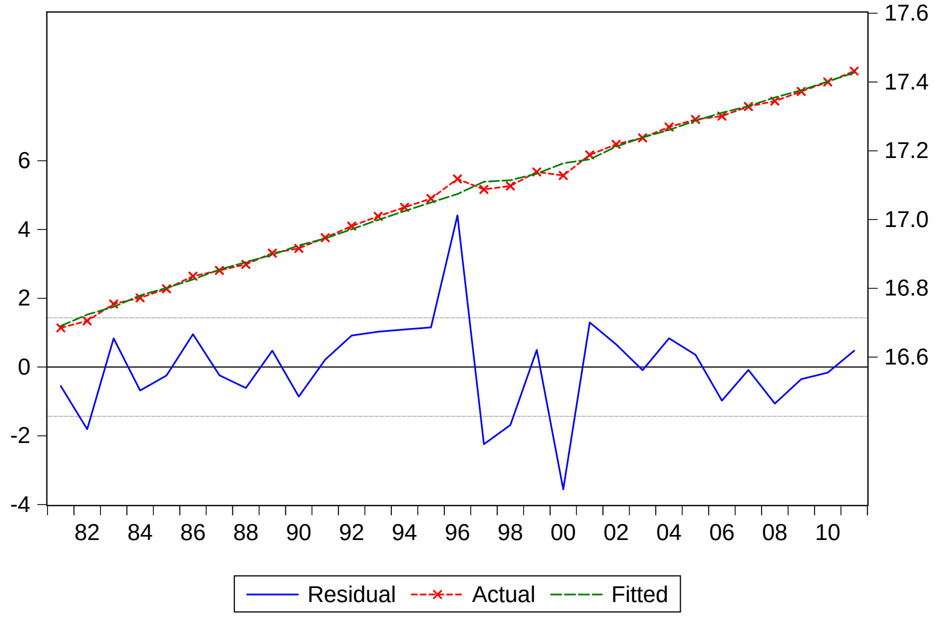


Figure 3.11: Logarithm of US Employment, Trend and Cycle

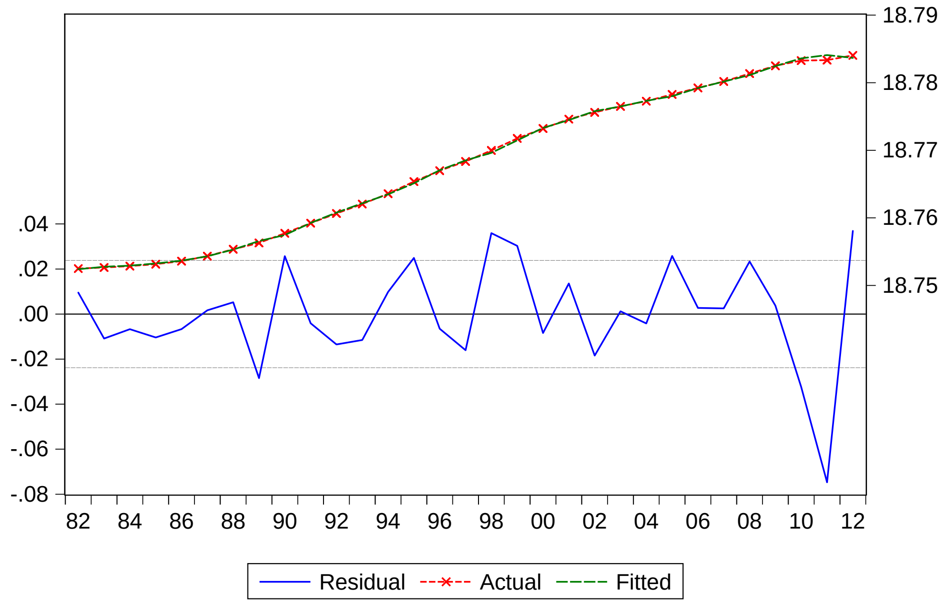


Figure 3.12: LN Saudi Employment

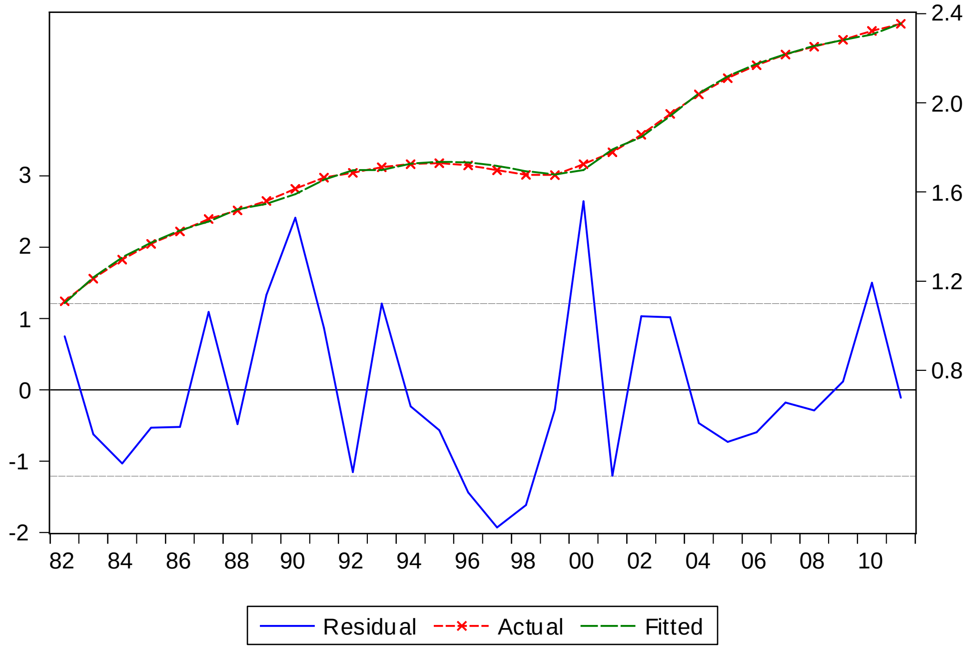


Figure 3.13: Logarithm of GDP per capita, Trend and Cycle

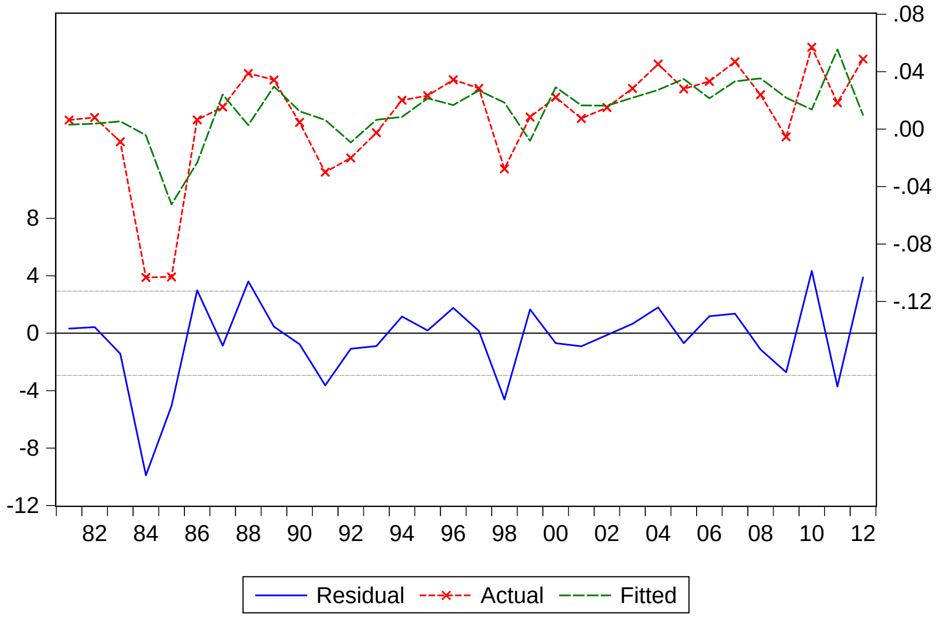


Figure 3.14: Logarithm of US GDP per capita, Trend and Cycle

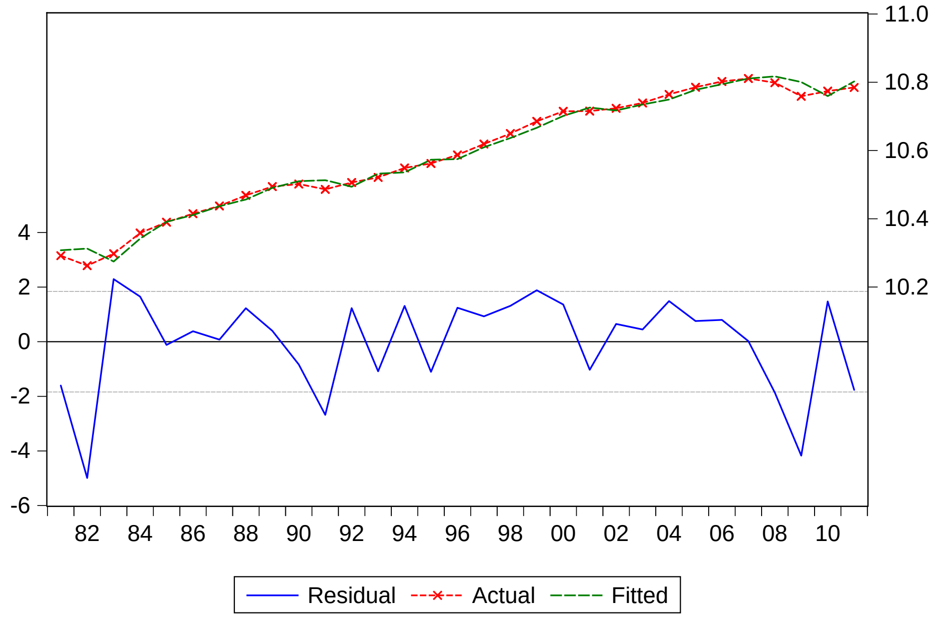


Figure 3.15: Logarithm of Saudi GDP per capita, Trend and Cycle

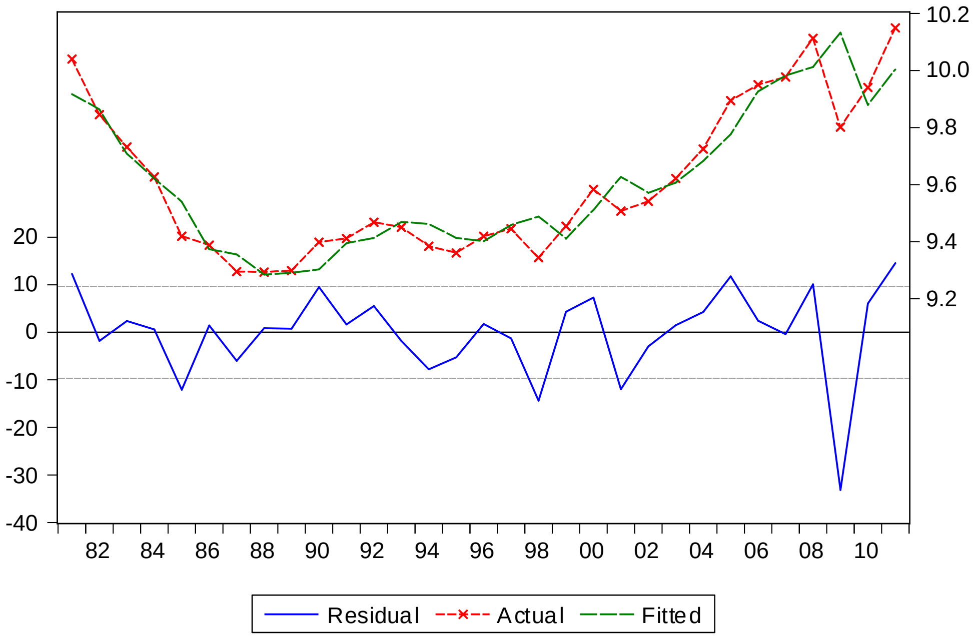


Figure 3.16: Logarithm of Labor Force, Trend and Cycle

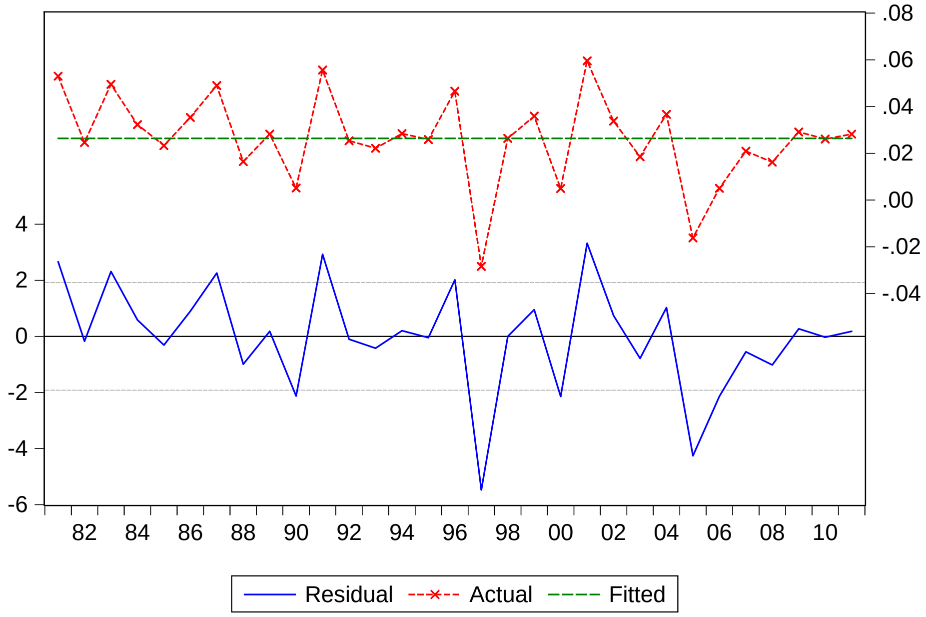


Figure 3.17: Logarithm of US Labor Force, Trend and Cycle

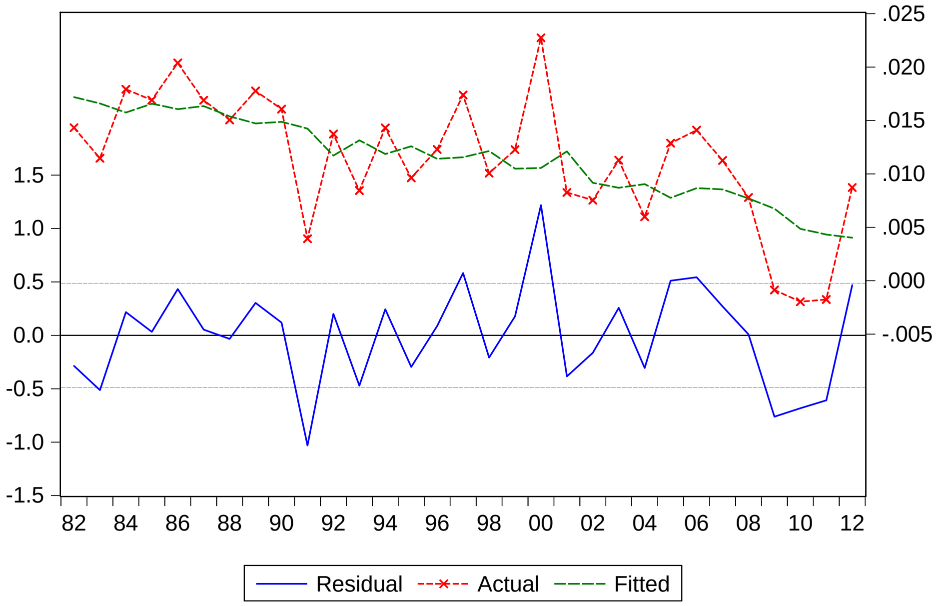
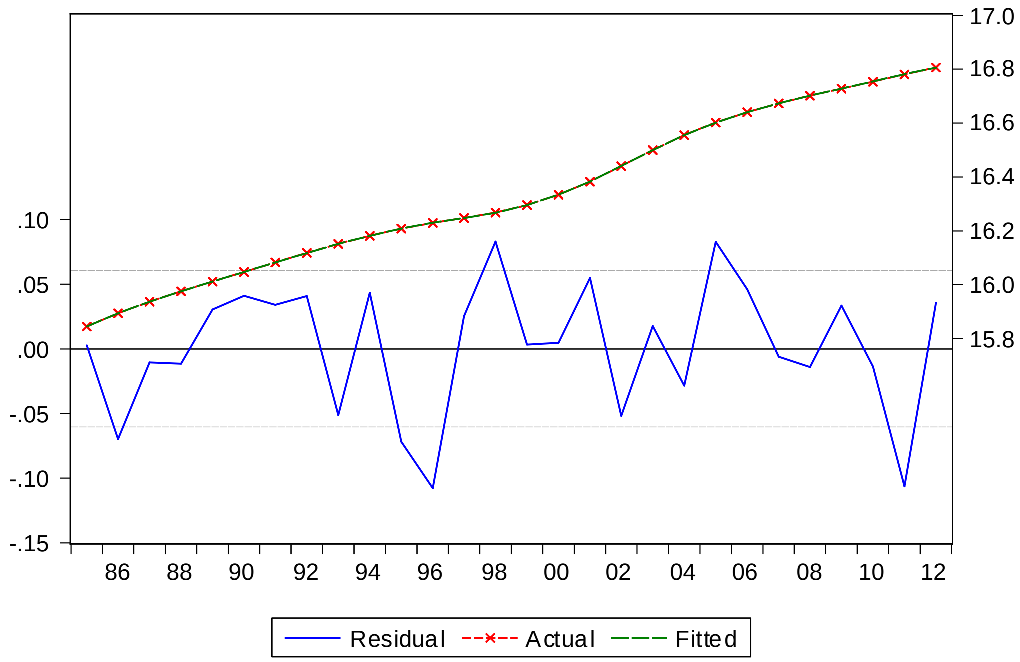


Figure 3.18: Logarithm of Saudi Labor Force, Trend and Cycle



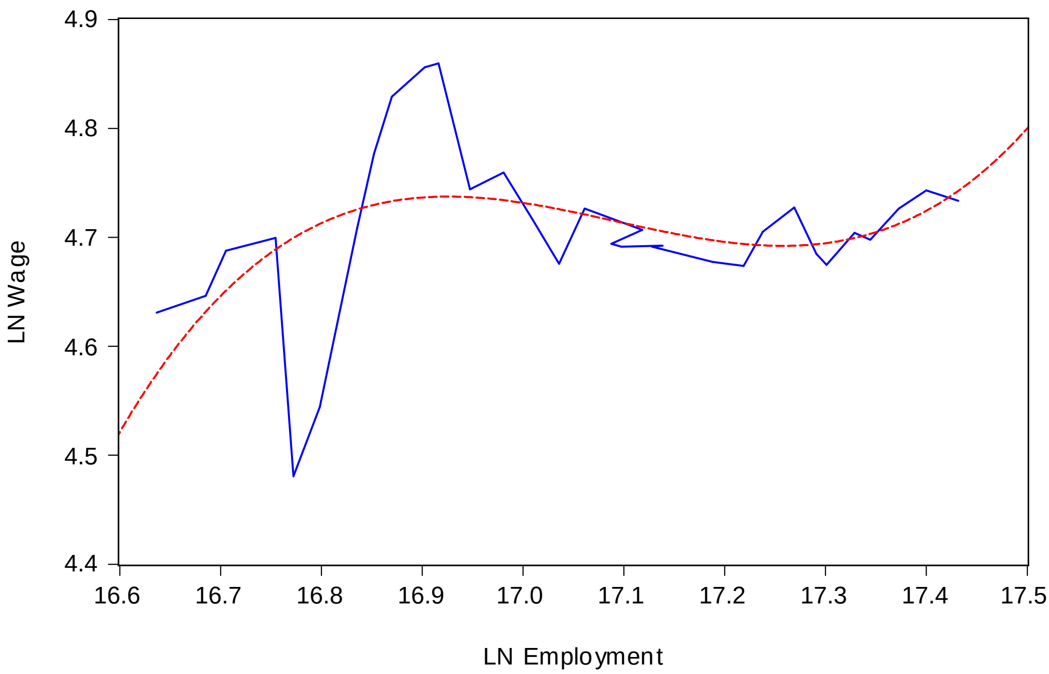
3.5 Regression Analysis

3.5.1 Permanent migration

Philippine labor market

Figure 3.19 graphs Philippine employment against wages. This is indicative of the long term movement of equilibrium employment and wages and the relative movements of labor demand and supply. The graph shows increasing wages and employment in 1980-1983. This is consistent with generally increasing income and labor force in this period (Figure 3.20). While employment increased with the labor force in 1984, wages decreased with income. However, wages and employment rose in 1985 as the labor force increased despite decreasing income. In 1986-1990, both wages and employment increased with increasing income and labor force. In 1991-1994, wages generally decreased as income decreased or fell below trend while employment increased with the labor force. Wages and employment were on trend for a couple of years as were income and labor force. In 1997, employment and wages declined as the labor force fell, despite rising income. Subsequent wages were declining / below trend as income and labor fell below trend. Wages rose as income rose in 2003-2004, but fell as labor force fell in 2005-2006. In 2007-2011, wages generally rose as income rose, with employment rising with the labor force. Overall, there is a cubic relationship between wages and employment, with wages rising with employment in the 1980s, declining in the 1990s to early 2000s, and then climbing back from the mid-2000s. On the other hand, there is a long term quadratic relationship between income and labor force, with income declining as the labor force grew in the 1980s, and rising with the labor force in the 1990s and 2000s.

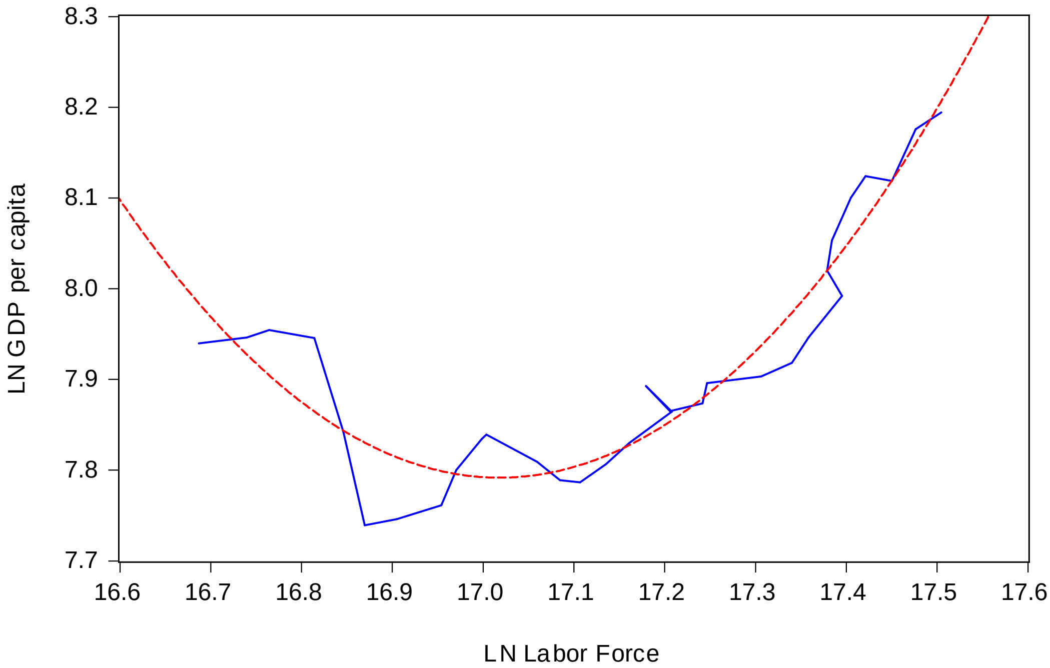
Figure 3.19: Philippine Employment by Wage



Philippine Wages

Table 3.7 shows the reduced form regression of wages on income and labor force also in ADL form. Wages are positively related to income but not related to labor force. As income increases by 1 percent, wages increase by 1.14 percent. Wages are not significantly related to labor force. Wages are self-reinforcing: wages rise by 49 percent of its previous value. Accounting for structural break (Table 3.8) shows that wages decrease by 0.4 percent as the labor force increases by 1 percent.

Figure 3.20: Philippine income by labor force



Philippine Employment

Table 3.9 shows the reduced form regression of employment on income and labor force in Auto-regressive Distributed Lag (ADL) form (insignificant lags are dropped). Employment is positively related to income and labor force. However, employment is inelastic to both income and labor force. As the labor force increases by 1 percent, employment increases by only 0.8 percent. The elasticity to income is even smaller. As income increases by 1 percent, employment increases by only 0.08 percent.

Philippine migrant supply

Figure 3.21 shows the long-run supply of Filipino migrants for 1980-2011. It relates local unemployment to destination wages and shows that Philippine unemployment is positively related to US wages. A simple regression shows that as US wages increase by 1 percent, the quantity of migrants supplied increases by 0.9 percent. Controlling for Philippine wages, income and labor force, the elasticity of migrant supply to US wages increases to 14.1. The supply of migrants is also positively related to Philippine wages, contrary to expectation. As Philippine wages increase

Table 3.7: Philippine Wage on Income and Labor

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LWAGE(-1)	0.487397	0.113721	4.285907	0.0002
LGDPPC	1.142604	0.265881	4.29743	0.0002
LGDPPC(-1)	-1.2589	0.266348	-4.7265	0.0001
LLBR	-0.04227	0.050723	-0.83334	0.4122
Constant	4.050152	0.895934	4.520591	0.0001
R-squared	0.689154	Mean dependent var		4.707597
Adjusted R-squared	0.641332	S.D. dependent var		0.073013
S.E. of regression	0.043727	Akaike info criterion		-3.27503
Sum squared resid	0.049712	Schwarz criterion		-3.04374
Log likelihood	55.76294	Hannan-Quinn criter.		-3.19963
F-statistic	14.4107	Durbin-Watson stat		1.717231
Prob(F-statistic)	0.000003			

by 1 percent, the supply of migrants increases by 0.5 percent. Controlling for income and labor force, an increase in wages increases excess supply of labor and the motivation to migrate for employment abroad. The supply of migrants is negatively related to Philippine income and positively related to Philippine labor force, as expected. Migrant supply is also elastic to the local labor force and income. As the local labor force increases by 1 percent, migrant supply increases by 5.5 percent. Migrant supply increases by 2.4 percent as GDP per capita decreases by 1 percent.

US labor market

Figure 3.22 plots US income against US labor force. The graph shows a long term positive relationship between US income and US labor force. The US labor force continuously rose except in 2009-2010. US income also generally increased but there are notable declines in 1982, 1991, and 2008-2009. Income grew faster than the labor force, growing at 1.5 percent for every percentage growth in the labor force. This led to the increase in US demand for migrants. Figure 3.23 plots US wages against US employment. The graphs shows a long term positive relationship between US wages and US employment. US wages increased with income but also with the labor force (Table 3.11). However, wages were inelastic to income. As income increased by 1 percent, wages increased by 0.08 percent, controlling for the labor force. On the other hand, wages increased by 0.47 percent as the labor force increased by 1 percent, holding income fixed. Employment increased with the increase in the labor force but fell with the rise in income (Table 3.12). As labor force increased by 1 percent, employment rose by 0.06 percent, controlling for income. Conversely,

Table 3.8: Philippine Wages on Income and Labor (with structural break)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
1981 - 1984 – 4 obs				
LLBR	-0.37881	0.073707	-5.13941	0
1985 - 2011 – 27 obs				
LLBR	-0.3675	0.071821	-5.11689	0
Non-Breaking Variables				
LWAGE(-1)	0.483295	0.080207	6.025568	0
LGDPPC	1.312046	0.190303	6.894508	0
LGDPPC(-1)	-0.99361	0.194594	-5.10607	0
Constant	6.235681	0.757897	8.22761	0
R-squared	0.851332	Mean dependent var		4.707597
Adjusted R-squared	0.821598	S.D. dependent var		0.073013
S.E. of regression	0.030839	Akaike info criterion		-3.94809
Sum squared resid	0.023776	Schwarz criterion		-3.67055
Log likelihood	67.19545	Hannan-Quinn criter.		-3.85762
F-statistic	28.63199	Durbin-Watson stat		2.296581
Prob(F-statistic)	0			

employment was negatively related to income. Employment rose (fell) by 0.007 percent as income fell (rose) by 1 percent. With wages rising against a growing labor force, employment rose disproportionately lower than the labor force and fell despite rising income.

US migrant demand

Figure 3.24 relates US migrant demand to Philippine wages for 1980-1999. It shows a negative relationship between quantity demanded and wages. However, a simple regression shows that the negative relationship is not significant. Controlling for US wages, income and labor force (Table 3.13), the relationship remains insignificant. This may be due to the fact that there are many other sources of US immigrants. The Philippines does not have a monopoly of migrants to the US. On the other hand, US migrant demand is negatively related to the US labor force, as expected. As the US labor force decreases by 1 percent, migrant demand increases by 12.8 percent. However, migrant demand is not related to US income. The coefficient of US GDP per capita is insignificant. This is due to the inelasticity of US wages to income and the negative relationship between employment and income.

Table 3.9: Philippine Employment on Income and Labor

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEMP(-1)	0.556239	0.131181	4.240257	0.0002
LGDPPC	0.077019	0.027123	2.839578	0.0085
LLBR	0.77696	0.092722	8.379443	0
LLBR(-1)	-0.37083	0.138698	-2.67366	0.0126
R-squared	0.998319	Mean dependent var		17.06706
Adjusted R-squared	0.998132	S.D. dependent var		0.220285
S.E. of regression	0.00952	Akaike info criterion		-6.35084
Sum squared resid	0.002447	Schwarz criterion		-6.16581
Log likelihood	102.4381	Hannan-Quinn criter.		-6.29053
Durbin-Watson stat	2.284033			

Table 3.10: Migration Suppy (Unemployment)

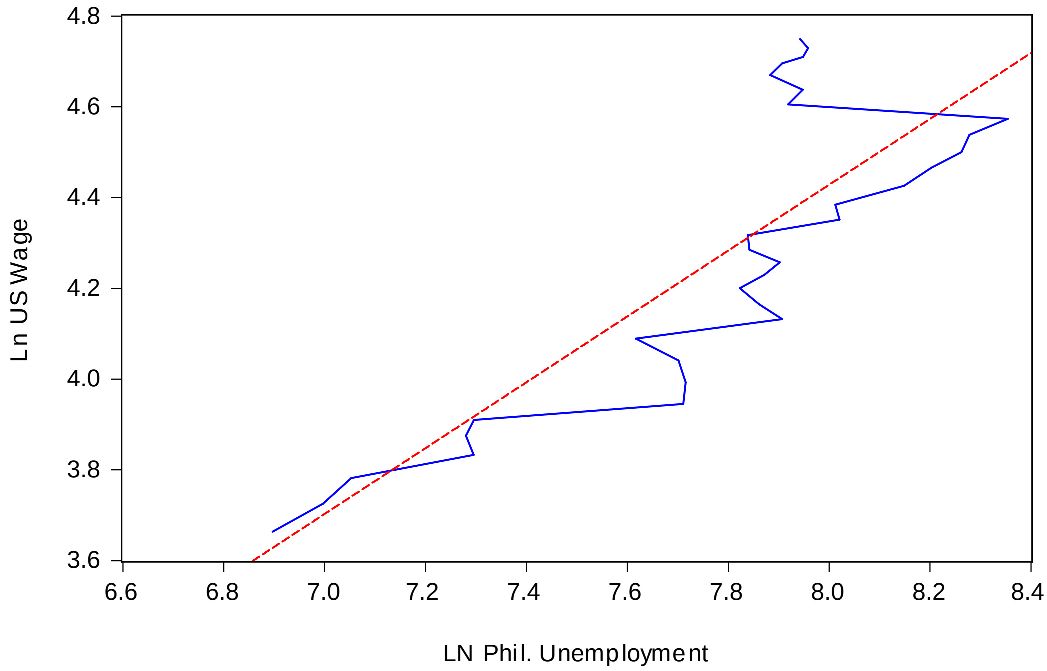
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LUNEMP(-1)	-0.29616	0.157389	-1.88172	0.0726
USLWAGE	14.122	2.866801	4.926047	0.0001
USLWAGE(-1)	-15.5907	2.873106	-5.42644	0
LWAGE	0.525495	0.207616	2.531084	0.0187
LGDPPC	-2.41234	0.345323	-6.98574	0
LLBR	5.472535	0.973774	5.61992	0
Constant	-61.4968	13.33632	-4.61123	0.0001
R-squared	0.962588	Mean dependent var		7.816542
Adjusted R-squared	0.952828	S.D. dependent var		0.33816
S.E. of regression	0.073445	Akaike info criterion		-2.18359
Sum squared resid	0.124067	Schwarz criterion		-1.85665
Log likelihood	39.75386	Hannan-Quinn criter.		-2.079
F-statistic	98.62893	Durbin-Watson stat		2.185027
Prob(F-statistic)	0			

Emigration

Emigration is positively related to the Philippine labor force, lagged US income and lagged emigration, and negatively related to contemporaneous US income and lagged US labor force (Table 3.14). As the local labor force increases by 1 percent, emigration increases by 3 percent. As the previous US income increases by 1 percent, emigration increases by 4.4 percent. Emigration also increases by 77 percent of its previous level. As concurrent US income increases by 1 percent, emigration decreases by 3.5 percent. Emigration decreases by 17 percent as lagged US labor force increases by 1 percent.

However, emigration is not significantly related to Philippine income and con-

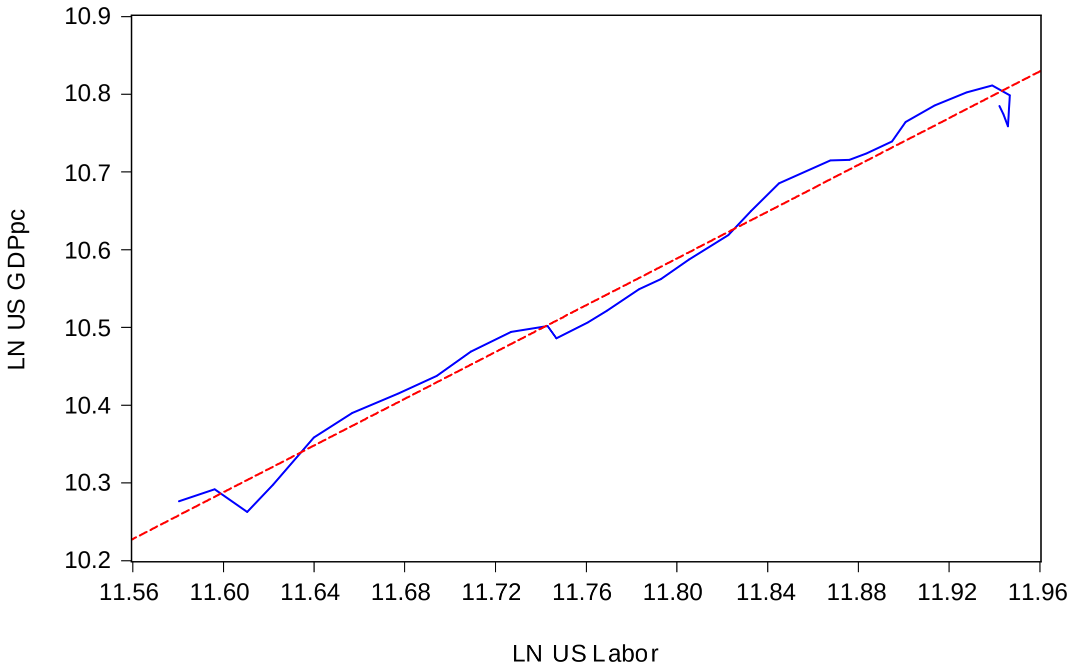
Figure 3.21: Philippine Migrant Supply



current US labor force. Accounting for structural break (Table 3.15) shows that emigration is positively related to Philippine income, contrary to expectation. As GDP per capita increased by 1 percent, emigration increased by over 0.4 percent. This may be due to the fact that wages were highly elastic to changes in income, especially in 1986-1995 when wages rose by 1.7 percent for every percentage increase in income. In 1986-1990, wages rose faster than income with a populist government taking over from an authoritarian regime. The rising wages were partly undone in 1991-1994 with wages falling faster than income, as a neo-liberal government took over. The disproportionate changes in wages meant that employment could not grow proportionately to income. Controlling for changes in the labor force, employment only grew by 0.07 percent as income grew by 1 percent. Consequently, unemployment increased with the increase in wages. As wages rose by 1 percent, unemployment increased by 0.53 percent.

Controlling for wages (Table 3.16), income remains insignificant and labor force becomes insignificant as well. On the other hand, domestic wages positively affects migration. As domestic wages increase by 1 percent, emigration increases by 0.7 percent. Controlling for income and labor force, the increase in wages increases

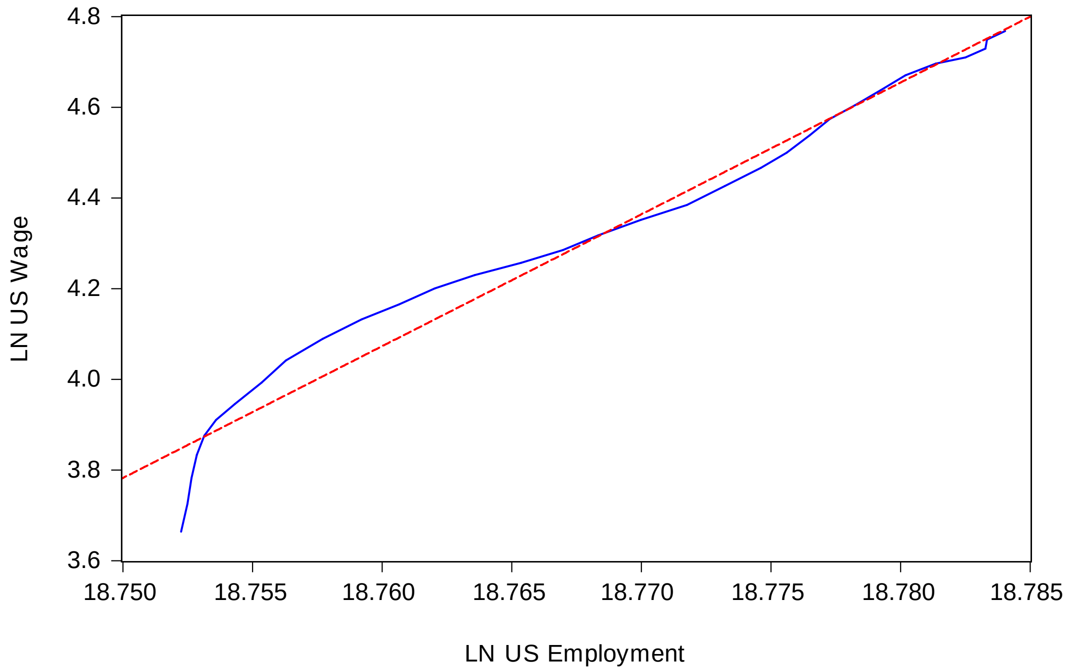
Figure 3.22: US Income by Labor Force



unemployment and therefore the supply of migration. As migration supply increases, controlling for migration demand, emigration increases. Controlling for US wages raises the positive effect of lagged US income and the negative effect of lagged US labor force. Emigration is positively related and highly elastic to US wages. As US wages increase by 1 percent, emigration increases by 5.6 percent. Controlling for US income and labor force, an increase in US wages decreases employment (quantity demanded of labor). To produce the optimal output and reach optimal employment, migrants are demanded to fill the decrease in domestic employment.

Accounting for remittances, emigration is negatively related to lagged income as expected. However, emigration is positively related to concurrent income. While this may be contrary to expectation, it would be reasonable if the direction of the positive relationship is from emigration to income as emigration may increase income apart from through remittances. On the other hand, emigration is negatively related to remittances. The negative relationship between emigration and remittances can be explained in several ways. Firstly, at the macro-level, remittances complements national income in promoting investment and creating employment. As employment increases, emigration decreases. Secondly, at the micro-level, as

Figure 3.23: US Employment by Wage



economic gain is the primary motivation for migration, since remittances provide economic gai, migration becomes unnecessary. Finally, as emigration becomes more difficult as destinations impose stringent requirements, dependents of migrants just have to rely to remittances rather than migrate themselves.

A VAR of emigration on wages and remittances (Table 3.18) shows that emigration depends on its previous value. This confirms the process of 'cumulative causation'. On the other hand, emigration does not respond to the lagged values of Philippine and US wages. Emigration is negatively related to remittances. Including employment (column 6) shows that emigration is positively related to domestic employment in the previous period but negatively related to employment 2 periods before. This may indicate that emigration actually responds to unemployment as far back as two years before and proceeds despite improvements in domestic employment. A VAR of emigration, income, remittances and labor (Table 3.19) shows that the lagged values of Philippine and US incomes and remittances are insignificant to emigration. Including employment [column 6] shows that emigration is positively related to Philippine income lagged two years, negatively related to remittances lagged two years, and positively related to the labor force lagged one year.

Table 3.11: US Wages

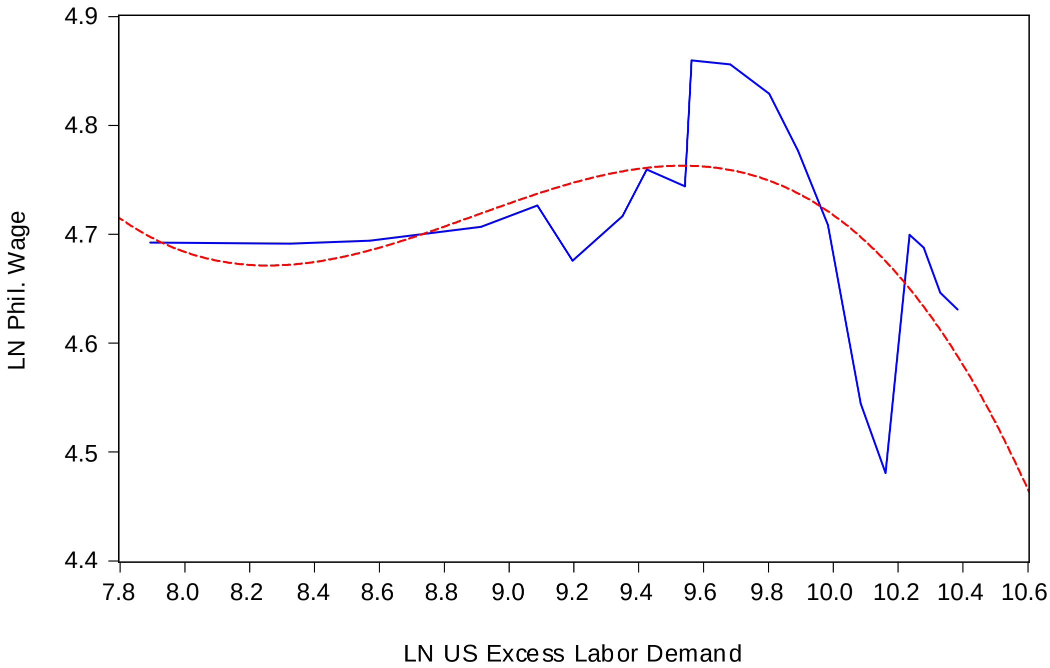
Variable	Coefficient	Std. Error	t-Statistic	Prob.
USLWAGE(-1)	0.661321	0.070323	9.404079	0
USLGDPPC	0.07956	0.036976	2.151648	0.0413
LUSLF(-1)	0.479691	0.173625	2.762796	0.0106
YEAR	0.003897	0.001426	2.732125	0.0114
Constant	-12.8044	3.274652	-3.91014	0.0006
R-squared	0.999775	Mean dependent var		4.293915
Adjusted R-squared	0.999739	S.D. dependent var		0.311946
S.E. of regression	0.005038	Akaike info criterion		-7.59266
Sum squared resid	0.000635	Schwarz criterion		-7.35912
Log likelihood	118.8898	Hannan-Quinn criter.		-7.51795
F-statistic	27791.06	Durbin-Watson stat		0.798579
Prob(F-statistic)	0			

Table 3.12: US Employment

Variable	Coefficient	Std. Error	t-Statistic	Prob.
USLEMP(-1)	1.019524	0.002929	348.0564	0
USLGDPPC	-0.00786	0.00291	-2.70265	0.012
USLGDPPC(-1)	-0.006	0.003312	-1.81245	0.0815
LUSLF	0.057243	0.007957	7.193977	0
YEAR	-0.00045	5.41E-05	-8.28689	0
R-squared	0.999488	Mean dependent var		18.7669
Adjusted R-squared	0.999409	S.D. dependent var		0.011062
S.E. of regression	0.000269	Akaike info criterion		-13.4578
Sum squared resid	1.88E-06	Schwarz criterion		-13.2266
Log likelihood	213.5965	Hannan-Quinn criter.		-13.3825
Durbin-Watson stat	1.287197			

A full VAR of emigration, wages, employment, remittances, income and labor (Table 3.20) shows that emigration is positively related to lagged domestic wages, controlling for domestic income. This confirms that wages are growing faster than the economy. Emigration is also positively related to US wages lagged one period but negatively related to US wages lagged two periods, controlling for US income. Emigration continues to be positively related to domestic employment, controlling for labor force. Emigration is negatively related to GDP per capita lagged one period. While wages may be increasing, the decline in the overall quality of life is motivating people to migrate. However, emigration is positively related to GDP per capita lagged two periods (significant at 10 percent). Controlling for employment, emigration is negatively related to the labor force. Emigration grows despite a

Figure 3.24: US Demand for Migrants



decline in the labor supply. Emigration is also negatively related to the US labor force. Emigration rises when the US labor supply is low relative to demand. A Granger causality test (Table 3.21) shows that domestic and US wages, remittances, domestic employment, Philippine and US incomes, and the US labor force help predict emigration.

Table 3.13: US Migration Demand

Variable	Coefficient	Std. Error	t-Statistic	Prob.
USMIGDEM(-1)	1.391163	0.061759	22.52555	0
LWAGE	-0.13677	0.142375	-0.96061	0.3557
USLWAGE	-0.63044	0.889748	-0.70856	0.4921
USLGDPPC	0.190784	0.481098	0.396559	0.6987
LUSLF	-11.9299	2.963213	-4.02599	0.0017
LUSLF(-1)	15.10326	2.921934	5.168928	0.0002
Constant	-39.6958	30.73756	-1.29144	0.2209
R-squared	0.998913	Mean dependent var		9.490173
Adjusted R-squared	0.998369	S.D. dependent var		0.690689
S.E. of regression	0.027895	Akaike info criterion		-4.04339
Sum squared resid	0.009338	Schwarz criterion		-3.69544
Log likelihood	45.41224	Hannan-Quinn criter.		-3.98451
F-statistic	1837.153	Durbin-Watson stat		3.082247
Prob(F-statistic)	0			

Table 3.14: Emigration on exogenous variables

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEMIG(-1)	0.769613	0.157961	4.872163	0.0001
LGDPPC	0.160335	0.274681	0.583712	0.5654
LLBR	2.97783	1.439365	2.068849	0.0505
USLGDPPC	-3.46658	1.771488	-1.95688	0.0632
USLGDPPC(-1)	4.402553	1.706333	2.580125	0.0171
LUSLF	10.17973	7.993905	1.273436	0.2162
LUSLF(-1)	-17.0532	8.189954	-2.08221	0.0492
Constant	21.2515	17.96674	1.182825	0.2495
R-squared	0.802729	Mean dependent var		10.98343
Adjusted R-squared	0.739962	S.D. dependent var		0.218331
S.E. of regression	0.111336	Akaike info criterion		-1.32936
Sum squared resid	0.272703	Schwarz criterion		-0.95571
Log likelihood	27.94036	Hannan-Quinn criter.		-1.20982
F-statistic	12.78886	Durbin-Watson stat		1.913666
Prob(F-statistic)	0.000002			

Table 3.15: Emigration (with structural break)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
1982 - 1994 – 13 obs				
LGDPPC	0.441055	0.23049	1.913554	0.0688
1995 - 2011 – 17 obs				
LGDPPC	0.403002	0.227106	1.774515	0.0898
Non-Breaking Variables				
LEMIG(-1)	0.477743	0.129386	3.692381	0.0013
LLBR	3.433068	1.020219	3.365032	0.0028
USLGDPPC	-3.8955	1.345451	-2.89531	0.0084
USLGDPPC(-1)	3.745965	1.037478	3.610644	0.0016
LUSLF	15.51494	5.676856	2.733017	0.0121
LUSLF(-1)	-20.1828	6.530712	-3.09044	0.0053
R-squared	0.87669	Mean dependent var		10.98343
Adjusted R-squared	0.837455	S.D. dependent var		0.218331
S.E. of regression	0.088024	Akaike info criterion		-1.79923
Sum squared resid	0.170462	Schwarz criterion		-1.42558
Log likelihood	34.98843	Hannan-Quinn criter.		-1.67969
Durbin-Watson stat	2.422218			

Table 3.16: Emigration (with wages)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEMIG(-1)	0.47026	0.188973	2.48851	0.0218
USLWAGE	5.641766	2.353467	2.397214	0.0264
LGDPPC	-0.12618	0.297703	-0.42384	0.6762
LLBR	1.507978	1.454719	1.036611	0.3123
LWAGE	0.715814	0.359939	1.988711	0.0606
USLGDPPC	-4.3388	1.671818	-2.59526	0.0173
USLGDPPC(-1)	5.334659	1.68828	3.159818	0.0049
LUSLF	5.797129	7.576891	0.765107	0.4531
LUSLF(-1)	-25.4093	8.244048	-3.08214	0.0059
Constant	174.1399	66.98404	2.599722	0.0171
R-squared	0.850371	Mean dependent var		10.98343
Adjusted R-squared	0.783038	S.D. dependent var		0.218331
S.E. of regression	0.101697	Akaike info criterion		-1.47244
Sum squared resid	0.206845	Schwarz criterion		-1.00538
Log likelihood	32.08661	Hannan-Quinn criter.		-1.32302
F-statistic	12.62932	Durbin-Watson stat		2.354296
Prob(F-statistic)	0.000002			

Table 3.17: Emigration with remittances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEMIG(-1)	0.293965	0.149568	1.965429	0.0627
USLWAGE	7.39139	1.704472	4.336468	0.0003
LGDPPC	2.362028	0.669461	3.528254	0.002
LGDPPC(-1)	-2.49175	0.643097	-3.87462	0.0009
USLGDPPC	-4.99432	1.200142	-4.16144	0.0004
USLGDPPC(-1)	4.745853	1.311686	3.618133	0.0016
LUSLF(-1)	-17.3752	4.99277	-3.48007	0.0022
LREMIT	-0.27111	0.091492	-2.96326	0.0074
Constant	190.7113	50.29006	3.792227	0.0011
R-squared	0.894133	Mean dependent var		10.98343
Adjusted R-squared	0.853803	S.D. dependent var		0.218331
S.E. of regression	0.08348	Akaike info criterion		-1.88509
Sum squared resid	0.146348	Schwarz criterion		-1.46473
Log likelihood	37.27631	Hannan-Quinn criter.		-1.75061
F-statistic	22.17036	Durbin-Watson stat		2.42549
Prob(F-statistic)	0			

Table 3.18: VAR: Emigration, Wages, Remittances and Employment

	(1)				(2)				
	lnEmig coef/se	Wage coef/se	US Wage coef/se	lnRemit coef/se	lnEmig coef/se	Wage coef/se	US Wage coef/se	lnRemit coef/se	lnEmp coef/se
L.lnEmig	0.425***	0.746	0.938*	0.518*	0.426***	-0.283	0.929*	0.491**	-0.011
	(0.159)	(9.617)	(0.528)	(0.286)	(0.136)	(8.269)	(0.527)	(0.250)	(0.028)
L2.lnEmig	-0.082	-7.865	-2.229***	-0.515**	-0.062	-2.670	-2.183***	-0.344	0.009
	(0.145)	(8.759)	(0.481)	(0.260)	(0.128)	(7.768)	(0.495)	(0.235)	(0.026)
L.Wage	0.000	0.668***	0.023**	-0.002	-0.000	0.623***	0.023**	-0.004	0.000
	(0.003)	(0.172)	(0.009)	(0.005)	(0.002)	(0.149)	(0.009)	(0.005)	(0.001)
L2.Wage	0.003	-0.126	0.001	0.007	0.003	-0.236	-0.000	0.003	-0.000
	(0.003)	(0.169)	(0.009)	(0.005)	(0.002)	(0.150)	(0.010)	(0.005)	(0.001)
L.US Wage	-0.007	-1.610	1.497***	-0.024	0.005	-0.593	1.506***	0.019	0.004
	(0.032)	(1.927)	(0.106)	(0.057)	(0.028)	(1.725)	(0.110)	(0.052)	(0.006)
L2.US Wage	0.032	2.365	-0.525***	0.029	0.017	0.619	-0.541***	-0.038	-0.002
	(0.032)	(1.946)	(0.107)	(0.058)	(0.030)	(1.831)	(0.117)	(0.055)	(0.006)
L.lnRemit	-0.124	-1.232	0.367	0.674***	-0.131	-7.071	0.316	0.502***	0.022
	(0.098)	(5.915)	(0.325)	(0.176)	(0.090)	(5.466)	(0.348)	(0.165)	(0.019)
L2.lnRemit	-0.276**	-12.929*	0.408	0.236	-0.284***	-14.876**	0.391	0.171	-0.019
	(0.121)	(7.310)	(0.401)	(0.217)	(0.104)	(6.322)	(0.403)	(0.191)	(0.021)
L.lnEmp					2.576***	-0.258	0.128	3.249**	0.418**
					(0.849)	(51.668)	(3.291)	(1.564)	(0.175)
L2.lnEmp					-2.210***	116.672**	0.901	0.473	0.262
					(0.774)	(47.098)	(3.000)	(1.425)	(0.160)
constant	13.932***	390.273***	-2.364	1.263	7.979	-1,399.510**	-18.198	-56.369***	5.254**
	(2.409)	(145.935)	(8.010)	(4.339)	(10.938)	(665.562)	(42.395)	(20.143)	(2.258)

Table 3.19: VAR: Emigration, Income, Remittances and Labor

	(1)				(2)					
	lnEmig	lnGDPpc	lnUSGDPpc	lnRemit	lnEmig	lnGDPpc	lnUSGDPpc	lnRemit	lnLabor	lnUSLabor
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
L.lnEmig	0.743***	0.080**	-0.004	0.522***	0.395**	0.056	0.002	0.534**	-0.015	0.010
	(0.178)	(0.040)	(0.021)	(0.197)	(0.201)	(0.051)	(0.023)	(0.267)	(0.033)	(0.006)
L2.lnEmig	0.027	-0.065*	-0.024	-0.227	0.127	-0.030	-0.025	-0.200	-0.027	-0.001
	(0.171)	(0.038)	(0.020)	(0.188)	(0.167)	(0.042)	(0.019)	(0.222)	(0.028)	(0.005)
L.lnGDPpc	-0.655	1.071***	-0.002	-0.727	-0.079	1.048***	0.012	-0.799	-0.009	-0.034*
	(0.700)	(0.157)	(0.083)	(0.772)	(0.636)	(0.162)	(0.074)	(0.846)	(0.106)	(0.021)
L2.lnGDPpc	1.036	-0.296*	-0.067	-0.722	1.282**	-0.246	-0.104	-0.574	-0.001	-0.004
	(0.676)	(0.152)	(0.080)	(0.745)	(0.601)	(0.153)	(0.070)	(0.800)	(0.100)	(0.019)
L.lnUSGDPpc	0.838	-0.455*	0.968***	-2.976**	-1.109	-0.459	1.261***	-2.737	-0.396	0.284***
	(1.167)	(0.262)	(0.139)	(1.286)	(1.636)	(0.417)	(0.190)	(2.178)	(0.273)	(0.053)
L2.lnUSGDPpc	0.825	0.559**	-0.247*	3.580***	1.492	1.117***	-0.093	3.180	-0.128	-0.006
	(1.160)	(0.260)	(0.138)	(1.278)	(1.515)	(0.386)	(0.176)	(2.016)	(0.253)	(0.049)
L.lnRemit	-0.082	0.004	0.019	0.350**	-0.188	0.001	0.019	0.386**	0.004	0.011***
	(0.132)	(0.030)	(0.016)	(0.145)	(0.123)	(0.031)	(0.014)	(0.164)	(0.021)	(0.004)
L2.lnRemit	-0.140	0.007	0.022	0.632***	-0.373***	0.010	0.030*	0.591***	-0.014	0.006
	(0.141)	(0.032)	(0.017)	(0.155)	(0.138)	(0.035)	(0.016)	(0.184)	(0.023)	(0.004)
L.lnLabor					4.466***	0.376	-0.072	1.457	0.250	0.001
					(1.604)	(0.408)	(0.186)	(2.135)	(0.268)	(0.052)
L2.lnLabor					-0.246	0.239	0.204	-1.474	0.105	-0.019
					(1.196)	(0.304)	(0.139)	(1.591)	(0.200)	(0.039)
L.lnUSLabor					6.802	-1.410	-2.970***	3.063	1.265	-0.044
					(7.902)	(2.012)	(0.919)	(10.516)	(1.319)	(0.256)
L2.lnUSLabor					-9.808	-0.706	1.874**	-2.659	0.907	0.455*
					(7.703)	(1.962)	(0.896)	(10.252)	(1.286)	(0.249)
constant	-13.157***	0.282	2.923***	2.471	-32.957	8.504	8.829***	-1.351	-8.211**	4.161***
	(4.972)	(1.115)	(0.592)	(5.479)	(21.511)	(5.478)	(2.501)	(28.628)	(3.592)	(0.697)

Table 3.20: VAR: Emigration, Wages, Employment, Remittances, Income, and Labor

	lnEmig	Wage	US Wage	lnEmp	lnRemit	lnGDPpc	lnUSGDPpc	lnLabor	lnUSLabor
L.lnEmig	-0.018	-1.651	1.498**	0.022	0.293	0.081**	-0.002	-0.037	0.001
L2.lnEmig	-0.084	15.842**	-1.872***	0.008	-0.149	-0.014	-0.028	-0.024	-0.006
L.Wage	0.017***	-0.134	0.032	0.001	-0.021***	0.001	0.001*	0.000	0.000
L2.Wage	0.023***	-0.457**	0.006	-0.000	0.006	-0.001	0.001	-0.000	0.001***
L.US Wage	0.208***	-12.733***	1.149***	0.009	-0.073	-0.027	0.006	0.023*	0.002
L2.US Wage	-0.054*	10.531***	-0.138	0.001	0.082	0.035**	0.001	-0.016	0.000
L.lnEmp	3.630***	-239.896**	-9.348	-0.522*	-0.917	-0.713*	-0.214	-0.339	0.152**
L2.lnEmp	-0.396	-4.756	-5.192	0.010	-2.556	-0.337	0.306	0.062	0.050
L.lnRemit	0.572***	-27.916***	0.971	0.034	0.134	0.022	0.062**	-0.004	0.023***
L2.lnRemit	0.108*	-13.988**	0.779	0.037*	0.475**	0.080***	0.056***	0.005	0.010**
L.lnGDPpc	-6.984***	227.959***	-2.076	-0.288	3.366	0.873**	-0.372	-0.053	-0.125**
L2.lnGDPpc	0.706*	-80.446*	2.257	-0.043	-4.461***	-0.388*	-0.021	-0.297*	-0.018
L.lnUSGDPpc	-2.304***	-4.665	14.201**	-0.065	-4.092*	0.230	1.378***	-0.716***	0.283***
L2.lnUSGDPpc	4.463***	188.506***	-0.020	-0.169	3.467	1.127***	0.064	-0.321	0.087*
L.lnLabor	-0.193	212.332**	5.287	0.243	-0.331	0.249	0.080	0.127	-0.117*
L2.lnLabor	-2.722***	128.231	4.785	0.009	1.184	0.322	-0.156	0.075	-0.094
L.lnUSLabor	1.768	-33.535	-30.412	-0.640	2.533	-3.728***	-3.544***	1.034	-0.230
L2.lnUSLabor	-37.057***	289.623	-1.217	0.774	5.621	0.199	0.588	1.255	0.057
constant	418.568***	-6,654.857*	259.605	22.358*	-27.830	35.901**	30.128***	5.233	10.353***

3.5.2 Temporary Migration

Saudi labor market

Figure 3.25 shows Saudi employment against wages (CPI). The graph shows wages increasing in 1980-1983, decreasing in 1984-1987, rebounding in 1988-1998, falling below trend in 1999-2005, and rising steeply in 2006-2009. On the other hand, employment generally rose except in 1998-1999. The fitted line shows a long term quadratic relationship between wages and employment. Figure 3.26 plots Saudi income against labor force. The graph shows declining income in 1982-1989, a recovery in 1990-1991, a decline in 1993-2002, and a resurgence in 2003-2010. On the other hand the labor force shows a monotonic increase from 1980 to 2010. The fitted line shows a long term quadratic relationship between income and labor force.

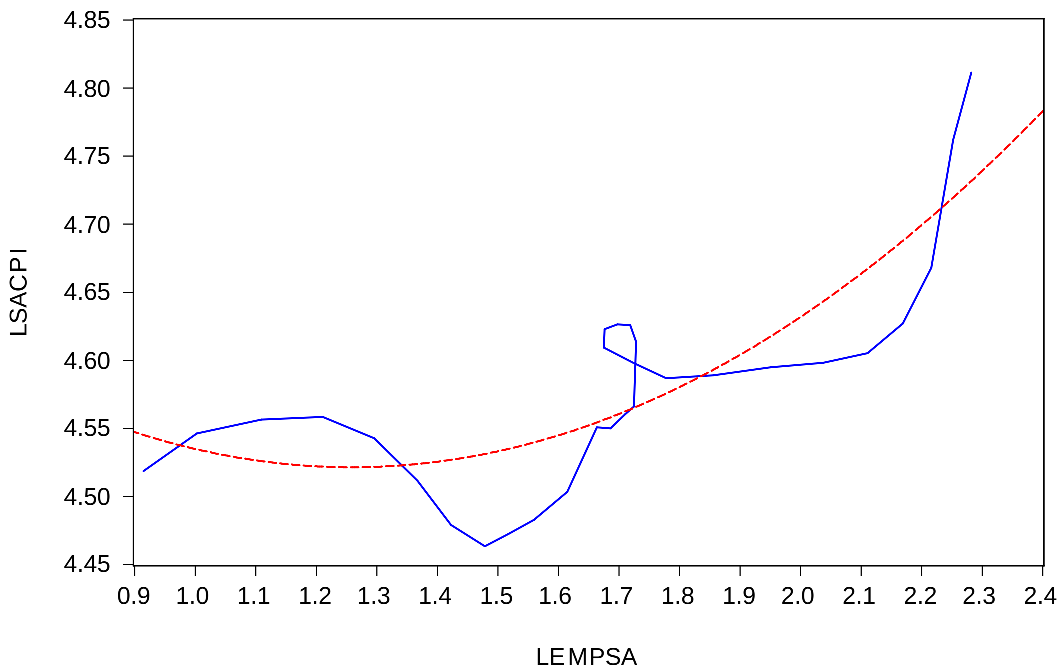


Figure 3.25: Saudi Employment by Wage (CPI)

Saudi wages

Saudi wages are positively related to Saudi income and negatively related to Saudi labor force, as expected. Table 3.22 shows the regression of Saudi wages on income and labor force. As Saudi income increases by 1 percent, Saudi wages increase by

Table 3.21: Granger Causality Test: Emigration

Dependent variable: LEMIG				Dependent variable: LREMIT			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
WAGE	17.77687	2	0.0001	LEMIG	8.422021	2	0.0148
USWAGE	57.54051	2	0	WAGE	0.96399	2	0.6176
LREMIT	11.83716	2	0.0027	USWAGE	0.622844	2	0.7324
LEMP	5.417393	2	0.0666	LEMP	2.257329	2	0.3235
USLEMP	1.272791	2	0.5292	USLEMP	29.4745	2	0
LGDPPC	20.85637	2	0	LGDPPC	1.080437	2	0.5826
USLGDPPC	18.74415	2	0.0001	USLGDPPC	4.833904	2	0.0892
LLBR	1.003084	2	0.6056	LLBR	6.827721	2	0.0329
LUSLF	21.23846	2	0	LUSLF	2.522379	2	0.2833
All	208.9241	18	0	All	125.1237	18	0
Dependent variable: WAGE				Dependent variable: USWAGE			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
LEMIG	1.876559	2	0.3913	LEMIG	4.466052	2	0.1072
USWAGE	3.22336	2	0.1996	WAGE	7.881766	2	0.0194
LREMIT	5.029791	2	0.0809	LREMIT	1.757255	2	0.4154
LEMP	2.790493	2	0.2478	LEMP	0.529392	2	0.7674
USLEMP	1.449114	2	0.4845	USLEMP	9.52763	2	0.0085
LGDPPC	1.352416	2	0.5085	LGDPPC	5.054088	2	0.0799
USLGDPPC	3.690142	2	0.158	USLGDPPC	7.989551	2	0.0184
LLBR	3.068167	2	0.2157	LLBR	1.478744	2	0.4774
LUSLF	0.088003	2	0.957	LUSLF	3.255278	2	0.1964
All	32.06926	18	0.0216	All	45.41873	18	0.0004
Dependent variable: LEMP				Dependent variable: USLEMP			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
LEMIG	0.209039	2	0.9008	LEMIG	0.440496	2	0.8023
WAGE	1.424652	2	0.4905	WAGE	0.327336	2	0.849
USWAGE	1.857623	2	0.395	USWAGE	0.134516	2	0.935
LREMIT	0.683255	2	0.7106	LREMIT	1.045271	2	0.593
USLEMP	1.88855	2	0.389	LEMP	0.543734	2	0.762
LGDPPC	0.074717	2	0.9633	LGDPPC	0.269434	2	0.874
USLGDPPC	0.286871	2	0.8664	USLGDPPC	0.356426	2	0.8368
LLBR	1.446945	2	0.4851	LLBR	0.005545	2	0.9972
LUSLF	0.285636	2	0.8669	LUSLF	0.326146	2	0.8495
All	23.79811	18	0.1618	All	16.81849	18	0.5356
Dependent variable: LGDPPC				Dependent variable: USLGDPPC			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
LEMIG	5.210905	2	0.0739	LEMIG	0.597573	2	0.7417
WAGE	4.952347	2	0.0841	WAGE	5.786441	2	0.0554
USWAGE	2.557989	2	0.2783	USWAGE	0.745063	2	0.689
LREMIT	1.560628	2	0.4583	LREMIT	2.782146	2	0.2488
LEMP	1.54262	2	0.4624	LEMP	1.754807	2	0.4159
USLEMP	5.066006	2	0.0794	USLEMP	5.667633	2	0.0588
USLGDPPC	12.62379	2	0.0018	LGDPPC	6.005255	2	0.0497
LLBR	1.428362	2	0.4896	LLBR	2.611572	2	0.271
LUSLF	8.040727	2	0.0179	LUSLF	8.895811	2	0.0117
All	78.52677	18	0	All	38.26272	18	0.0036
Dependent variable: LLBR				Dependent variable: LUSLF			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
LEMIG	0.323609	2	0.8506	LEMIG	0.519994	2	0.7711
WAGE	0.218369	2	0.8966	WAGE	2.178435	2	0.3365
USWAGE	0.979487	2	0.6128	USWAGE	1.657265	2	0.4366
LREMIT	0.086566	2	0.9576	LREMIT	4.121561	2	0.1274
LEMP	0.507725	2	0.7758	LEMP	1.405899	2	0.4951
USLEMP	0.156346	2	0.9248	USLEMP	0.317631	2	0.8532
LGDPPC	1.011354	2	0.6031	LGDPPC	2.574985	2	0.276
USLGDPPC	2.883334	2	0.2365	USLGDPPC	9.03904	2	0.0109
LUSLF	0.518464	2	0.7716	LLBR	1.536965	2	0.4637
All	22.76907	18	0.1996	All	45.83543	18	0.0003

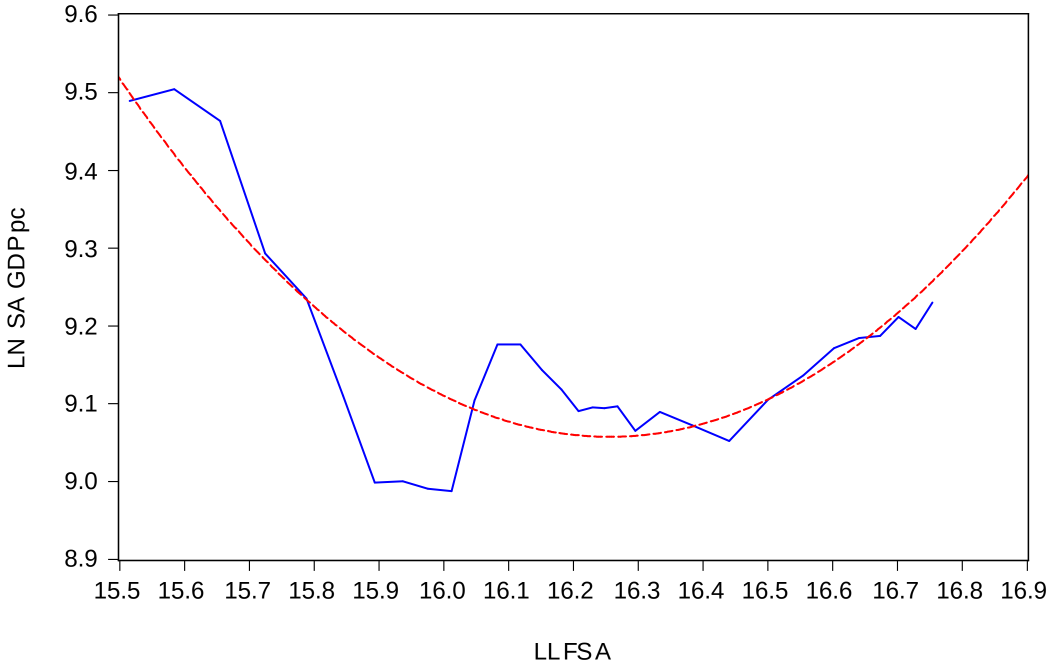


Figure 3.26: Saudi Labor Force by Income

0.2 percent, controlling for labor supply. As Saudi labor force increases by 1 percent, Saudi wages decrease by 0.86 percent, holding income fixed. Saudi wages also depend on their previous values. Saudi wages grow by 79 percent of their previous values.

Oil prices appears to be a poor proxy for Saudi wages. The oil price series does not depend on either Saudi output or labor force, nor on previous oil price (regression results omitted). For this reason, I choose the CPI as a proxy for Saudi wages.

Saudi employment

Saudi employment is positively related to Saudi income, labor force and previous employment. Table 3.23 shows the regression of Saudi employment on Saudi income and labor force. Saudi employment is elastic to the labor force but inelastic to income. As the Saudi labor force increases by 1 percent, employment increases by 2.8 percent. As Saudi income increases by 1 percent, Saudi employment increases by 0.9. Employment increases by 1.12 times its previous value.

Table 3.22: Saudi wages

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LSACPI(-1)	0.792761	0.090599	8.75021	0
LSAUGDPPC	0.197822	0.038814	5.096702	0
LLFSA	-0.86328	0.284744	-3.03177	0.0058
LLFSA(-1)	0.956034	0.283292	3.374733	0.0025
YEAR	-0.00116	0.000236	-4.91635	0.0001
R-squared	0.954034	Mean dependent var		4.58215
Adjusted R-squared	0.946373	S.D. dependent var		0.077314
S.E. of regression	0.017904	Akaike info criterion		-5.052
Sum squared resid	0.007693	Schwarz criterion		-4.81626
Log likelihood	78.25398	Hannan-Quinn criter.		-4.97817
Durbin-Watson stat	1.41088			

Table 3.23: Saudi employment

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEMPSA(-1)	1.125833	0.03006	37.45283	0
LSAUGDPPC	0.097447	0.033134	2.941	0.0071
LSAUGDPPC(-1)	-0.09718	0.031943	-3.04234	0.0056
LLFSA	2.807204	0.155382	18.06648	0
LLFSA(-1)	-2.90534	0.170665	-17.0237	0
Constant	1.306571	0.450681	2.899106	0.0079
R-squared	0.999506	Mean dependent var		1.718672
Adjusted R-squared	0.999403	S.D. dependent var		0.343532
S.E. of regression	0.008391	Akaike info criterion		-6.54654
Sum squared resid	0.00169	Schwarz criterion		-6.2663
Log likelihood	104.1981	Hannan-Quinn criter.		-6.45689
F-statistic	9717.57	Durbin-Watson stat		1.475272
Prob(F-statistic)	0			

OFW deployment

For OFW deployment, the regression starts with an Auto-regressive Distributed Lag model with one lag for the dependent variables and the following independent variables: emigration; Philippine and Saudi income and labor force; remittances and trend. A step-wise deletion of insignficant variables yields the final regression in Table 3.24. The results show that OFW deployment is positively related to lagged deployment, Philippine labor force, lagged Saudi income and labor force, and negatively related to concurrent Saudi labor force. Most of these results are as expected except for the effect of lagged Saudi labor force. An increase in Saudi labor force would increase OFW deployment if Saudi wages are downward-rigid and Saudi native employment remains the same. The resulting additional demand is filled up by migrants at lower wages. Philippine income and remittances are not significant. Increases in Philippine income and remittances would not affect emigration if wages rise proportionately more, making employment and unemployment unchanged.

Controlling for Philippine and Saudi wages (Table 3.25), Philippine income and remittances become negatively related to OFW deployment, as expected. OFW deployment is also negatively related to concurrent Saudi incomes. As Saudi labor demand increases, fixed wages increase the quantity of Saudi labor demanded relative to the quantity supplied. This increases Saudi native employment and decreases the demand for migrants. On the other hand, OFW deployment is positively related to lagged Saudi income. An increase in destination income would increase the demand for migrants. Controlling for wages increases the quantity demanded even more. The elasticity of OFW deployment to income increases from 0.47 to 1.8. OFW deployment is also positively related to lagged Philippine and Saudi wages. Controlling for Philippine income, an increase in Philippine wages would increase unemployment, increasing the supply of migrants. An increase in Saudi wages, controlling for income, would decrease the quantity demanded for native Saudi labor. Optimal employment is filled with migrant labor.

Table 3.24: OFW Deployment on exogenous factors

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOFW(-1)	0.323956	0.151215	2.142349	0.0421
LLBR	1.09595	0.59175	1.852049	0.0759
LSAUGDPPC(-1)	0.471051	0.136815	3.44297	0.002
LLFSA	-3.41181	1.426708	-2.39139	0.0246
LLFSA(-1)	3.568693	1.355565	2.632623	0.0143
Constant	-16.4104	5.129516	-3.19921	0.0037
R-squared	0.976065	Mean dependent var		13.44299
Adjusted R-squared	0.971277	S.D. dependent var		0.475233
S.E. of regression	0.080541	Akaike info criterion		-2.02811
Sum squared resid	0.162172	Schwarz criterion		-1.75057
Log likelihood	37.43572	Hannan-Quinn criter.		-1.93764
F-statistic	203.8954	Durbin-Watson stat		1.854462
Prob(F-statistic)	0			

A VAR of OFW deployment, wages and remittances (Table 3.26) also shows that OFW deployment is dependent on previous deployment. However, OFW deployment is also not affected by wages. However, OFW deployment is positively related to employment. Again, this means that employment may be increasing but

Table 3.25: OFW Deployment with wages

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LSACPI(-1)	0.817347	0.278753	2.93216	0.0077
LGDPPC	-1.11552	0.217105	-5.13816	0
LWAGE(-1)	1.356057	0.184608	7.345612	0
LSAUGDPPC	-1.2116	0.276526	-4.38149	0.0002
LSAUGDPPC(-1)	1.832552	0.304907	6.010192	0
LREMIT(-1)	-0.13341	0.058672	-2.27381	0.0331
YEAR	0.077707	0.008521	9.118965	0
Constant	-145.718	16.23836	-8.97369	0
R-squared	0.989512	Mean dependent var		13.41312
Adjusted R-squared	0.986175	S.D. dependent var		0.452803
S.E. of regression	0.05324	Akaike info criterion		-2.80483
Sum squared resid	0.06236	Schwarz criterion		-2.43117
Log likelihood	50.07238	Hannan-Quinn criter.		-2.68529
F-statistic	296.5233	Durbin-Watson stat		2.398095
Prob(F-statistic)	0			

not enough to cope with the labor supply. A VAR of OFW deployment, income, labor and remittances (Table 3.27) shows that OFW deployment does not seem to be related to Philippine and Saudi GDP per capita. However, OFW deployment is negatively related to labor supply in Saudi Arabia lagged one year, as expected. OFW deployment rises when the labor supply is low relative to demand. A full VAR (Table 3.28) of OFW deployment, wages, employment, remittances, income and labor shows that OFW deployment is positively related to lagged domestic wages. Deployment is also positively related to destination wages lagged two periods. However, deployment is not related to employment. OFW deployment is negatively related to domestic income (lagged two year) and positively related to destination income (lagged two years). OFW deployment is negatively related to domestic labor force, positively related to destination labor force lagged two year but negatively related to destination labor force lagged two years. A Granger causality test (Table 3.29) shows that only Philippine and Saudi wages and domestic income help predict OFW deployment.

Table 3.26: VAR: OFW Deployment, Wages, Remittances and Employment

	(1)				(2)					
	lnOFW	Wage	SA CPI	lnRemit	lnOFW	Wage	SA CPI	lnRemit	lnEmp	lnSAEmp
	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
L.lnOFW	0.449**	0.391	-2.156	0.044	0.230	0.085	-7.072*	0.044	0.061**	0.001
	(0.214)	(12.087)	(4.386)	(0.387)	(0.187)	(9.146)	(4.250)	(0.369)	(0.028)	(0.027)
L2.lnOFW	0.091	12.093	2.676	0.121	-0.102	-6.856	0.656	-0.253	0.071***	0.044*
	(0.176)	(9.986)	(3.623)	(0.320)	(0.168)	(8.209)	(3.815)	(0.331)	(0.026)	(0.024)
L.Wage	0.003	0.573***	0.063	-0.005	0.004	0.353**	0.061	-0.010*	-0.000	0.001**
	(0.003)	(0.197)	(0.072)	(0.006)	(0.003)	(0.149)	(0.069)	(0.006)	(0.000)	(0.000)
L2.Wage	0.001	-0.438**	-0.069	0.001	0.005*	-0.391***	-0.023	0.002	-0.001***	-0.000
	(0.003)	(0.181)	(0.066)	(0.006)	(0.003)	(0.137)	(0.064)	(0.006)	(0.000)	(0.000)
L.SA CPI	0.010	0.545	1.631***	0.008	0.005	1.200***	1.184***	0.024	0.004***	0.001
	(0.008)	(0.448)	(0.163)	(0.014)	(0.009)	(0.439)	(0.204)	(0.018)	(0.001)	(0.001)
L2.SA CPI	-0.004	-1.707**	-0.873***	-0.033	0.024	-2.592***	-0.229	-0.056*	-0.008***	-0.001
	(0.013)	(0.710)	(0.258)	(0.023)	(0.015)	(0.754)	(0.350)	(0.030)	(0.002)	(0.002)
L.lnRemit	0.074	0.477	0.611	0.741***	-0.029	-12.960**	5.020*	0.429*	0.010	-0.019
	(0.119)	(6.743)	(2.447)	(0.216)	(0.121)	(5.913)	(2.748)	(0.239)	(0.018)	(0.017)
L2.lnRemit	0.057	-1.969	0.752	0.286	-0.246*	-9.819	1.681	0.129	0.022	-0.024
	(0.121)	(6.828)	(2.477)	(0.219)	(0.136)	(6.643)	(3.088)	(0.268)	(0.021)	(0.019)
L.lnEmp					0.633	58.893	-19.114	4.330**	0.283*	0.394***
					(0.956)	(46.667)	(21.689)	(1.883)	(0.145)	(0.137)
L2.lnEmp					2.017**	159.073***	-31.321	0.591	0.404***	0.045
					(0.926)	(45.184)	(21.000)	(1.824)	(0.141)	(0.132)
L.lnSAEmp					0.557	-96.314***	13.720	-2.460**	0.119	1.825***
					(0.587)	(28.625)	(13.304)	(1.155)	(0.089)	(0.084)
L2.lnSAEmp					-0.609	52.211*	9.182	1.373	-0.164*	-1.037***
					(0.622)	(30.374)	(14.116)	(1.226)	(0.094)	(0.089)
constant	2.318**	73.761	-12.196	0.301	-31.106*	-2,794.507***	759.835**	-65.355**	3.555	-6.917***
	(0.906)	(51.261)	(18.600)	(1.643)	(16.300)	(795.459)	(369.698)	(32.105)	(2.474)	(2.327)

Table 3.27: VAR: OFW Deployment, Income, Remittances and Labor

	(1)				(2)					
	lnOFW coef/se	lnGDPpc coef/se	lnSAGDPpc coef/se	lnRemit coef/se	lnOFW coef/se	lnGDPpc coef/se	lnSAGDPpc coef/se	lnRemit coef/se	lnLabor coef/se	lnSALabor coef/se
L.lnOFW	0.648***	-0.021	-0.021	0.213	0.406**	-0.086**	-0.101	-0.263	0.012	0.008
	(0.208)	(0.052)	(0.188)	(0.327)	(0.195)	(0.044)	(0.187)	(0.255)	(0.038)	(0.010)
L2.lnOFW	0.087	0.051	0.031	0.120	-0.090	-0.002	-0.010	0.015	0.033	0.000
	(0.202)	(0.050)	(0.182)	(0.317)	(0.181)	(0.041)	(0.173)	(0.236)	(0.035)	(0.009)
L.lnGDPpc	0.268	1.315***	1.150*	0.235	0.056	1.311***	1.240**	0.403	-0.101	0.007
	(0.696)	(0.174)	(0.629)	(1.094)	(0.627)	(0.140)	(0.599)	(0.818)	(0.122)	(0.032)
L2.lnGDPpc	0.223	-0.741***	-0.064	-2.759**	0.593	-0.624***	0.125	-1.814**	0.035	0.032
	(0.809)	(0.202)	(0.730)	(1.271)	(0.678)	(0.152)	(0.648)	(0.884)	(0.132)	(0.035)
L.lnSAGDPpc	0.189	-0.071	0.420**	0.433	0.204	-0.093**	0.349*	0.542**	-0.031	0.000
	(0.225)	(0.056)	(0.203)	(0.354)	(0.196)	(0.044)	(0.188)	(0.256)	(0.038)	(0.010)
L2.lnSAGDPpc	-0.234	0.177***	0.012	0.341	0.040	0.260***	0.055	0.978***	-0.026	-0.005
	(0.213)	(0.053)	(0.192)	(0.335)	(0.221)	(0.050)	(0.211)	(0.288)	(0.043)	(0.011)
L.lnRemit	0.087	0.030	0.057	0.494**	-0.073	-0.027	0.005	0.025	0.061**	0.001
	(0.132)	(0.033)	(0.119)	(0.207)	(0.150)	(0.034)	(0.143)	(0.196)	(0.029)	(0.008)
L2.lnRemit	-0.031	-0.009	-0.043	0.460**	-0.124	-0.056**	-0.144	0.049	0.002	-0.003
	(0.131)	(0.033)	(0.118)	(0.205)	(0.127)	(0.028)	(0.121)	(0.165)	(0.025)	(0.006)
L.lnLabor					1.284	0.663**	1.799	7.475***	0.263	0.098*
					(1.156)	(0.259)	(1.105)	(1.507)	(0.226)	(0.059)
L2.lnLabor					1.479	0.346	-0.545	2.336	-0.110	0.026
					(1.356)	(0.303)	(1.296)	(1.768)	(0.265)	(0.069)
L.lnSALabor					-5.444**	-0.868*	1.315	-12.310***	0.912**	1.779***
					(2.114)	(0.473)	(2.020)	(2.755)	(0.412)	(0.108)
L2.lnSALabor					4.847***	0.666*	-1.458	8.982***	-0.594*	-0.872***
					(1.616)	(0.362)	(1.545)	(2.107)	(0.315)	(0.082)
constant	-1.059	1.487**	-3.590	9.226**	-31.343*	-10.106**	-19.794	-93.371***	8.431**	-0.938
	(2.548)	(0.636)	(2.301)	(4.004)	(18.450)	(4.128)	(17.631)	(24.052)	(3.600)	(0.941)

Table 3.28: VAR: OFW Deployment, Wages, Employment, Remittances, Income and Labor

	$\ln OFW_t$	$Wage_t$	$SACPI_t$	$\ln Emp_t$	$\ln SAEmp_t$	$\ln Remit_t$	lnGDPpc	lnSAGDPpc	lnLabor	lnSALabor
$\ln OFW_{t-1}$	-0.498***	-8.770	2.555	-0.073***	0.004	-0.396	0.014	0.094	-0.064**	0.005
$\ln OFW_{t-2}$	-0.289*	-6.680	16.467***	0.000	0.075***	-0.147	-0.007	0.014	0.010	0.011***
$Wage_{t-1}$	0.013***	0.087	0.224***	-0.000	0.002***	-0.010	0.000	0.001	0.001**	0.000***
$Wage_{t-2}$	0.022***	-0.184	-0.158*	0.000	0.000	0.007	-0.004***	-0.015***	0.002***	0.000**
SA CPI_{t-1}	0.004	1.308***	0.815***	0.004***	0.000	0.016	0.002	-0.036***	0.006***	0.000**
SA CPI_{t-2}	0.066***	-1.495*	-0.596**	-0.002*	-0.002**	-0.002	-0.011***	-0.013	-0.001	-0.000
$\ln Emp_{t-1}$	-1.233	-121.318	134.411***	-0.976***	0.604***	-0.705	0.220	-0.421	-0.384	0.056
$\ln Emp_{t-2}$	1.566	-48.340	100.452**	-0.786***	0.266*	-7.275**	-0.790	-2.991	0.105	0.032
$\ln SAEmp_{t-1}$	-1.142	-162.213	115.363***	0.310**	0.713***	9.003***	0.648	5.533***	-0.143	-0.023
$\ln SAEmp_{t-2}$	0.011	84.761	-100.469**	-0.459***	-0.107	-10.972***	-0.797	-4.261**	-0.279	-0.123**
lnRemit(-1)	0.321**	-22.647***	-4.899*	0.090***	-0.026**	0.137	-0.068*	0.132	0.098***	-0.001
lnRemit(-2)	-0.045	-18.775***	-8.612***	0.072***	-0.056***	0.248	-0.001	0.079	0.053***	-0.009***
$\ln GDPpc_{t-1}$	-3.851***	125.382**	9.552	-0.344***	-0.145**	0.340	1.141***	0.438	-0.746***	-0.084***
$\ln GDPpc_{t-2}$	-1.250	-100.201*	36.787**	-0.155**	0.222***	-3.985***	-0.250	2.944***	-0.192	0.030
$\ln SAGDPpc_{t-1}$	0.149	-29.286**	-8.774**	-0.000	0.029**	-0.044	-0.029	0.662***	0.007	0.005
$\ln SAGDPpc_{t-1}$	0.776***	38.576***	19.151***	0.060***	0.013	1.862***	0.226***	-0.079	0.043	0.015***
$\ln Labor_{t-1}$	-2.206	109.854	16.906	0.278**	-0.271**	5.091**	0.646	5.221***	-0.354	-0.039
$\ln Labor_{t-2}$	-2.885*	173.777*	-9.328	0.162	-0.185	6.825**	1.280***	1.891	-0.560**	-0.049
$\ln SALabor_{t-1}$	11.744*	64.263	-501.195***	0.295	2.172***	-35.569***	-4.551**	-24.145***	2.628**	1.751***
$\ln SALabor_{t-2}$	-5.897	75.220	355.066***	0.909**	-1.841***	37.093***	4.087***	19.594***	-1.069	-0.591***
constant	27.195	-3,120.083*	-2,130.611***	20.870***	-12.053***	-57.286	-13.716*	-14.158	16.510***	-2.195***

3.6 Summary

Over the past three decades, permanent migration from the Philippines has grown by an average of two percent per year. The number of registered emigrants has further grown by 74 percent of its previous value, confirming the process of 'cumulative causation'. The cycle of emigration is characterized by an increase in the 1980s, a decrease in the 1990s and a resurgence in the 2000s.

Emigration is driven by a growing labor force as expected. The corresponding decrease in wages would shift the migrant supply curve outward raising the wage differential between the US and the Philippines. As a result, more Filipino workers are willing to migrate at any given US wage. Emigration is significantly related to Philippine income only when accounting for structural break. However, the positive relationship is contrary to expectation. This is due to wages rising faster than income. Consequently, employment was not rising fast enough and unemployment was growing. This suggests that a migration hump (where migration increases with income) occurs only in as much as wages are growing faster than income thereby depressing employment and motivating migration. Emigration is positively related to lagged US income. As US income increases, the corresponding increase in US wages compels employers to substitute US workers with migrant labor. The lagged effect is understandable given the information and transactions cost for migration. Conversely, emigration is negatively related to lagged US labor force. As the US labor force increases, the resulting decrease in wages would increase the quantity demand for US labor.

Standard models of migration relate migration to wages and employment in the origin and destination countries. Others model migration as a function of income and labor force underlying labor demand and supply. Both implicitly assume no distortions in the economy and that wages and employment respond to income and labor in a free market. In a world of legislated wages and regulated employment, the effects on migration of changes in income and labor force may not be as expected. Moreover, either set of factors may be capturing the effects of the other, generating biased estimates. Accounting for distortions has an implication on the effects of changes in labor demand and supply on migration.

Controlling for wages, emigration is not significantly related to income and labor force. On the other hand, wages have a positive effect even when controlling for income and labor force. Holding income and labor force fixed, an increase in wages creates / increases excess labor supply, motivating migration. Like making bricks without straw makes the work harder, higher wages without corresponding

Table 3.29: Granger Causality Test: OFW Deployment

Dependent variable: LOFW				Dependent variable: LREMIT			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
WAGE	10.57381	2	0.0051	LOFW	0.160487	2	0.9229
SACPI	5.859322	2	0.0534	WAGE	1.617313	2	0.4455
LREMIT	0.956637	2	0.6198	SACPI	1.612021	2	0.4466
LEMP	1.715729	2	0.4241	LEMP	1.51033	2	0.4699
LEMPSA	2.912554	2	0.2331	LEMPSA	1.440182	2	0.4867
LGDPPC	7.931628	2	0.019	LGDPPC	4.030378	2	0.1333
LRGDPEPCSA	1.124105	2	0.57	LRGDPEPCSA	0.766985	2	0.6815
LLBR	3.468241	2	0.1766	LLBR	0.547889	2	0.7604
LLFSA	2.902377	2	0.2343	LLFSA	4.344218	2	0.1139
All	47.81165	18	0.0002	All	37.62406	18	0.0043
Dependent variable: WAGE				Dependent variable: SACPI			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
LOFW	1.528793	2	0.4656	LOFW	7.282983	2	0.0262
SACPI	2.82164	2	0.2439	WAGE	2.267524	2	0.3218
LREMIT	2.262908	2	0.3226	LREMIT	3.432484	2	0.1797
LEMP	0.246431	2	0.8841	LEMP	5.739144	2	0.0567
LEMPSA	0.058357	2	0.9712	LEMPSA	7.918002	2	0.0191
LGDPPC	7.42438	2	0.0244	LGDPPC	3.078259	2	0.2146
LRGDPEPCSA	1.697157	2	0.428	LRGDPEPCSA	5.499196	2	0.064
LLBR	0.271121	2	0.8732	LLBR	4.935641	2	0.0848
LLFSA	0.21431	2	0.8984	LLFSA	3.759809	2	0.1526
All	48.47521	18	0.0001	All	54.02303	18	0
Dependent variable: LEMP				Dependent variable: LEMPSA			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
LOFW	0.653631	2	0.7212	LOFW	170.1047	2	0
WAGE	0.248948	2	0.883	WAGE	58.13901	2	0
SACPI	5.375179	2	0.068	SACPI	28.1922	2	0
LREMIT	0.252512	2	0.8814	LREMIT	21.15045	2	0
LEMPSA	4.186038	2	0.1233	LEMP	54.34114	2	0
LGDPPC	4.854956	2	0.0883	LGDPPC	48.01553	2	0
LRGDPEPCSA	5.419738	2	0.0665	LRGDPEPCSA	112.757	2	0
LLBR	4.227312	2	0.1208	LLBR	177.7005	2	0
LLFSA	2.891121	2	0.2356	LLFSA	97.28008	2	0
All	42.30222	18	0.001	All	1973.591	18	0
Dependent variable: LGDPPC				Dependent variable: LRGDPEPCSA			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
LOFW	0.00675	2	0.9966	LOFW	0.182283	2	0.9129
WAGE	3.150716	2	0.2069	WAGE	6.489731	2	0.039
SACPI	2.093063	2	0.3512	SACPI	5.140358	2	0.0765
LREMIT	1.459775	2	0.482	LREMIT	0.009145	2	0.9954
LEMP	0.348467	2	0.8401	LEMP	0.506988	2	0.7761
LEMPSA	0.009775	2	0.9951	LEMPSA	4.409067	2	0.1103
LRGDPEPCSA	0.094224	2	0.954	LGDPPC	8.545485	2	0.0139
LLBR	0.453492	2	0.7971	LLBR	0.836324	2	0.6583
LLFSA	0.037581	2	0.9814	LLFSA	1.302075	2	0.5215
All	15.85172	18	0.6029	All	59.79593	18	0
Dependent variable: LLBR				Dependent variable: LLFSA			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
LOFW	0.180397	2	0.9137	LOFW	15.95003	2	0.0003
WAGE	2.510324	2	0.285	WAGE	14.15856	2	0.0008
SACPI	3.312317	2	0.1909	SACPI	2.33228	2	0.3116
LREMIT	0.57619	2	0.7497	LREMIT	6.889636	2	0.0319
LEMP	0.422817	2	0.8094	LEMP	3.769471	2	0.1519
LEMPSA	6.173991	2	0.0456	LEMPSA	34.48577	2	0
LGDPPC	4.693654	2	0.0957	LGDPPC	0.147554	2	0.9289
LRGDPEPCSA	2.057232	2	0.3575	LRGDPEPCSA	0.44017	2	0.8025
LLFSA	2.829428	2	0.243	LLBR	11.82893	2	0.0027
All	27.03256	18	0.0784	All	401.1735	18	0

increase in income makes employment more difficult. Controlling for US wages raises the effects of US income and labor force. An increase in income, controlling for labor force and wages, raises the quantity of labor demanded relative to quantity supplied, thereby increasing migrant demand. An increase in labor force raises the quantity of US labor supplied relative to quantity demanded, holding income and wages fixed, decreasing migrant demand. Emigration is positively related and highly elastic to US wages. Controlling for US income and labor force, an increase in US wages decreases US employment, requiring migrants to fill the decrease in US native employment. Emigration is negatively related to remittances. An increase in remittances increases local labor demand, increasing employment and decreasing the supply of migrants.

Accounting for employment using a vector auto-regression model shows that permanent migration is positively related to domestic wages, holding labor demand and supply and employment fixed. Higher wages raise the quantity of labor supplied creating unemployment even at existing employment levels. Emigration is also positively related to domestic employment, controlling for labor demand and supply and wages. Higher employment reduces wages relative to what workers are willing to accept. Emigration is negatively related to national income. A decrease in income reduces the quantity of labor demanded at the same wage, creating unemployment. Otherwise, employers are willing to pay a lower wage at existing employment levels. Emigration is negatively related to the domestic labor force, with labor demand, wage and employment fixed. With higher labor supply at the same wage, producer surplus rises, increasing the quantity of labor supplied.

Permanent migration increases with destination wages. As US wages increase, the quantity of US labor demanded decreases. If migrants can be paid lower than the wages for US labor, migrants can fill the decrease in US labor. Emigration increases with destination income as this increases the demand for labor; but is undeterred by subsequent declines. Emigration decreases as the destination labor force increases as this creates excess labor supply at prevailing wages and employment levels. Emigration is positively related to remittances. If remittances increase labor demand holding wages constant, the increase in the quantity of labor supplied had wages increased would have to migrate.

Like permanent migration, temporary migration is also positively related to the Philippine labor force but also not related to income and remittances. Increases in income and remittances would not affect OFW deployment if wages rise proportionately more, making employment and unemployment unchanged. OFW deployment is positively related to lagged Saudi income. As Saudi income increases, Saudi wages increase attracting more migrants. At the same wages, the quantity of labor demanded also increases relative to the quantity supplied increasing the demand for migrant labor. OFW deployment is positively related to lagged Saudi labor force, contrary to expectation. An increase in Saudi labor force would increase OFW deployment if Saudi wages are downward-rigid, with native employment not increasing. The additional labor demand would have to be filled up with migrant labor at lower wages.

Controlling for Philippine wages, Philippine income and remittances are negatively related to OFW deployment, as expected. A decrease in income and remittances, holding wages fixed, would decrease quantity of labor demanded relative to quantity supplied, increasing the supply of migrants. Controlling for lagged Saudi wages, the elasticty of OFW deployment to lagged Saudi income increases. As Saudi labor demand increases, fixed wages increase the quantity of Saudi labor demanded relative to quantity supplied, increasing the demand for migrant labor. OFW deployment is positively related to lagged Philippine and Saudi wages. Controlling for Philippine income, an increase in Philippine wages would increase unemployment, increasing the supply of migrants. An increase in Saudi wages, controlling for income, would decrease the quantity demanded for native Saudi labor. Optimal employment is filled with migrant labor.

Accounting for employment, temporary migration is also positively related to domestic wages, as well as to Saudi wages. However, OFW deployment is not significantly related to domestic employment and Saudi employment. Temporary migration is also negatively related to domestic income and positively related to Saudi income. OFW deployment is also negatively related to the local labor force. On the other hand, OFW deployment is positively related to Saudi labor force. Controlling for wages and employment, the increase in the quantity of labor demanded has to be filled with migrants at lower wages. OFW deployment is also positively related to remittances.

Chapter 4

Of Milk and Honey: Returns to Migration and Education of Overseas Filipino Workers

> "So I have come down to rescue them from the hand of the Egyptians and to bring them up out of that land into a good and spacious land, a land flowing with milk and honey..." - Exodus 3:8

The third study aims to estimate the returns to migration and education for overseas Filipino workers. It finds that earnings of overseas Filipino workers in most key destinations are higher than those of domestic workers, but their returns to schooling are not significantly different from, or are even lower than, those of domestic workers. These findings together with the result of a Heckman selection model confirm the negative selection of temporary migrants. Apart from purchasing power parity gains to either earnings or returns to schooling, there are also monetary gains in the conversion of foreign earnings to the local currency through the US dollar as in the case of remittances.

4.1 Context and Objectives

While much is known about the benefits of migration in the Philippines at the household and national levels, not much is known about the private returns that are motivating migration in the first place. This paper aims to determine the returns to migration of Filipinos and to the education of Filipino migrants. It extends earlier research on returns to education of local workers. Estimates of domestic returns to education are suspected to be underestimated considering the migration especially of the more able from the periphery to the capital or abroad. The inability to account for migration in domestic returns to education led this author to analyze returns to education for migrants.

Most existing studies on the Philippines focus on remittances, such as the benefits of remittances and the motives for remittances. Other studies analyzed the determinants of migration. Existing studies of income gains from migration are quite limited. Some compare incomes across destinations, but not between migrants and non-migrants. They also estimate returns to education over all destinations, but do not compare returns across destinations nor with the Philippines. Another study compares wages of Filipinos in the US and in the Philippines, accounting for both their observed and unobserved differences. However, to my knowledge, there is still no study comparing the wages and returns to education of Filipinos in various destinations and the Philippines. This is the research gap that this study seeks to fill.

The third part of this dissertation aims to determine the returns to temporary migration and education of overseas Filipino workers. Return to migration is the income gain from working overseas relative to what one would earn in the Philippines. Return to education for overseas Filipino workers is the income gain per year of schooling relative to return to education for domestic workers. It uses a unique data-set on overseas workers rarely used in previous studies including income data which are not available from widely-used survey data. Gains to income and returns to schooling are estimated for overseas workers altogether, for workers in major destinations and in other destinations as separate groups, and for individual top destination countries. Earnings and returns to schooling are also disaggregated by sex, and estimated in purchasing power parity and in US Dollars.

The study finds that earnings are higher but returns to education are lower for overseas workers in general and in most top destinations. In some destinations, earnings are not higher but returns to schooling are higher. However, there are no apparent gains in a few key destinations for males and females, either to labor or to human capital, nor to work experience. Nevertheless, gains may be realized through the exchange rate as earnings are brought home and converted to local currency.

The study is organized as follows: Section 4.2 reviews the literature on the impacts of migration and return on migration. Section 4.3 discusses the econometric model and methodology. Section 4.4 describes the data sources and the variables. Section 4.5 presents the descriptive statistics. Section 4.6 analyzes the econometric results. Finally, Section 4.7 provides a summary discussion.

4.2 Literature Review

4.2.1 Impacts of Migration

Much has been written about the benefits and costs of migration. UNDP (2009) surveys the literature on the impacts of migration to origin and host countries. In origin countries, at the household level, migration provides remittances that help improve nutrition, health and general household welfare. Remittances serve as an alternative income source, mitigate against income shocks and encourage household entrepreneurship, investments, and savings for further migration. Moreover, remittances raise education spending, enhancing the formation of human capital. Even when used for consumption, remittances boost economic activity. There are also migration costs to the household, such as negative emotional effects and adverse effects on child and elderly care.

Across countries, mobility is said to reduce income disparities. At the national level, remittances can provide macroeconomic stability more than foreign aid and foreign investment do. Migrants also provide collective remittances that finance community infrastructure and services. Migration has social and political effects as well, such as political participation and the development of political institutions. Migration also provides ideas and good practices from abroad such as egalitarian gender relations and a 'culture of migration'.

On the other hand, emigration of skilled workers is feared to decrease the quality of services. Remittances can be a 'resource curse', resulting in currency appreciation and reducing competitiveness. Migration also affects income distribution depending on which segment of the economy moves more. Remittances from international migration tend to benefit the better off while those from internal migration benefit the poor more. Migration also has negative cultural effects such as the gang culture from the United States, and migrants with revolutionary ideas can spur civil wars.

In destination countries such as the OECD, immigration has been found to raise employment, stimulate business, encourage investment, and enhance innovation. While there are concerns that immigrants drive wages down, the effect is found to be small and depends on whether the skills of immigrants complement or compete with the skills of locals. The effect on employment also depends on market segmentation; displacements are unlikely if migrants take on low-skilled jobs that allow locals to move up the value chain. The negative impact on employment is small in light of the institutional discrimination against migrants which compel them to settle for informal employment.

Migration can also push rapid urbanization putting a stress on services and driving migrants into informal settlement subject to environmental and social risks. In some European countries, migrants are viewed as a fiscal burden, "tak(ing) more than they give". In the U.S., the newer generations of migrants are a source of fiscal surplus rather than costs. Other concerns about migrants relate to security and crime, and cultural diversity. In Europe, there are twice more immigrants in prison than locals while in the U.S., proportionately less immigrants are in prison. Nations established by migrants tend to be more accepting of migrants, and some cultural characteristics such as food are easier to adopt than others such as religion. Attitude toward migrants is determined by education, age, employment, and migration background.

Migration provides various benefits to the household. Reviewing the literature on the economic impact of migration and remittances in the Philippines on households, Orbeta (2008) finds remittances raising household consumption, as well as the shares of housing, durable goods, education, health, and recreation. While remittances increase education spending and promotes school enrolment over youth employment, they also increase inequality in this spending. Remittances also reduce poverty incidence. Labor force participation rates among households with overseas workers are lower than among households without, as household incomes and demand for leisure increase.

At the national level, the largest benefit from migration appears to be remittances, reaching over 17 billion dollars in 2011 and amounting to 7.6 percent of GDP. The national Socio-Economic Report 2010-2012 identifies growth in remittances as complementary to overall economic growth, contributing to a stronger domestic currency, stabilizing private consumption, and keeping the current account in surplus (NEDA, 2013). Overseas Filipinos also provide funding support through government and NGOs for "relief and rehabilitation, education and scholarships, health equipment/facilities and medical missions, water and sanitation facilities, and livelihood assistance" (CFO, 2010). They also facilitate transfer of technology through return-visits to and sharing in the Philippines such as through the Department of Science and Technology's Balik (Return)-Scientist Program.

There are also economic, social and political costs of migration. Baggio (2009) analyzes the costs of Filipino international migration. The economic costs of migration include increasing inequality as remittances accrue to households with higher incomes and education. Overseas workers come from richer regions so remittances go to these regions widening regional inequalities. The social costs of migration includes separation in the family which threatens relationships and the unity of the family. The stability of the family appears to be threatened more with the migration of mothers, as certain roles such as care-giving are under stress. Children face school, emotional, psychological and health problems, especially in cases where the mothers migrate, although these are mitigated in extended families. A long history of migration has created a 'culture of migration' with 60 percent of children of overseas workers considering working abroad, and taking up education oriented toward the international labor market. The exodus of professionals such as doctors and nurses is also showing adverse effects on the health care system. The political costs of migration includes the excessive reliance on remittances that has prevented government from developing sustainable development policies. The deployment of huge numbers of emigrants has also placed Filipino migrants at the mercy of destination countries, facing discrimination and human rights violations.

Much of the literature on migration focuses on the social benefits and costs of migration. Analyses on benefits focus on the effects of remittances to the household and the nation. On the other hand, analyses on costs focus on 'brain drain' and negative externalities to non-migrants. Little is known about the private benefits and costs to the migrant himself. However, while remittances have only second-order effects on welfare, individual income gains from migration have first-order effects on welfare (Clemens, 2011). Clemens describes the potential gains from unrestricted migration as "trillion dollar bills on the sidewalk", estimated at 50-150 percent of world GDP. The gains from migration of 5 percent of the world population alone is said to exceed gains from the removal of all barriers to trade and capital flow.

4.2.2 Return to Migration

Migration theory developed in the context of economic development. The movement of labor was considered to depend on relative supplies of and demand for labor, and on the corresponding productivities. Lewis (1954) observed that unlimited supplies of labor in agriculture kept rural wages at subsistence level and excess labor moved to urban areas for industrial employment at wages higher than subsistence rates. Similarly, Harris and Todaro (1970) argued that labor migrates from rural to urban areas as long as urban incomes exceed rural outputs. The disparities in labor supplies and wages that drove internal migration were also thought to be driving international migration. Migration proceeded from labor-abundant low-wage countries to labor-scarce high-wage countries. Conversely, investment flowed from rich capital-abundant countries to poor capital-scarce countries where returns are higher.

In microeconomic theory, migration is seen as an investment in human capital (Sjaastad, 1962). As such, return on investment in migration can be determined by the income gain from moving relative to the monetary and opportunity costs of migration. Migration is essentially a response to differences in earnings and a movement towards higher pay. Accordingly, the emigration rate is positively related to average income in the destination country, and negatively related to average income in the home country and migration costs (Borjas, 1987). Institutional restrictions limit mobility by raising migration costs generating migration selection. Migration also depends on the probabilities of obtaining a job in the destination and origin countries (Todaro, 1969; Todaro and Maruszko, 1987). Human capital tends to raise the likelihood of employment and wages in the destination and therefore the probability of migration (Massey et al., 1993). Governments regulate migration through policies affecting employment, wages and costs.

Determining the returns to migration can be considered as an evaluation problem. The framework of analysis is adapted from the theory of impact evaluation (Khandker et al., 2010) with migration as the treatment. It involves comparing the actual earnings of migrants with their counterfactual earnings had they not migrated. The difference is called the *treatment effect on the treated*:

$$TOT = E(Y_i(1)|M_i = 1) - E(Y_i(0)|M_i = 1).$$

The problem is that the counterfactual is unobserved. Given this missing data problem, the second best option is to compare the earnings of migrants with those of non-migrants, endeavouring to choose a non-migrant comparison group that is much like the migrant group. The basic econometric model can be written as:

$$Y_i = \alpha X_i + \beta M_i + \varepsilon_i$$

where M is a dummy equal to 1 for migrants and 0 for non-migrants/domestic workers; β is the income effect of migration; X is a vector of other observed characteristics; and ε is the error term. If migration were random, the migration dummy would be uncorrelated with the error term, and the OLS estimate of the effect of migration would be unbiased. The average effect of migration would then be:

$$D = E(Y_i(1)|M_i = 1) - E(Y_i(0)|M_i = 0).$$

The problem is that migration is not random: migrants and non-migrants may not be similar in the absence of migration. Rather, migrants self-select based on observed as well as unobserved characteristics (e.g. ability, motivation).[1] The difference in earnings between migrants and non-migrants may not due to migration alone. The discrepancy between the average effect of migration and the treatment effect on the treated creates selection bias:

$$D{-}TOT = [E(Y_i(1)|M_i = 1){-}E(Y_i(0)|M_i = 0)]{-}[E(Y_i(1)|M_i = 1){-}E(Y_i(0)|M_i = 1)].$$

$$D - TOT = [E(Y_i(0)|M_i = 1) - E(Y_i(0)|M_i = 0)].$$

$$D - TOT = Bias.$$

If migrants were randomly selected as in McKenzie et al. (2010), there would be no selection bias. However, if random selection is not feasible, non-experimental methods can be used to evaluate the impact of migration. One option is to use propensity score matching to create a comparison group based on a model of the probability of migration, using observed characteristics. Migrants are then matched to non-migrants based on the likelihood of migration or propensity score. Matching is valid only if earnings are independent of migration given observed characteristics (Rosenbaum and Rubin, 1983) (that is, unobserved characteristics do not affect migration), and there is sufficient overlap in the propensity scores between migrants and non-migrants. The treatment of treated for the propensity score matching is the mean difference in earnings between the migrants and the comparison group:

$$TOT_{PSM} = E_{P(X)|M=1}[E[Y^T|M = 1, P(X)] - E[Y^C|M = 0, P(X)]].$$

As migration is affected by unobserved characteristics such as ability, propensity score matching estimates may still be biased. A similar bias is cited in Chiquiar and Hanson (2005) by Moraga (2010). In this case, the double-difference method may be used as it assumes the presence of unobserved heterogeneity affecting migration. However, these unobserved characteristics are time-invariant and can be differenced out. The double-difference technique usually uses panel data as did Clemens et al.

[1] In the latter case, the migration dummy is correlated with the error term, making the estimates biased.

(2009). The technique involves estimating the changes (differences) in earnings for both migrants and non-migrants over time. The average income effect of migration is the difference between these differences:

$$DD = E(Y_1^M - Y_0^M | M_1 = 1) - E(Y_1^C - Y_0^C | M_1 = 0).$$

where Y_t^M and Y_t^C are the earnings of migrants and non-migrants, respectively, at time t. However, given the single time period for our data, we can not apply double difference.

If unobserved characteristics are time-varying, the double difference method estimates may also be biased. To allow for time-varying unobserved heterogeneity, instrumental variable regression can be used. It involves finding an instrument that is highly correlated with migration but not correlated with unobserved characteristics affecting earnings. As no suitable instrument is available at this time, instrumental variable regression can not be employed as yet. Data limitations notwithstanding, useful estimates of income gains from migration which have not been derived until now can still be derived.

Income gains from migration depend on the origin and destination countries and can be substantial. Among migrants to OECD countries, those coming from least developed countries earn about 14 times more than the average income in their country. Those from moderately developed countries, highly developed countries and very highly developed countries earn about 4.4 times more, 2 times more, and 10 percent more, respectively, than the average income in their country (Ortega, 2009). While the poorest countries stand to gain the most from migration, their emigration rates are the lowest as they are constrained by poverty (UNDP, 2009).

Existing studies on the Philippines compare earnings across key destinations (relative to the top destination, Saudi Arabia), across occupations (relative to nurses), by age and sex. They also estimate returns to education with primary education as reference. Tan (2005) analyzed the wage structure of overseas Filipino workers in 2003. She found that newly hired overseas Filipino workers in the US and Canada earned 194 percent more than those in Saudi Arabia (the destination with the largest flow of overseas workers). Those in the UK and Ireland earned 153 percent more, Japan 140 percent more, Israel 98 percent, Singapore 32 percent, Africa 30 percent, Hong-Kong 102 percent, and Taiwan 44 percent. Relative to nurses, other professionals earned 4 percent less, domestic helpers earned 68 percent less, salespersons 60 percent less, skilled manual workers 46 percent less, and clerks 33 percent less. Wages of entertainers were not significantly different from those of nurses. Overseas workers with complete tertiary education earned 12 percent more than those with only primary education, but the wages for other levels of education were not significantly different from that for primary education. Overseas workers earn 0.85 percent more per year as they age. Females earn 9.6 percent less than males.

A similar analysis for rehires yields lower advantages for the US and Canada, UK and Ireland, Israel, Hong-Kong and Taiwan, and even a disadvantage for Japan, but higher advantages for Singapore and Africa, relative to Saudi Arabia. Other rehired professionals earn as much as nurses, while the rest of the occupations earn even much less than nurses. Relative to new hires, rehires with complete tertiary education earn much more than those with only primary education. The coefficient of age rose to 1.3 percent while wages for females are much lower than for males.

Tan (2006) found that overseas Filipino workers earned 46.6 percent higher in Europe than in Saudi Arabia, 27.5 percent higher in Taiwan, 35.1 percent more in Hong Kong, 56.7 percent more in Africa, 67.8 percent more in Japan, 116.5 percent more in UK, and 47.4 percent more in the US. Overseas Filipino workers' earnings rose by 25 percent with a college education (relative to vocational training), and rose by 3.2 percent per year of stay in the host country. She also analyzed the determinants of remittances. She found that remittances rose by 5.3 percent for every 10 percent increase in migrant wage. Permanent migrants remit 41 percent less than do temporary migrants. This confirms the remittance motive of temporary migration. US migrants remit even less, up to 61 percent less. Females remit less than males, and overseas workers remit 3.4 percent less per working household member.

Several points are worth noting from the foregoing studies. First, the destination with the most Filipino workers does not necessarily provide the highest wage. While Saudi Arabia hosted the largest flow of Filipino workers, it pays lower wages than most other key countries. It is possible that the probability of employment has a stronger effect than wages in this case. Second, growing occupations provide the highest wages. Nurses are part of the smallest but only growing occupational category (administrative and managerial workers) in 2002-3 (Philippine Overseas Employment Administration, 2003) and have the highest wages. Third, tertiary education is important for overseas employment.

A few comments are also in order. First, while these estimates show comparative earnings across destinations, they do not determine income gains from migration. While these estimates are useful in understanding the selection of destinations, choosing a destination is secondary to the decision to migrate. Comparing the incomes of migrants to non-migrants is of primary importance. Second, return to education is estimated over all destinations. It would be useful to compare returns to education across different destinations. Third, using age instead of work experience generates biased estimates. Experience can be approximated by deducting years of education and age before schooling from current age.

Even if one can compare the wages and returns to education between migrants and non-migrants, one has to confront another key issue. The income gains from migration may be overstated given selectivity. Selection can occur in observed characteristics such as education. If return to education is higher in the host country, migrants tend to have more schooling (Borjas, 1999). Otherwise, if return to education is higher in the home country, migrants tend to have less schooling. Given the importance of tertiary education for overseas employment, Filipino migrants must be positively selected in terms of education.[2]

Evidence suggests that Filipino migrants are positively selected in terms of education. Docquier and Marfouk (2005) show that in 2000, the Philippines had the fifth highest selection rate; the share of skilled emigrants to the emigrant stock was 67.1 percent compared to the average of 51.4 percent for Southeast Asia and 46.8 percent for Asia. Schiff and Sjoblom (nd) compile the shares of Filipino migrants in six key OECD destination countries (U.S.A., U.K., Australia, Canada, France, and Germany) by education level for 1975-2000 [Table 3.5]. The table shows the proportion of highly educated migrants (i.e. those with tertiary education) rising from 51.5 percent in 1975 to 72.2 percent in 2000. In the U.S., the proportion highly educated migrants rose from 51 percent in 1975 to 73 percent in 2000. In Canada, the proportion of Filipino migrants with a high level education rose from 71 percent in 1975 to over 81 percent in 2000. In Australia, most (86 percent) Filipino migrants in 1975 had a low level of education (i.e. only primary education). However, since 1980, most migrants had a high level education although this dropped from 84 percent in 1980 to 66 percent in 2000. These figures show that Filipino migrants to the OECD, particularly in the U.S., Canada, and Australia are positively selected in terms of education. If the educational attainment of migrants is positively correlated with unobserved characteristics affecting their migration, standard estimates of income

[2]Given the earnings functions, $lnw_0 = \mu_0 + \delta_0 s + \varepsilon_0$ and $lnw_1 = \mu_1 + \delta_1 s + \varepsilon_1$, where w_0 and w_1 are the wages for the home and destination countries, respectively, and s is years of schooling; the education distribution in the home country, $s = \mu_s + \varepsilon_s$; the migration rate, $P(z^*) = Pr[\tau > -[(\mu_1 - \mu_0) - (\delta_1 - \delta_0)\mu_s - \pi]] = 1 - \Phi(z^*)$, where $\tau = (\varepsilon_1 - \varepsilon_0) + (\delta_1 - \delta_0)\varepsilon_s$, and $z^* = -[(\mu_1 - \mu_0 + (\delta_1 - \delta_0 - \pi]/\sigma_\tau$. The mean schooling of migrants, $E(s|\mu_s, I > 0) = \mu_s + \frac{\sigma_s^2}{\sigma_\tau}(\delta_1 - \delta_0)\lambda$ is $> \mu_s$ if $\delta_1 > \delta_0$ and $< \mu_s$ if $\delta_1 < \delta_0$.

gains from migration would be biased upward.

Accounting for observed characteristics, there appears to be huge income gains for Filipino migrants. Using the US Census and household survey data across various countries, Clemens et al. (2009) estimate the ratio, R_0, between the wages of workers in the United States and those of observably identical (in terms of country of birth, country of education, education level, age, sex, and urbanity) workers in 42 other countries including the Philippines. They find a median real wage ratio of between 4 and 14 depending on the exchange rate used and the proportion of income spent in the home country assumed. Observable characteristics account for a third of wage differences across countries. The ratio for the Philippines is 3.82 using PPP, 4.53 if 20 percent of the income is consumed in the Philippines, 7.16 if 60 percent is consumed in the Philippines, and 17.09 using the official exchange rate.

The importance of the exchange rate is apparent in light of the "new economics of labor migration". According to this perspective, the decision to migrate is made not only by the migrant but also his non-migrant family (Stark and Bloom, 1985). Migration costs and returns are shared among family members with an implicit agreement as to their distribution. Returns to migration for the family include remittances. Lucas and Stark (1985) presents three motivations for remittances. The first is 'pure altruism' where the migrant's utility is enhanced not only by his consumption, but also by that of his family in the home country. The second is 'pure self-interest' where the migrant sends remittances with a view to gaining an inheritance, or to ensure that business interests/property are cared for, or to promote social standing upon return. The third is 'tempered altruism or enlightened self-interest' where the migration of some members is a household strategy to spread risk. Remittances are a contractual obligation of the migrant to the sending household. It includes repayment of the household's investment in the migrant's education.

The exchange rate is important not just in determining income gains across countries but also changes over time. Yang (2008) found that remittances rose by 6 percent for every 10 percent increase in the exchange rate. Improvements in the exchange rate also tend to keep migrants from returning home. Higher exchange rates also led to higher household income essentially through remittances. However, while the exchange rate does not affect consumption, it does affect investment (in consumer durables) positively. Positive exchange rate shocks also led to more child schooling and less child labor, and more self-employment. While positive exchange rate shocks increase the likelihood of new entrepreneurial activity particularly in transportation, communication and manufacturing, they have no effect on entrepreneurial income. Yang concludes that household investment is primarily affected by exchange rate shocks rather than real economic shocks.

Income gains from migration may also be over-estimated due to unobserved characteristics. Returns from migration are higher for people with higher ability and motivation as these raise earnings relatively more than migration costs (Chiswick, 1978).[3] The quality of migrants depends on the correlation between income disparities in the home and destination countries on one hand and the ratio between the disparities on the other (Borjas, 1987).[4] *Positive selection*, where the most able persons migrate and earn more than the average person in the destination country, occurs to the extent that income disparities between home and destination countries are highly correlated and income inequality is higher in the destination country. This suggests that the more able are taxed more in their home country and less in the destination country, so they choose to move. Otherwise, if income inequality is higher in the home country, *negative selection* occurs, where the less able migrate but earn lower than the average person in the destination country. This means that the less able benefit from redistribution in the destination country. If the correlation in income disparities is lower than their ratio, the less able migrate but earn higher than average wages in the destination country, a phenomenon which Borjas (1987) calls *refugee sorting*.

Findings on the selection of earlier migrants to the United States in terms of earnings and returns to schooling are mixed. Chiswick (1978) found that US immigrants have three percent higher earnings than native-born Americans, holding schooling, work experience, residence, and labor effort constant. While returns to schooling for immigrants are lower than those of the native born, these rise when considering the number of years since migration. Borjas (1987) found that the quality of immigrants who arrived in the US in 1979 measured by entry wage is lower for those from higher inequality countries. A rise in income inequality reduces the motivation to migrate for people in the higher segments of the income

[3]The rate of return to migration for person i is $r_i = (W_{d,i} - W_{o,i})/(C_o + C_d)$ where $W_{d,i}$ and $W_{o,i}$ are the earnings in the destination and origin countries, respectively, $C_o = pW_{o,i}$ is the opportunity cost of migration and is a fraction p of domestic earnings $W_{o,i}$, and C_d is the direct cost of migration. Return to migration for a more able person j, $r_j = (W_{d,j} - W_{o,j})/(pW_{o,j} + C_d)$, is greater than that for a less able person i, $r_i = (W_{d,i} - W_{o,i})/[pW_{o,i} + (C_d/1 + l)]$, if greater ability does not raise migration costs more than earnings. Migrants are also likely to have higher ability and motivation than natives of destination countries.

[4]Given the conditional means $E(lnw_0|I > 0) = \mu_0 + \frac{\sigma_0\sigma_1}{\sigma_v}(\rho - \frac{\sigma_0}{\sigma_1})\lambda$ and $E(lnw_1|I > 0) = \mu_1 + \frac{\sigma_0\sigma_1}{\sigma_v}(\frac{\sigma_1}{\sigma_0} - \rho)\lambda$, where ρ is the correlation between ε_0 and ε_1, $\lambda = \frac{\phi(z)}{1-\Phi(z)}$; $E(lnw_0|I > 0) > \mu_0$ if $\rho > \frac{\sigma_0}{\sigma_1}$, and $E(lnw_1|I > 0) > \mu_1$ if $\frac{\sigma_1}{\sigma_0} > \rho$. Otherwise, $E(lnw_0|I > 0) < \mu_0$ if $\rho < \frac{\sigma_0}{\sigma_1}$, and $E(lnw_1|I > 0) < \mu_1$ if $\frac{\sigma_1}{\sigma_0} < \rho$.

distribution, decreasing the quality of migrants. Entry wage is 26 percent higher for those with English proficiency, is lower for the older, and rises 1.2 percent per 10 percent growth in origin country. Immigrants' assimilation into the economy, measured by their earnings growth over ten years, is found to be higher for those with English proficiency, rise with age at immigration, and be higher for those from richer countries. The change in cohort quality measured by the difference in wages between the 1955 and 1979 immigrant cohorts, is 13 percent higher for those from countries that shifted from political competition to repression, increased for those from Western Europe, decreased for those from less developed countries, and is higher for countries with migrant quotas. Finally, emigration rate decreases with distance and origin country GDP per capita, and is lower for countries with higher inequality.

Findings on the selection of Mexican migrants to the United States are also mixed. Chiquiar and Hanson (2005) found that returns to education among Mexican immigrants in the U.S. are lower than those in Mexico. Using wage densities and immigrant population shares by decile from the 1990 and 2000 Mexican and U.S. Census of Population and Housing, they found that Mexican male migrants come from the middle to upper-middle segment of the wage distribution, indicating intermediate selection among Mexican males. Similarly, Mexican female migrants are drawn from upper-middle segment of the wage distribution, indicating moderate positive selection. These seem to be inconsistent with higher inequality in Mexico relative to the US. Moraga (2010) criticize these results on three grounds. Firstly, these results, estimated from the U.S. census, pertain more to the selection of the stock rather than the flow of migrants. Secondly, the methodology does not account for unobserved characteristics such as wage shocks prior to migration. Thirdly, U.S. data underestimate immigrants from Mexico, especially the undocumented.

Conversely, Moraga (2010) presents new evidence supporting the negative selection of Mexican migrants to the U.S. He uses the nationally-representative Quarterly National Labor Survey (ENET) for 2000-2004, capturing the flow rather than the stock of migrants. Based on density and cumulative distribution functions, he finds that migrants have from 11 to 38 percent lower wages than non-migrants. Using frequency distributions, he finds that male migrants have three years less schooling than non-migrants, but female migrants have three years more schooling than non-migrants. Comparing the wage density distributions of non-migrants and migrants on one hand, and non-migrants and a counterfactual on the other, he finds that 62 percent of the difference in wages is due to observable characteristics while the remaining 38 percent is due to unobservables.

The foregoing findings confirm the hypothesis of negative selection of migrants from countries with relatively higher inequality. If migrants are also negatively selected in the destination countries, standard estimates on returns to their migration would be downward biased.

Filipino migrants appear to be positively selected in terms of unobservable characteristics. Clemens et al. (2009) estimate the *place premium*, R_e, (i.e. the ratio of the wages of observably and unobservably identical workers) in the United States and nine other countries including the Philippines. They estimate a place premium of 3.5 for the Philippines. This means that based on both observable and unobservable characteristics, Filipino workers in the US earn 3.5 times more than observably and unobservably idential workers in the Philippines. They then derive the ratio, $\frac{R_0}{R_e}$, to determine selection, and find a value of 1.08 for the Philippines. This means that the ratio of wages of observably identical workers in the US and the Philippines of 3.8 would be biased by 8 percent. Using panel data, the corresponding place premia and $\frac{R_0}{R_e}$ for Mexico are 2.49 and 1.03, and for South Africa 2.3 and 1.2, respectively. Using wage histories, the figures are 2.35 and 1.07 for Mexico, 3.08 and 0.96 for Guatemala, 3.28 and 1.07 for Nicaragua, 1.68 and 1.23 for Costa Rica, 1.87 and 1.06 for Dominican Republic, 7.84 and 1.32 for Haiti, and 2.61 and 1.45 for Peru. These figures suggest modest positive selection for most. Using residual wage kernel densities, they find that the median migrant comes from the 58th percentile of non-migrants in the Philippines, 56th percentile in Mexico, and 60th percentile in South Africa. This means that migrants from the Philippines are above average in terms of unobserved characteristics.

McKenzie et al. (2010) study the migration of Tongans to New Zealand, generating the only random experimental estimate of the returns to migration together with non-experimental estimates. With higher inequality in New Zealand than in Tonga, they predict positive selection of Tongans. They analyze New Zealand's Pacific Access Category, which accepts a yearly quota of Tongans into Zealand from a lottery of applicants. They find that lottery winners earn 88 percent more income than non-winners with similar characteristics and that migrants earn 263 percent more than non-migrants. Using non-experimental methods, they find that the instrumental variable estimate using a bad instrument is biased upward by 82 percent, while OLS overestimates by 31 percent. Propensity score matching overstates by 19-33 percent, while single-difference method is biased by 25 percent. Double-difference overestimates by 20 percent, while instrumental variable estimation with a good instrument has the lowest bias at 9 percent. The results confirm positive selection in unobserved characteristics.

To sum up, migration is primarily motivated by income gain. Therefore, we would expect income gains to be higher in destination countries hosting more Filipinos. Existing studies suggest that this is not always true as there may be constraints or restrictions to migration or employment in certain destinations. On the other hand, occupational choice appears to follow market signals, with Filipinos taking up occupations providing the highest possible wages. However, existing studies of income gains from migration are quite limited. Some compare incomes across destinations but not between migrants and non-migrants. They also estimate returns to education over all destinations, but do not compare returns across destinations nor with the Philippines. Another study compares wages of Filipinos in the US and in the Philippines accounting for both their observed and unobserved differences. However, to my knowledge, there is still no study comparing the wages and returns to education of Filipinos in various destinations and the Philippines. This is the research gap that this study seeks to fill.

4.3 Model and Methodology

The basic model is an augmented human capital earnings function (Mincer, 1974):

$$ln(W_i) = \alpha_1 + \beta_1 S_i + \gamma_1 t_i + \gamma_2 t_i^2 + \alpha_2 M_i + \beta_2 (M_i S_i) + \gamma_3 (M_i t_i) + \gamma_4 (M_i t_i^2) + X_i' \theta + \varepsilon_i \tag{4.1}$$

where $ln(W_i)$ is the natural logarithm of the wage of individual i, S_i is years of schooling, t_i is work experience, and M_i is a dummy variable for temporary migrants (non-migrants as reference). X_i is a vector of observable characteristics including dummy variables for male (female as reference), civil status, 16 regions (the national capital region as reference), and nine occupations (officials in government and special interest organizations, executives, managers, and supervisors as reference). ε is the error term.

β_1 is the return on schooling for non-migrants, $\beta_1 + \beta_2$ is the return on schooling for migrants. The coefficient of a quantitative regressor in a semi-logarithmic model measures the semi-elasticity of the dependent variable with respect to that regressor. However, to obtain the elasticity with respect to a dummy variable, Halvorsen and Palmquist (1980) suggest that the coefficient be transformed as follows: $exp(\beta) - 1$. Thus, the return on migration without schooling is $100 * [exp(\alpha_2) - 1]$. However, Kennedy (1981) argues that the resulting estimate is biased and suggests $exp(\beta - 1/2V(\beta)) - 1$. Giles (1982) shows that while this is also biased, it approximates his own minimum variance unbiased estimator with a large sample, and is easier to compute. While the Halvorsen and Palmquist (HP) estimator positively corrects for interpretation, the Giles estimator negatively corrects for bias (van Garderen and Shah, 2002). In choosing the estimator, van Garderen and Shah suggest that uncertainty be considered. They find that while the standard errors for the unbiased estimator is lower than that for the HP estimator, the naive estimator can have the lowest standard error, as well as lower mean squared error than even the unbiased estimator. Thus, in case of uncertainty (loss of significance) in the unbiased estimates, we can still rely on the standard estimates.

The foregoing model is expanded by accounting for differences by sex. This is done by including a dummy variable for males, B_i:

$$
\begin{aligned}
ln(W_i) = {} & \alpha_1 + \beta_1 S_i + \delta_1 t_i + \gamma_1 t_i^2 + \alpha_2 M_i + \beta_2(M_i S_i) + \delta_2(M_i t_i) + \gamma_2(M_i t_i^2) \\
& + \alpha_3 B_i + \alpha_4 B_i M_i + \beta_3(B_i S_i) + \beta_4(B_i M_i S_i) + \delta_3(B_i t_i) + \gamma_3(B_i t_i^2) \\
& + \delta_4(B_i M_i t_i) + \gamma_4(B_i M_i t_i^2) + X_i'\theta + \varepsilon_i
\end{aligned} \tag{4.2}
$$

where α_1 is the average wage for non-migrant females, $\alpha_1 + \alpha_2$ is the average wage for migrant females, $\alpha_1 + \alpha_3$ is the average wage for non-migrant males, and $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4$ is the average wage for migrant males. The return to schooling for non-migrant females is β_1 while $\beta_1 + \beta_2$ is the return to schooling for migrant females, $\beta_1 + \beta_3$ is the return to schooling for non-migrant males, and $\beta_1 + \beta_2 + \beta_3 + \beta_4$ is the return to schooling for migrant males. Henceforth, return to labor or labor wage is used interchangeably with return to migration. Likewise, return to human capital is used interchangeably with return to schooling.

The migration dummy M_i in Equations 4.4 and 4.2 are then replaced with dummy variables for major destinations and other countries, and then with a dummy variable for each key destination country to determine return to migration and return to schooling for Filipino workers in each of these countries.

In estimating returns to migration and the education of migrants, both wages and schooling for the same sample are needed. However, these data are not available in a single dataset but are found in separate datasets. Migrant wage data are derived from the Philippine Overseas Employment Administration (POEA) while migrant education data are found in the Survey of Overseas Filipinos (SOF). Several characteristics, namely age, civil status, region, destination country, sex, and occupation, are common to both datasets. To combine the information from the two data-sets, two sample two stage least squares (TS2SLS) regression (Inoue and Solon, 2010) is employed. This is superior to two sample instrumental variable (TSIV) estimation using the General Method of Moments (GMM) (Angrist and Krueger, 1992) as it corrects for differences in the distribution of instruments between the two samples thereby enhancing efficiency (Inoue and Solon, 2010). In the first stage, schooling is regressed on the aforementioned characteristics namely age, civil status, region and the interactions between destination country, sex, and occupation using the SOF dataset:

$$S_i = X_i'B + \epsilon_i \tag{4.3}$$

The predictions $\hat{S}_i = X_i'B$ are then applied to the POEA dataset. The LFS and POEA datasets are then combined for the estimation of an augmented human capital earnings function in the second stage:

$$ln(W_i) = \alpha_1 + \beta_1 S_i + \gamma_1 t_i + \gamma_2 t_i^2 + \alpha_2 M_i + \beta_2(M_i \widehat{S}_i) + \gamma_3(M_i t_i) + \gamma_4(M_i t_i^2) + X_i'\theta + \varepsilon_i \tag{4.4}$$

allowing the estimation of returns to education for migrants.

Interpreting the estimated returns to education of migrants as causal effects using this approach relies on several assumptions. Firstly, the quality of the SOF and POEA datasets are assumed to be the same. We discuss the quality of the datasets in the next section. Secondly, the samples in the SOF and POEA datasets are assumed to be similar in unobserved characteristics on the whole. These assumptions may not always be realistic. For this reason, an alternative approach is also employed.

If wage is a function of destination, $w = f(d)$, destination is a function of occupation, $d = g(o)$, and occupation is a function of schooling, $o = h(s)$, then return to schooling can be derived by multiplying the derivative of wage with respect to destination by the derivative of destination with respect to occupation and the derivative of occupation with respect to schooling.

$$\frac{dw}{ds} = \frac{dw}{dd}\frac{dd}{do}\frac{do}{ds} \tag{4.5}$$

All elements in the product on the right hand side can be estimated separately and without merging datasets. Returns to various occupations across destinations are estimated using the POEA dataset and compared to those in the Philippines using the LFS dataset:

$$ln(W_i) = \alpha + \beta_1 O_i + \beta_2(D_i O_i) + X_i'\theta + \varepsilon_i \tag{4.6}$$

where D_i is the destination country, O_i is occupation, β_1 is the return on a particular occupation in the Philippines and $\beta_1 + \beta_2$ is the return on that occupation in destination D.

The probabilities of taking on different occupations across different destinations are derived using the following equation:

$$P(O_i) = \frac{1}{1 + e^{-Z_i}} \tag{4.7}$$

where $Z_i = \alpha_1 + \beta_1 S_i + X_i'\theta + \varepsilon_i$, S_i is the schooling of person i, and X_i is a vector of demographic characteristics including age, sex, civil status, and region.

$$\frac{P(O_i)}{1 - P(O_i)} \tag{4.8}$$

is the odds of person i taking on a certain occupation O relative to being a laborer or unskilled worker. Taking the natural logarithm of equation 4.8 yields:

$$L_i = ln(\frac{P(O_i)}{1 - P(O_i)}) = Z_i = \alpha_1 + \beta_1 S_i + X_i'\theta + \varepsilon_i \tag{4.9}$$

where β_1 is the change in the log odds per additional year of schooling.

As discussed in the literature review, we acknowledge the issue of migration selection. However, given the data constraints, we settle on standard estimation. Nevertheless, the estimation of returns to migration and education of Filipino migrants of this kind is novel in itself and is the main contribution of this paper. The methodology for addressing migration selection is discussed in the Appendix.

4.4 Data

The study uses merged cross-sectional data from the Labor Force Survey (LFS) July 2011 round and the Philippine Overseas Employment Administration (POEA) Balik-Manggagawa (returning overseas workers) micro-data for 2011, data from the Survey of Overseas Filipinos 2011 round. A list of variables, description and sources is given in Table 4.1.

4.4.1 Labor Force Survey

The Labor Force Survey primarily aims to generate statistics on employment, unemployment, and underemployment for the Philippines at the national, regional, provincial and key city levels. It includes a sample of 41,000 households sufficient to provide reliable estimates at the provincial and key city levels, with a master sample covering 3,421 villages (both urban and rural) as primary sampling units (PSUs) for provincial estimates and a sub-sample of 2,219 villages as PSUs for regional estimates. A multi-stage design is used in sample selection. First, sample villages are selected with probabilities proportional to size. Second, enumeration areas are selected in sample villages. Finally, households are selected within enumeration areas. The survey uses a structured questionnaire with the information collected through personal interviews by National Statistics Office personnel.

The Labor Force Survey is used for data on domestic workers including wage, schooling, work experience, sex, marital status, occupation, and region. Wages for local workers are measured in terms of hourly wage, as annual or weekly wage would yield returns to education that include the effect of time spent at work. *Hourly wage* is computed as basic pay per day divided by the normal number of hours worked per day. *Years of schooling* is derived from the variable 'highest grade completed' where 'no grade' is assigned 0, incomplete elementary = 3, elementary graduate = 6, incomplete high school = 8, high school graduate = 10, college undergraduate = 12, college graduate =14, and completed post-graduate = 16.[5]

Consistent with the literature, *work experience* is used rather than age as using age leads to omitted variable bias that would underestimate return to schooling. Work experience is computed as age minus years of schooling minus six (6), the normal age before the start of schooling. This assumes continuous work experience after schooling and does not account for periods of unemployment and unpaid work. Sex is recoded as a *male* dummy variable with females as reference. A variable *occupation* is created by classifying various occupations into the ten major occupations in the 1992 Philippine Standard Occupation Classification (PSOC). The variable *region* is a categorical variable of the 17 regions of the country with the national capital region as reference.

The labor force survey also records observations of household members who are overseas, classified into overseas contract workers (temporary migrants), workers other than OCWs (irregular migrants), employees in Philippine embassies and

[5]The educational system that applies to the data comprise six years of elementary education starting around age seven, four years of secondary education starting around age 13, and tertiary education starting around age 17. The Philippine Constitution promotes the right to education and provides a system of free public education at the primary and secondary levels, and mandates primary education as compulsory. Starting in 2012, the Department of Education has implemented the K-12 program, a new system with Kindergarten, six years of primary education, four years of junior high school, and two years of senior high school.

consulates, and students abroad or tourists. However, while the data include demographic characteristics, they do not include wages. For this reason, other datasets on overseas workers are used, particularly the Survey of Overseas Filipinos and the POEA micro-data on re-deployed overseas workers.

4.4.2 Survey of Overseas Filipinos

The Survey of Overseas Filipinos (SOF) is a national survey that collects information on overseas Filipinos including contract workers who left within the last five years. Conducted as a rider to the October round of the Labor Force Survey, it has the same sampling frame as the LFS, but collects data with the past six months as reference period. Aimed at providing information on overseas Filipinos, particularly their economic contribution, it collects data on remittances and other socio-economic characteristics.

The Survey of Overseas Filipinos (SOF) collects data on overseas Filipinos including contract workers (temporary migrants), workers in Philippine embassies and consulates, workers other than contract workers (irregular migrants), tourists, students, immigrants, and those on official missions. The survey includes data on age, sex, education, marital status, occupation, region, and destination country. However, there are also no data on overseas workers' incomes, although the survey includes data on remittances in cash sent or brought home and in kind. For data on income of overseas workers, data from the Philippine Overseas Employment Administration are used.

4.4.3 POEA Micro-data

The Philippine Overseas Employment Administration (POEA) collects data on the re-deployment of overseas contract workers using the "Balik Manggagawa" (returning overseas workers) information sheet completed by vacationing overseas Filipino workers as a requirement for the re-issuance of their overseas employment certificate. The dataset includes personal information such as birth date, sex, civil status, province of origin; contract information including country of employment, salary and currency, and occupation (position); and beneficiary information. The data from this registry appears quite reliable considering that overseas contract workers certify the truthfulness and accuracy of the information under penalty of perjury.

As wage (salary) is reported in various periods, we derive *hourly wage* by dividing daily wage by 8, weekly wage by 8x5, monthly wage by 8x5x4, and annual wage by 8x5x50. Salary is generally reported in host country currency so to make them comparable, we convert them to International Dollars (PPP) by dividing the amount in host country currency by the PPP conversion factor (local currency unit per international dollar) from the World Development Indicators. With remittance as a motive for migration (Baines, 1994) and possibly the primary motive for temporary migration, the exchange rate matters a great deal to the size of the income or this case consumption gain from migration. Thus, conversion from international dollars to the local currency through the US dollar may be more relevant.

The dataset also includes data on age, sex, civil status, occupation, and region. However, the dataset does not include education. A similar questionnaire, the OFW Information Sheet, asks for the highest educational attainment, but the data are unavailable given that different information from the questionnaire is compiled separately by different agencies and not equally/readily available. To derive *schooling*, the Survey of Overseas Filipinos data-set is used where schooling data is available. Schooling is fitted on age, civil status, region and the interactions between destination country, sex, and occupation. Dummy variables are used for each of the 20 major destination countries in the SOF where there are sufficient observations ($N \geq 30$) and the rest are combined into 'others'. This allows a precise prediction of the education levels of overseas workers in various occupations in various countries. The idea is that each destination country requires a certain level of education for a worker of a particular sex in a particular occupation. The prediction is then applied onto the POEA data for the same set of explanatory variables.

4.5 Descriptive Statistics

The merged Labor Force Survey - Philippine Overseas Employment Administration (LFS-POEA) data includes 131,148 local workers comprising 54.2 percent and 110,809 overseas workers (45.8 percent). Local workers are equally divided by sex with 50.02 percent females and 49.98 males. On the other hand, most (67.48 percent) overseas workers are males while the other third (32.52 percent) are females.

The top destinations can be classified into Western Europe and Offshoots including UK, Italy, USA, Canada, and Australia; North-East Asia including Japan, Korea, China, Hong Kong, and Taiwan; South-East Asia including Singapore and Malaysia; and Middle East including Saudi Arabia, United Arab Emirates, Qatar, Kuwait, and Bahrain. Table 4.2 shows the sample distribution by top destination and sex. The Middle East is the predominant destination, with Saudi Arabia being the number one destination accounting for over 41 percent of overseas workers, followed by the United Arab Emirates with 17 percent, while Qatar accounts for nine percent and Kuwait 3.5 percent. Singapore, Canada, Taiwan, Italy, Korea, and China each account for less than two percent of overseas Filipino workers while Hong Kong, Bahrain, USA, Malaysia, Australia, Japan, and UK account for less than one percent each. Other countries account for 15 percent of overseas Filipinos workers.

Within destinations, there are more males in Australia (89 percent), Korea (86 percent), Qatar (80 percent), Saudi Arabia (74 percent), Malaysia (69 percent), China (59 percent), Japan (58 percent), UAE (56 percent), USA (54 percent), and in all other countries (73 percent). There are more females in Hong Kong (92 percent), UK (68 percent), Italy (66 percent), Taiwan (60 percent), Canada (57 percent), Singapore (53 percent), and Kuwait (52 percent). There is an almost equal distribution in Bahrain between males (50.8 percent) and females (49.2 percent).

Table 4.3 shows the sample distribution by country and occupation. In the Philippines, the largest group of workers are laborers and unskilled workers comprising a third of workers, followed by farmers. Similarly, most Filipino workers in Hong Kong and Italy are laborers and unskilled workers. In contrast, most Filipino workers in the US and China and the largest group of Filipinos in Japan, UK, Singapore, Saudi Arabia and Malaysia are professionals. The largest group of Filipino workers in Australia and Qatar are trade workers. Most Filipino workers in Korea and Taiwan are clerks. Most workers in Canada and the largest group in United Arab Emirates and Bahrain are service and sales workers. In other countries, the largest group of Filipino workers are professionals.

The distribution by sex in each country is a function of occupational choice. Table 4.4 shows the distribution of males by country and occupation. In Australia, most males (53 percent) are engaged in trade and related work. In Korea, most males (70 percent) do clerical work. In Qatar, over a third (35 percent) of males are engaged in trade. Table 4.5 shows the distribution of females by country and occupation. Most female workers in Hong-Kong (96 percent) and Italy (85 percent) and 36 percent in Kuwait are laborers and unskilled workers. In Canada, most females (72 percent) are service and sales workers. In Taiwan, most females are either service and sales workers (49 percent) or clerks (45 percent).

Occupational choice is in turn a function of educational attainment. Table 4.6 shows the average schooling of local workers and the predicted schooling for overseas workers overall and for top destinations. Overseas workers on average are expected to have higher education than local workers. On average, males overseas have 12.2 years of expected schooling, equivalent to incomplete tertiary education, compared to 8.4 years for male domestic workers, equivalent to incomplete secondary education. Females overseas have an expected average of 11.6 years of schooling whereas female domestic workers have only 8.9 years of schooling. Females in top destinations are expected to have the same schooling (11.6) as in other destinations. In contrast, males in top destinations are expected to have slightly less schooling (12.1) than those in other destinations (12.6).

Table 4.1: List of Variables and Sources

Variable	Description	Source
Hourly wage	Basic Pay per Day (Primary Occupation) divided by Normal Working Hours for the Day for the Past Week; Salary: daily divided by 8, weekly divided by 8x5, monthly divided by 8x5x4, and annual divided by 8x5x50	LFS POEA
Years of Schooling	Highest Grade Completed: no grade = 0, incomplete elementary= 3, elementary graduate = 6, incomplete high school = 8, high school graduate = 10, college undergraduate = 12, college graduate =14, and completed post-graduate = 16	LFS, SOF
Experience	Age as of Last Birthday minus years of schooling minus 6 (age before start of schooling)	LFS, POEA
Male	Sex recoded as a dummy variable = 1 for males, 0 for females	LFS, POEA
Civil Status	Marital Status: Single = 1, Married = 2, Widowed = 3, Divorce/Separate = 4, Unknown = 5	LFS, POEA
Occupation	1 Officials of Government and Special-Interest Organizations, Corporate Executives, Managers, Managing Proprietors and Supervisors; 2 Professionals, 3 Technicians and Associate Professionals, 4 Clerks, 5 Service Workers and Shop and Market Sales Workers, 6 Farmers, Forestry Workers and Fishermen, 7 Trades and Related Workers, 8 Plant and machine Operators and Assemblers, 9 Laborers and Unskilled Workers, 10 Special Occupation	LFS, POEA
Region	0 NCR (reference), 1 Ilocos, 2 Cagayan Valley, 3 Central Luzon, 5 Bicol, 6 Western Visayas, 7 Central Visayas, 8 Eastern Visayas, 9 Zamboanga Peninsula, 10 Northern Mindanao, 11 Davao, 12 SOCSKSARGEN, 14 Cordillera, 15 ARMM, 16 Caraga, 41 CALABARZON, 42 MIMAROPA	LFS, POEA

Table 4.2: Sample Distribution by Top Destination Country and Sex

	Freq.	Percent	Females	Males
Saudi Arabia	43,654	41.3	25.6	74.5
UAE	17,942	17.0	44.0	56.0
Qatar	9,319	8.8	19.6	80.4
Kuwait	3,668	3.5	52.0	48.0
Singapore	2,077	2.0	53.3	46.7
Canada	1,876	1.8	57.3	42.7
Taiwan	1,706	1.6	59.9	40.1
Italy	1,388	1.3	65.6	34.4
Korea	1,361	1.3	14.3	85.7
China	1,291	1.2	41.2	58.8
Hongkong	1,043	1.0	92.3	7.7
Bahrain	1,042	1.0	49.2	50.8
USA	809	0.8	45.9	54.1
Malaysia	746	0.7	30.7	69.3
Australia	676	0.6	11.4	88.6
Japan	589	0.6	41.8	58.2
Great Britain	372	0.4	68.0	32.0
Other	16,032	15.2	26.9	73.1
Total	105,591	100		

Table 4.3: Sample Distribution by Country and Occupation

	PHL	AUS	BHR	CAN	CHN	HKG	ITA	KOR	KWT	JPN
Officials, Managers, and Executives	14.3	9.4	9.8	13.6	25.2	3.0	3.0	1.2	9.9	8.2
Professionals	4.4	16.2	18.6	3.8	52.5	2.5	0.7	7.3	16.5	43.3
Technicians and Assoc. Professionals	2.5	7.6	9.8	2.9	5.1	2.0	0.2	0.8	10.1	6.0
Clerks	5.1	5.8	7.2	3.8	6.3	0.3	4.5	69.7	9.5	9.1
Service and Sales Workers	10.0	7.9	20.9	59.2	2.0	0.2	11.7	0.7	21.0	9.4
Farmers, Forestry Workers, & Fishermen	17.6	0.3	0.4	1.1	0.0	0.0	0.2	0.4	0.0	2.4
Trades and Related Workers	7.2	48.1	11.4	6.4	4.5	0.0	1.2	14.6	9.0	7.7
Plant and Machine Operators	5.4	2.1	2.7	1.8	0.4	0.0	0.2	1.8	2.4	0.9
Laborers and Unskilled Workers	33.1	2.1	18.6	7.4	2.3	91.5	78.2	3.7	21.3	12.0
Special Occupation	0.4	0.7	0.5	0.2	1.6	0.6	0.1	0.1	0.4	1.2
Total	100	100	100	100	100	100	100	100	100	100
	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	OTHER	Total
Officials, Managers, Executives	7.6	10.5	10.0	18.2	0.2	9.9	10.8	6.4	18.7	12.5
Professionals	34.7	14.1	24.1	36.4	1.8	14.2	29.0	53.2	21.7	13.5
Technicians and Assoc. Professionals	7.6	10.5	12.4	12.9	0.8	11.9	3.8	4.2	8.0	7.0
Clerks	11.8	11.4	9.3	7.9	58.7	17.1	0.8	1.9	8.7	9.0
Service and Sales Workers	10.3	11.0	6.6	4.2	30.6	19.7	28.0	7.4	6.8	10.7
Farmers, Forestry Workers & Fishermen	1.1	0.0	0.2	0.5	0.1	0.2	0.3	0.0	0.2	7.7
Trades and Related Workers	10.8	28.6	23.8	5.1	6.3	13.6	5.1	22.5	20.5	14.2
Plant and Machine Operators	2.0	4.2	5.0	0.9	0.2	2.5	1.1	0.1	4.7	4.5
Laborers and Unskilled Workers	12.0	9.4	8.4	12.2	1.3	10.6	20.7	3.6	10.2	20.6
Special Occupation	2.0	0.5	0.3	1.7	0.0	0.5	0.5	0.6	0.7	0.4
Total	100	100	100	100	100	100	100	100	100	100

Table 4.4: Distribution of Males by Country by Occupation

	PHL	AUS	BHR	CAN	CHN	HKG	ITA	KOR	KWT	JPN
Officials, Managers, and Executives	11	8	11	16	26	19	5	1	13	10
Professionals	2	12	24	3	53	23	1	6	17	44
Technicians and Assoc. Professionals	2	8	11	4	5	20	0	1	10	8
Clerks	3	6	5	5	4	0	10	70	11	9
Service and Sales Workers	8	8	18	42	3	1	14	0	22	4
Farmers, Forestry Workers & Fishermen	25	0	1	2	0	0	1	0	0	3
Trades and Related Workers	9	53	22	14	7	0	3	16	18	13
Plant and Machine Operators	8	2	5	3	1	0	1	2	5	1
Laborers and Unskilled Workers	31	2	3	10	0	33	66	3	5	6
Special Occupation	1	1	1	0	1	5	0	0	0	1
Total	100	100	100	100	100	100	100	100	100	100

	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	OTHER	Total
Officials, Managers, and Executives	8	11	12	20	0	11	11	4	20	12
Professionals	37	14	14	36	3	14	32	36	18	10
Technicians and Assoc. Professionals	8	10	12	17	1	12	8	4	9	7
Clerks	14	11	11	7	80	14	1	2	10	9
Service and Sales Workers	11	9	7	4	4	17	20	11	6	9
Farmers, Forestry Workers & Fishermen	1	0	0	1	0	0	1	0	0	10
Trades and Related Workers	15	35	31	11	12	24	16	42	27	21
Plant and Machine Operators	3	5	7	2	0	3	3	0	6	7
Laborers and Unskilled Workers	2	3	4	1	0	4	7	0	4	15
Special Occupation	1	0	0	1	0	0	2	1	1	1
Total	100	100	100	100	100	100	100	100	100	100

Table 4.5: Distribution of Females by Country by Occupation

	PHL	AUS	BHR	CAN	CHN	HKG	ITA	KOR	KWT	JPN
Officials, Managers and Executives	20	19	9	12	24	2	2	1	7	6
Professionals	8	49	13	5	52	1	0	15	16	42
Technicians and Assoc. Professionals	3	8	8	2	5	1	0	0	11	3
Clerks	8	3	10	3	9	0	2	69	8	9
Service and Sales Workers	13	8	24	72	1	0	11	3	20	16
Farmers, Forestry Workers & Fishermen	7	0	0	0	0	0	0	0	0	1
Trades and Related Workers	4	5	1	0	1	0	0	6	1	1
Plant and machine Operators	1	0	0	1	0	0	0	1	0	0
Laborers and Unskilled Workers	36	5	34	5	5	96	85	6	36	20
Special Occupation	0	3	0	0	2	0	0	0	0	1
Total	100	100	100	100	100	100	100	100	100	100
	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	OTHER	Total
Officials, Managers and Executives	6	6	3	17	0	8	11	9	16	13
Professionals	30	16	54	37	1	14	28	73	32	20
Technicians and Assoc. Professionals	6	11	13	10	1	12	2	5	5	7
Clerks	8	13	3	8	45	21	1	2	6	9
Service and Sales Workers	10	17	5	5	49	22	32	4	10	14
Farmers, Forestry Workers & Fishermen	2	0	0	0	0	0	0	0	0	3
Trades and Related Workers	1	1	2	0	3	1	0	0	3	3
Plant and Machine Operators	0	1	0	0	0	1	0	0	0	1
Laborers and Unskilled Workers	35	34	20	22	2	19	27	7	27	30
Special Occupation	4	0	0	2	0	1	0	1	0	0
Total	100	100	100	100	100	100	100	100	100	100

Table 4.6: Years of Schooling, Local and Overseas Workers (predicted), Top and Other Destinations, by Sex

	Domestic		OCW		Top Destinations		Other Destinations	
	Female	Male	Female	Male	Female	Male	Female	Male
All	8.9	8.4	11.6	12.2	11.6	12.1	11.6	12.6
Officials, Managers and Executives	9.5	10.0	13.1	12.7	13.5	12.7	11.0	12.7
Professionals	14.0	14.0	13.9	14.0	13.9	14.0	14.0	14.0
Technicians and Assoc. Professionals	11.6	11.8	12.8	13.3	12.8	13.2	14.0	13.5
Clerks	12.6	11.9	13.4	12.9	13.4	12.9	13.6	13.1
Service and Sales Workers	9.9	10.2	11.9	12.2	11.9	12.3	11.7	12.1
Farmers, Forestry Workers & Fishermen	6.2	6.1		9.6		10.0		8.5
Trades and Related Workers	7.9	8.6	11.0	11.3	11.0	11.3	10.0	11.0
Plant and Machine Operators	10.4	9.0	12.3	12.3	12.2	12.1	13.0	13.2
Laborers and Unskilled Workers	7.1	7.2	10.9	11.0	10.9	11.0	11.1	11.8

Predicted schooling by top destination and sex is given in Table 4.7. Across top destinations, overseas workers in Canada, Australia, and USA, have the highest expected educational attainment at over 13 years followed by UK, China, Germany, Japan, Italy, Singapore, Korea, and Taiwan at over 12 years. Overseas workers in United Arab Emirates, Hong-Kong, Saudi Arabia, Qatar, Malaysia, and Bahrain have over 11 years of expected schooling.

Table 4.7: Predicted Years of Schooling, by Top Destination Country and Sex

Country	Female	Male	Total
AUS	13.25	13.05882	13.09524
BHR	10.62069	11.85714	11.02326
CAN	13.36111	12.66667	13.10526
CHN	12.41667	13.11765	12.82759
DEU	11.5	12.96296	12.77419
GRC	11.77778	13.6087	13.30909
HKG	11.57936	12.25	11.6194
ITA	12.07143	12.51429	12.31746
KOR	11.88889	12.27451	12.17391
KWT	10.57233	11.80488	10.825
JPN	11.44186	13.15447	12.71084
LBN	10.32143		10.32143
MYS	11.31915	10.92593	11.17568
QAT	11.18898	11.3522	11.27972
SAU	11.49521	11.54942	11.53247
SGP	11.67742	13.52941	12.2583
CHN	12.10784	11.90476	12.0303
ARE	11.85561	12.02593	11.92702
GBR	12.68571	13.05882	12.86957
USA	13.17391	12.9697	13.03448

Table 4.8 shows the predicted years of schooling for overseas workers by occupation and sex. Among overseas workers across occupations, professionals have the highest expected years of schooling at 14 years, equivalent to having completed tertiary education, as would be expected. Technicians and associate professionals and clerks follow at 13.1 years of schooling (incomplete tertiary or vocational education). Officials in government, managers and executives are expected to have an average of 12.8 years of schooling, followed by plant and machine operators (12.3), service and sales workers (12.0), and trades and related workers (11.2), all equivalent to incomplete tertiary education. The occupations with the lowest educational attainment are farmers, forestry workers and fishermen (9.6)(i.e. incomplete secondary education), laborers and unskilled workers (10.9)(i.e. complete secondary

education).

Table 4.8: Predicted Years of Schooling by Occupation and Sex

Occupation	Female	Male	Total
Officials of Government and Special-Inte	13.1	12.7	12.8
Professionals	13.9	14.0	14.0
Technicians and Associate Professionals	12.8	13.3	13.1
Clerks	13.4	12.9	13.1
Service Workers and Shop and Market Sale	11.9	12.2	12.0
Farmers, Forestry Workers and Fishermen		9.6	9.6
Trades and Related Workers	11.0	11.3	11.2
Plant and machine Operators and Assemble	12.3	12.3	12.3
Laborers and Unskilled Workers	10.9	11.0	10.9

Table 4.9 shows the predicted schooling of Filipino workers by country and occupation. Overseas Filipino workers across destinations are expected to have a higher level of education than local workers. This is also true for most occupations. As in the Philippines, professionals across practically all destinations are expected to have complete tertiary education, except in Italy. While technicians and associate professionals in the Philippines on average have only incomplete tertiary education (11.7 years of schooling), those in Australia, Canada, Hongkong, Bahrain and Kuwait are expected to have on average complete tertiary education. While those in other countries are also expected to have on average less than complete tertiary education, they have no less than 12 years of expected schooling. Local clerks are expected to have only incomplete tertiary education. Clerks overseas are generally expected to have a higher education level than those in the Philippines, with those in China and Italy even having complete tertiary education. However, those in Bahrain and Qatar are expected to have slightly less schooling. Officials, managers and executives and service workers across destinations are expected to have more schooling than those in the Philippines. Trade workers in most destinations are expected to have more schooling than those in the Philippines, except in Malaysia where they are expected to have the same schooling. Plant and machine operators and assemblers, and laborers and unskilled workers overseas are also expected to have more schooling than their local counterparts. Tables 4.10 and 4.11 show the predicted schooling by country and occupation for males and females, respectively.

Table 4.9: Predicted Years of Schooling by Country and Occupation

	PHL	AUS	BHR	CAN	CHN	HKG	ITA	KOR	KWT	JPN
All	8.6	13.1	11.0	13.1	12.8	11.6	12.3	12.2	10.8	12.7
Officials of Government and Special-Inte	9.8	14	14	13.2		12.7		12	13.4	14
Professionals	14	14	14	14	14	14	13	14	14	14
Technicians and Associate Professionals	11.7	14	14	14	12.4	14	12	12.5	14	13.1
Clerks	12.3		12	12.8	14	12.7	14		13	14
Service Workers and Shop and Market Sale	10	13.3	11.6	13.1	12.4	11.7	12.4	11.5	11	12.1
Farmers, Forestry Workers and Fishermen	6.2	10								10
Trades and Related Workers	8.4	12.2	10	13	13.7	11.3	11.3	12.7	10.7	12.5
Plant and machine Operators and Assemble	9.1	13.7	12	12.6	13.8	12	12.8	12.1	10.3	13.3
Laborers and Unskilled Workers	7.1	12.5	10	13	12	11.6	12.1	11.5	10.3	11.7
	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	OTHER	
All	11.2	11.3	11.5	12.3	12.0	11.9	12.9	13.0	12.3	
Officials of Government and Special-Inte	12	12.2	12.6	13.8	14	12.3	12.7	13.3	12.4	
Professionals	14	13.9	14	13.9	13	13.9	14	14	14	
Technicians and Associate Professionals	12	13.5	12.7	13.5	12	13.1	14	13.7	13.6	
Clerks	12.5	12.1	13.2	13.8	13.3	13.3	12.8	13.8	13.3	
Service Workers and Shop and Market Sale	12.3	12	11.5	13.2	11.5	11.9	12.7	12.7	11.9	
Farmers, Forestry Workers and Fishermen		14	10	8	10	10	8		8.5	
Trades and Related Workers	10	10.7	11	13.3	11.1	11.1	12.8	11.3	11	
Plant and machine Operators and Assemble	13.5	10.6	10.8	13.6	12.1	11.3	13.6	13.5	13.2	
Laborers and Unskilled Workers	10.3	10.4	10.2	11.2	12.2	10.8	11.6	10.9	11.3	

Table 4.10: Predicted Years of Schooling by Top Destination by Occupation: Males

	AUS	BHR	CAN	CHN	DEU	GRC	HKG	ITA	KOR	KWT
Officials, Managers and Executives	14	12		14	16	12	13.2	14		
Professionals	14	14	14	14	14	14	14	14	14	14
Technicians and Associate Professionals	14	14	14	12.7	14	13.6	14	14	14	14
Clerks		12.7	14		14	13	14			
Service and Sales Workers	13.6	12.7	12.6	12.3	11.5	12.7	11.3	12.3	11.5	11.3
Farmers, Forestry Workers and Fishermen	10					10				
Trades and Related Workers	12.2	10	13	13.7	12.8	13.3	12	11.3	13	11.3
Plant and Machine Operators and Assemblers	13.7	12	12.6	13.8	13.3	13.8	12	13	12.2	10.3
Laborers and Unskilled Workers	13.3	12	12	12	12	11.3	13.3	10.6	10.6	13

	JPN	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	0
Officials, Managers and Executives		10	12.2	12.6	13.7	14	11.8	12.7	13	12.7
Professionals		14	13.8	14.0	13.9	14	14	14	14	14.0
Technicians and Associate Professionals		14	13.3	12.7	13.5	12	12.8	14	13.6	13.5
Clerks		12	10.75	13.1	14	12	13.0	12	13.3	13.1
Service and Sales Workers	13.1	12.7	12.1	11.8	13.2	14	12.2	13.1	12.4	12.1
Farmers, Forestry Workers and Fishermen		14	10	8	10	10	8			8.5
Trades and Related Workers	12.5	10	10.7	11.0	13.3	10.9	11.1	13.3	11.3	11.0
Plant and Machine Operators and Assemblers	13.4	13.5	10.6	10.7	13.6	12.1	11.3	13.6	13.5	13.2
Laborers and Unskilled Workers		8.5	10.6	10.4	13.3	12	11.4	12.7	11.5	11.8

Table 4.11: Predicted Years of Schooling by Top Destination by Occupation: Females

	AUS	BHR	CAN	CHN	DEU	GRC	HKG	ITA	KOR	KWT	JPN
Officials, Managers and Executives	14	14		11		14					
Professionals	14	14	14	14		12	14	14			
Technicians and Assoc. Professionals	14	14	12		12	11.6	14	11.71			
Clerks	12	13	14	12	12.7		13	14			
Service and Sales Workers	12	11	13.3	12.7	10	12.7	11.8	13	11.5	10.9	11.3
Trades and Related Workers				10	10	9.3	13				
Plant and Machine Operators			12	14	12	11.3	12				
Laborers and Unskilled Workers	10	9.9	13.2	12	12	10	11.6	11.9	13	10.3	11.1
	LBN	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	OTHER	
Officials, Managers and Executives	14	14	14	14	13.2	14				11	
Professionals		14	13.9	14	12	13.9	14	14		14	
Technicians and Assoc. Professionals	12	11.5	14	12.7	13.5	12	13.5	14	14	14	
Clerks	14	13	13.5	13.7	14	13.4	13.3	14		13.6	
Service and Sales Workers	10	12.2	11.9	11.1	13.2	11.3	11.8	12.4	13.1	11.7	
Trades and Related Workers		10.7	11	12	12					10	
Plant and Machine Operators	14		12	14	12.1	14				13	
Laborers and Unskilled Workers	10.2	10.9	10.4	10.1	11.1	12.3	10.7	11.3	10.6	11.1	

4.6 Regression Analysis

Table 4.12 shows the results of the first stage regression of schooling on age, sex (female as reference), destination country (other countries as reference), civil status (single as reference) and region (National Capital as reference) using the data on the Survey of Overseas Filipinos. It shows that years of schooling decreases with age. Males have more schooling than females. Across destinations, workers in roughly half of the countries have on average complete college education, namely in Europe, the North America, but also in China, Japan and Hong Kong. In the other major Asian destinations and in the Middle East, the average worker has less than complete college education. Across occupations, only professionals have at least complete college education on average. Most overseas workers in other occupations have only incomplete college education and farmers and fishermen have only an average of complete secondary education. Across regions of origin, workers from over 4 out of 10 regions have at least complete college education, higher than the educational attainment of those from the National Capital. Workers from almost quarter of the regions have the same education as those from the capital. Workers from almost 3 out of 10 regions have less education than those from the capital. The table also shows the different schooling by marital status.

4.6.1 Returns to migration and education

Overseas versus domestic workers

Using equation 4.4, earnings and returns to schooling of overseas workers relative to domestic workers are estimated by relating wages in the POEA dataset to predicted schooling from the SOF dataset. Results show that earnings are higher but returns to education are lower for overseas workers. Table 4.6.1 shows the results of the regression of wage on the interactions between migration and schooling, experience and its square, and on civil status, region, and occupation. Overseas Filipino workers on average earn more than their domestic counterparts. Overseas workers earn almost 3.1 times more than domestic workers, controlling for experience, sex, civil status, occupation and region. While return on labor is higher for overseas workers, return to schooling is higher for local workers. The return to schooling for local workers is six percent per year, while that for overseas workers is 2.9 percentage points lower, or about half that of local workers. This is not at all surprising and consistent with the fact that labor is more abundant in Philippines but human capital is more scarce. Thus, labor wage is lower in the Philippines and higher

Table 4.12: 1st Stage Regression: Schooling on Age, Sex, Destination Country, Civil Status, and Region

	Coefficient	Robust S.E.
Age	-0.0176***	0.0038
Male	0.2424***	0.0705
Australia	0.6192**	0.2372
Bahrain	-0.7076*	0.3259
Canada	0.9596***	0.1601
China	0.5773**	0.2204
Germany	0.4530	0.2705
Greece	0.8420***	0.2138
Hong Kong	0.3394*	0.1492
Italy	0.5084*	0.2395
Korea	-0.0457	0.2497
Kuwait	-0.8365***	0.1806
Japan	0.4608**	0.1479
Lebanon	-1.0039**	0.3392
Malaysia	-0.8046**	0.2615
Qatar	-0.7073***	0.1369
Saudi Arabia	-0.6892***	0.1013
Singapore	0.0994	0.1199
Taiwan	-0.0100	0.1734
United Arab Emirates	-0.3717***	0.1106
Great Britain	0.3255	0.2322
United States	0.4211**	0.1381
Professionals	1.1000***	0.1645
Technicians and Assoc. Professionals	0.1013	0.1839
Clerks	0.2943	0.1874
Service and Sales Workers	-0.9371***	0.1777
Farmers, Forestry and Fishermen	-3.5792***	0.5888
Trades and Related Workers	-1.5054***	0.1795
Plant and machine Operators...	-0.8005***	0.1787
Laborers and Unskilled	-1.8187***	0.1766
Married	-0.2963***	0.0691
Widowed	-0.8273**	0.2804
Separated	-0.4406**	0.1639
Unknown	-1.4708*	0.5857
Common-law	0.4305	0.5234
Ilocos	0.0538	0.1093
Cagayan Valley	-0.1133	0.1266
Central Luzon	-0.3798***	0.1127
Bicol	0.1363	0.1502
Western Visayas	0.4628***	0.1222
Central Visayas	0.3770**	0.1335
Eastern Visayas	0.5915***	0.1557
Zamboanga	0.5232*	0.2300
Northern Mindanao	0.4028*	0.1571
Davao	-0.3304	0.2007
SoCSKSarGen	-0.4050*	0.1725
Cordillera	0.2789	0.1615
ARMM	-1.0870***	0.2507
Caraga	0.3499*	0.1747
CaLaBaRZon	-0.2235*	0.1040
MiMaRoPa	0.0208	0.1842
Constant	13.8166***	0.2297
Adjusted R^2	0.3075	
Observations	4322	

legend: * p<.05; ** p<.01; *** p<.001

abroad, while return to schooling is higher in the Philippines and lower abroad. This is consistent with the stylized fact of diminishing returns to income: returns to education decrease as a country's per capita income increases (Psacharopoulos, 1993; Psacharopoulos and Patrinos, 2002). Higher return on labor warrants temporary migration despite lower return on human capital.

Table 4.13: Return on Labor and Human Capital, Local and Overseas Workers, and by Sex

	(1)		(2)	
	coef.	std.err.	coef.	std.err.
OCW	1.421***	(0.103)	1.161***	(0.175)
Male	0.0102	(0.0106)	0.787***	(0.0283)
OCW*Male			0.566**	(0.202)
Semi-Elasticity				
OCW	3.11858***	0.423209	2.14533***	0.545072
Male			1.1961***	0.062079
OCW*Male			0.724987**	0.34432
Schooling	0.0604***	(0.00175)	0.0934***	(0.00261)
MALE*Schooling			-0.0411***	(0.00220)
OCW*Schooling	-0.0287***	(0.00736)	0.00150	(0.0118)
OCW*Male*Schooling			-0.0772***	(0.0135)
Experience	0.0321***	(0.00104)	0.0281***	(0.00143)
Male*Experience			-0.000883	(0.00162)
OCW*Experience	-0.0432***	(0.00374)	-0.0216**	(0.00702)
OCW*Male*Experience			-0.0137	(0.00839)
Experience Squared	-0.000451***	(0.0000198)	-0.000320***	(0.0000295)
Male*Exper.Sq.			-0.0000562	(0.0000346)
OCW*Exper.Sq.	0.000492***	(0.0000849)	-0.0000575	(0.000177)
OCW*Male*Exper.Sq			0.000443*	(0.000203)
constant	-0.428***	(0.0420)	-0.959***	(0.0479)
N	95475		95475	

legend: * p<.05; ** p<.01; *** p<.001

4.6.2 Overseas versus domestic workers by sex

Regression results for Equation 4.2 decomposing returns to labor and human capital for local and overseas workers by sex are shown in Table 4.6.1 column (2). Local male workers on average earn 119 percent more than their female counterparts, but return on schooling for local male workers is 4.1 percentage points lower, or 5.2 percent. Relative to local female workers, female overseas workers earn 215 percent more. The return to schooling for local female workers is 9.3 percent. The return to schooling for female overseas workers is not significantly different from that of local female workers. Male overseas workers earn 73 percent more than their local or female counterparts, but the return to schooling for male overseas workers is 7.7 percentage points lower than that of their local or female counterparts. So even if overseas workers earn less for their level of education, they work overseas because they earn much more for sheer labor. This is the case on average and applies to men in particular. Filipino women overseas earn more for their labor than their local counterpart, but earn as much for their human capital.

4.6.3 Major and other destinations

Return on labor is lower but return on education is higher in top destinations. Table 4.14 disaggregates returns to labor and human capital for overseas workers into that for the 20 major destinations and all others. Surprisingly, return on labor in top destination countries is 26 percent less than that for local workers. If theory suggests that higher incomes in destination countries motivate migration, then why do most Filipinos work in countries that pay less for their labor? It turns out that while these countries pay less for labor, they pay more for human capital. Return on schooling in top destinations are 11 percentage points more than that in the Philippines (7.3 percent). So, human capital abroad is not as cheap after all, not in top destination countries as a whole. Obviously, this matters only if you have sufficient education. A Filipino worker without schooling would not choose to work in these countries. However, those with more education would. Not surprisingly, Filipinos in top destinations on average have more years of schooling (12.2) than local workers. Returns to labor in other countries is 96 percent higher than that for local workers. However, they have lower returns to schooling. These results seem to be driving those for overseas workers at large. Labor returns are sufficiently attractive to warrant temporary migration. It appears that other countries provide a different incentive system for temporary migrants from that of top destinations, one that is not based so much on education. In fact, workers who are unable to work in top destinations due to lack of education or skill might be the ones who end up in other destinations.

Table 4.14: Earnings Function by Domestic, Top and Other Destinations

	(1)		(2)	
	coef.	std.err.	coef.	std.err.
Top Destinations	-0.300***	(0.0798)	0.538***	(0.114)
Other Destinations	0.956*	(0.464)	4.184***	(1.088)
Male			0.825***	(0.0278)
Top*Male			-1.202***	(0.128)
Other*Male			-4.514***	(1.191)
SEMI-ELASTICITY				
Top Destinations	-0.261306***	0.058823	0.701704***	0.192964
Other Destinations	1.33642	1.02887	35.3126	30.2426
Male			1.28105***	0.06347
Top*Male			-0.701808***	0.037881
Other*Male			-0.994611***	0.004693
Schooling	0.0727***	(0.00164)	0.106***	(0.00243)
Top Destinations*Schooling	0.106***	(0.00590)	0.0509***	(0.00782)
Other Destinations*Schooling	-0.146***	(0.0316)	-0.315***	(0.0734)
Male*Schooling			-0.0462***	(0.00215)
Top*Male*Schooling			0.0672***	(0.00855)
Other*Male*Schooling			0.223**	(0.0803)
Experience	0.0275***	(0.000986)	0.0250***	(0.00139)
Top Destination*Experience	-0.0203***	(0.00252)	-0.00700	(0.00454)
Other*Experience	-0.0465**	(0.0175)	-0.111*	(0.0437)
Male*Experience			-0.00242	(0.00159)
Top*Male*Experience			-0.00730	(0.00549)
Other*Male*Experience			0.104*	(0.0478)
Experience Squared	-0.000374***	(0.0000189)	-0.000262***	(0.0000290)
Top*Exper.Sq.	0.000390***	(0.0000555)	-0.0000392	(0.000109)
Other*Exper.Sq.	0.000603	(0.000359)	0.000899	(0.00100)
Male*Exper.Sq.			-0.0000465	(0.0000341)
Top*Male*Exper.Sq.			0.000382**	(0.000127)
Other*Male*Exper.Sq.			-0.000876	(0.00108)
_cons	-0.505***	(0.0374)	-0.996***	(0.0422)
N	95475		95475	
Standard errors in parentheses				

legend: * p<.05; ** p<.01; *** p<.001

4.6.4 Major and other destinations by sex

Table 4.14 Column (2) disaggregates returns to labor and human capital further by sex. Female overseas workers in top destination countries earn 70 percentage points more for their labor than their local counterparts. On top of this, the return to their schooling is 5.1 percentage points higher than that for their local counterparts (10.6 percent). The top destinations seem to be attractive to females, both skilled and unskilled. On the other hand, male overseas workers in top destinations earn 70 percentage points less for their labor than their local and female counterparts. However, the return to their schooling is 6.7 percentage points higher. The top destinations are more attractive to skilled men than unskilled men. Returns to labor for female overseas workers in other destinations are 4.2 times higher than that for their local counterparts, although returns to their schooling is less. Conversely, although male overseas workers in other countries earn less than their local counterparts, return on their schooling is up to 22 percentage points more. Other destinations are more attractive to unskilled than skilled females but more attractive to skilled than unskilled men.

4.6.5 Individual major destinations

Earnings are higher but returns to education are lower in most top destinations. Table 4.15 shows return on labor and human capital in top destination countries. Returns to labor in most of the top destination countries are higher than in the Philippines. Overseas Filipino workers earn over five times more in Australia, Italy, and Japan, over three times more in Canada, China, Taiwan, and USA, two times more in Kuwait, over twice as much in Bahrain and Malaysia, and almost 40 percent more in UAE than in the Philippines. The wage differentials are sufficient to explain why these countries are top destinations. Human capital does not receive additional incentive. Returns to schooling in Bahrain, Canada, Malaysia, and the United States are not significantly different from those in the Philippines. Actually, returns to schooling resembling those of developing countries like the Philippines are already high for developed countries considering the stylized fact of decreasing returns to income. Returns to schooling are lower in Australia, China, Italy, Korea, Kuwait, Japan, Malaysia, and Taiwan than in the Philippines. The return to schooling is higher only in UAE.

Table 4.15: Human Capital Earnings Function by Destination in PPP (Philippines as reference)

	Destination		Semi-elasticity		Dest*Schooling		Dest*Experience		Dest*ExperSquared	
	Coef.	Std.Err.	Coef.	Std. Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Australia	5.11***	0.761	123.08	82.262	-0.19***	0.045	-0.06	0.036	0	0.001
Bahrain	1.71***	0.396	0.00	0.000	-0.04	0.025	-0.04	0.022	0.00*	0.001
Canada	3.50***	0.751	0.00	0.000	-0.05	0.050	-0.08*	0.033	0.00*	0.001
China	3.38***	0.822	20.00	14.717	-0.14*	0.056	-0.01	0.022	0	0.000
Hongkong	0.93	0.600	0.00	0.000	0.09*	0.045	-0.07**	0.025	0.00*	0.001
Italy	5.43***	1.144	0.00	0.000	-0.29**	0.093	-0.03	0.044	0	0.001
Korea	7.92	4.136	-0.47	0.532	-0.76**	0.272	0.12	0.166	-0.01	0.005
Kuwait	2.07***	0.230	6.69***	1.747	-0.11***	0.015	0.03**	0.011	0	0.000
Japan	5.51**	1.918	38.19	38.690	-0.36**	0.138	-0.01	0.060	0	0.001
Malaysia	1.08**	0.329	1.78**	0.890	-0.01	0.017	0.03	0.021	0	0.000
Qatar	-1.22***	0.143	0.00	0.000	0.15***	0.010	-0.03***	0.006	0.00***	0.000
Saudi Arabia	0.01	0.080	0.00	0.000	0.06***	0.006	-0.02***	0.003	0.00***	0.000
Singapore	0.23	0.413	0.16	0.458	0.08**	0.028	0.03**	0.011	-0.00*	0.000
Taiwan	3.46***	0.185	0.00	0.000	-0.04***	0.010	-0.02**	0.007	0.00**	0.000
UAE	0.39**	0.148	0.00	0.000	0.03**	0.011	0.01	0.005	-0.00*	0.000
Great Britain	0.95	1.263	0.00	0.000	0.04	0.083	0.02	0.047	0	0.001
United States	3.18***	0.931	14.54	11.831	-0.06	0.054	-0.04	0.035	0	0.001
Other	1.41**	0.465	2.67*	1.618	-0.18***	0.032	-0.05**	0.018	0	0.000

legend: * p<.05; ** p<.01; *** p<.001

Earnings are not higher for some destinations but returns to schooling are higher. While the return to labor is lower in Qatar than in the Philippines, the return to schooling is 15.1 percentage points higher. Returns to labor for overseas workers in Hong Kong, Korea, Saudi Arabia, Singapore, and U.K. are not significantly different from that of local workers. Nevertheless, returns to schooling are higher in Saudi Arabia, Singapore, and Hong Kong. This is surprising considering that 91 percent of overseas workers in Hong Kong are laborers and unskilled workers.

There are no income and return on schooling gains for a few destinations. The return to schooling in the U.K. is not significantly different from that in the Philippines, and they are even lower in Korea. The puzzle is why do Filipinos work in the U.K. and Korea without apparent gains to either their labor or human capital? Does experience pay where labor and education do not? Column 6 shows returns to experience. While returns to experience are higher in Kuwait and Singapore, returns to experience in Korea and the U.K. are not significantly different from those in the Philippines.

4.6.6 Individual major destinations by sex

Earnings are lower but returns to schooling are higher for males in some top destinations. With no apparent gains to labor, schooling, and experience in some countries, are the gains obscured by the averages? Disaggregating by sex might shed light on the issue. Table 4.16 shows the returns to labor and schooling for male overseas Filipino workers by destination. Returns to male labor is lower in top destination countries particularly in Hong Kong, Kuwait, Qatar, Taiwan, and the United Kingdom than in the Philippines. Nevertheless, returns to male schooling are higher in Hong Kong, Kuwait, Taiwan, and the UK than in the Philippines. Over 63 percent of male Filipino workers in Hong-Kong are either managers and executive, professionals, or associate professionals. In Taiwan, 80 percent of male Filipino workers do clerical work. However, return to male schooling in Qatar is not significantly different from that in the Philippines.

Table 4.16: Human Capital Earnings Function by Destination in PPP: Males

	Destination		Schooling		Experience		Experience Squared	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Australia	1.77	1.40	-0.12	-0.12	-0.06	0.121	0	0.0033
Bahrain	0.83	1.19	-0.04	-0.04	-0.06	0.054	0	0.0013
Canada	1.24	1.88	-0.2	-0.20	0.15*	0.065	0	0.0017
China	0.03	1.88	-0.07	-0.07	0.11**	0.044	-0.00**	0.0009
Hongkong	-3.73**	1.18	0.20**	0.20	0.15	0.081	0	0.0016
Italy	0.3	1.84	-0.14	-0.14	0.09	0.080	0	0.0017
Korea	41.90***	9.09	-2.93***	-2.93	0.13	0.296	-0.01	0.0081
Kuwait	-2.91***	0.45	0.22***	0.22	-0.04	0.022	0.00**	0.0005
Japan	-0.49	4.42	0.26	0.26	-0.2	0.129	0	0.0030
Malaysia	0.29	0.67	-0.05	-0.05	0.04	0.051	0	0.0012
Qatar	-1.02***	0.31	0.03	0.03	0.04*	0.017	0	0.0004
Saudi Arabia	0.33*	0.13	-0.04***	-0.04	0	0.005	0	0.0001
Singapore	1.68*	0.82	-0.11*	-0.11	-0.01	0.025	0	0.0007
Taiwan	-2.34***	0.35	0.16***	0.16	0.01	0.019	0	0.0005
UAE	0.68*	0.27	-0.07***	-0.07	0	0.010	0	0.0003
Great Britain	-10.26***	2.41	0.76***	0.76	0.06	0.113	0	0.0023
USA	2.89	2.32	-0.19	-0.19	-0.04	0.075	0	0.0015
Other	-4.32***	1.19	0.21**	0.21	0.10*	0.048	0	0.0011

legend: * $p<.05$; ** $p<.01$; *** $p<.001$

Earnings and returns to schooling are higher for a few top destinations. Returns to male labor are higher only for Korea, Saudi Arabia, Singapore and UAE, and return on male schooling is higher in Singapore but lower in Korea, Saudi Arabia, and UAE. In Singapore, over 72 percent of male workers are either managers and executives, professionals or associate professionals.

Earnings and returns to schooling for males are not higher in some top destinations. Returns to male Filipino labor in Australia, Bahrain, Canada, China, Italy, Japan, Malaysia, and the USA are not significantly different from that in the Philippines. Moreover, returns to male schooling in Australia, Bahrain, Canada, China, Italy, Japan, Malaysia, and USA are not significantly different from that in the Philippines. So why do Filipino males work in these countries if there are no apparent gains on either their labor or human capital? Does work experience pay for what sheer effort and education cannot? Returns to experience are higher in Canada, China, and Qatar, but not significantly different in Australia, Bahrain, Italy, Japan, Malaysia, and USA.

Earnings are higher but returns to schooling are the same or lower for females in most top destinations. Table 4.17 shows the returns to labor and schooling for female overseas workers. Returns to labor for female overseas workers are higher in most destination countries. Returns to labor for females is 7.5 times more in Japan than in the Philippines, 5.4 times more in Taiwan, 4.7 times more in the U.K., over 3 times more in Australia, China, Hong Kong, Italy, Kuwait, and twice as much in Malaysia. This is expected for Hong Kong, Italy, Kuwait and Malaysia where 96 percent, 85 percent, 36 percent and 35 percent of the female overseas workers, respectively, work as laborers and unskilled workers. However, returns to female schooling in Australia, China, Italy and Malaysia are not significantly different from that in the Philippines, and lower in Hong-Kong, Kuwait, Japan, Taiwan and the UK. While return to female labor is lower in Korea than in the Philippines, return to female schooling is higher. So for the preceding countries, female workers either gain on their labor or their human capital.

Table 4.17: Human Capital Earnings Function by Destination in PPP: Females

	Destination		Schooling		Experience		Experience Squared	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Australia	3.77***	1.08	-0.11	0.06	0	0.116	0	0.0032
Bahrain	1.29	1.03	-0.03	0.06	0	0.046	0	0.0011
Canada	2.17	1.68	0.08	0.12	-0.13**	0.047	0.00*	0.0013
China	3.64**	1.17	-0.12	0.08	-0.07*	0.033	0	0.0007
Hongkong	3.16***	0.51	-0.08*	0.04	-0.08**	0.026	0.00**	0.0007
Italy	3.69***	0.92	-0.09	0.06	-0.09	0.048	0	0.0010
Korea	-19.55*	8.02	1.15*	0.55	-0.12	0.211	0.01	0.0060
Kuwait	3.05***	0.30	-0.19***	0.02	0.06***	0.015	-0.00***	0.0003
Japan	7.53*	3.44	-0.67*	0.26	0.13	0.093	0	0.0018
Malaysia	1.05*	0.49	0.01	0.02	0.01	0.044	0	0.0011
Qatar	-0.45	0.27	0.13***	0.02	-0.06***	0.016	0.00**	0.0004
Saudi Arabia	-0.12	0.11	0.08***	0.01	-0.01***	0.004	0.00**	0.0001
Singapore	-0.04	0.56	0.09*	0.04	0.04*	0.019	0	0.0006
Taiwan	5.43***	0.19	-0.17***	0.01	-0.04***	0.006	0.00***	0.0001
UAE	0.15	0.19	0.06***	0.01	0.01	0.007	-0.00*	0.0002
Great Britain	4.76***	1.40	-0.22*	0.09	-0.02	0.063	0	0.0014
USA	0.5	2.03	0.12	0.13	0	0.063	0	0.0013
Other	4.60***	1.09	-0.35***	0.07	-0.11*	0.044	0	0.0010

legend: * p<.05; ** p<.01; *** p<.001

Earnings are not different but returns to schooling are higher for females in a few top destinations. In contrast, returns on female labor in Bahrain, Canada, Qatar, Saudi Arabia, Singapore, UAE and USA are not significantly different from that in the Philippines. Nevertheless, returns to female schooling are higher in Qatar, Saudi Arabia, Singapore, and UAE. In Saudi Arabia, 54 percent of female overseas workers are professionals. In Singapore, 37 percent are professionals, another 17 percent are managers and executives, and another 18 percent are associate professionals and clerks.

Earnings and returns to schooling for females are not different in a few top destinations. However, returns to female schooling in Bahrain, Canada, and USA are not signficantly different from that in the Philippines. Again, why would Filipino women work in Bahrain, Canada and the USA without apparent gains on either their labor or their human capital? 73 percent of female overseas workers in the United States are professionals. Do income gains from experience make up for low returns to labor and education? While return on experience is higher in Kuwait, returns in Bahrain and the USA are not significantly different from that in the Philippines, and the return in Canada is even lower. Are they gaining enough with returns to schooling comparable to that in the Philippines? Considering the cost of living (i.e. in PPP), they may not, but converted to Philippine pesos, they might.

4.6.7 Individual major destinations, in US Dollars

There are exchange rate gains on top of income gains or where there are no income gains. With no apparent income gains to labor, schooling and experience in some countries, why do Filipinos choose to work in these destinations? Do differences in cost of living create gains that otherwise seem non-existent? Table 4.18 shows the human capital earnings function by destination country in US Dollars. The table shows that there are monetary gains from differences in cost of living between destination countries and the Philippines. If we take the ratio of the returns in US dollars to those in PPP, we find gains of 18 percent in Australia, 31 percent in Bahrain, 22 percent in Canada, 8 percent in China, 10 percent in Italy, 32 percent in Kuwait, 16 percent in Japan, 8 percent in Malaysia, 3 percent in Taiwan, 15 percent in the US and 117 percent in UAE. Moreover, while there are no real income gains in Korea and Saudi Arabia, exchange rate gains are 8.16 times and 34 percent respectively. There are also gains in returns to schooling from exchange rate conversions ranging from 3 percent in Hongkong and Qatar, 5 percent in Singapore, 8 percent in China and Saudi Arabia, 14 percent in UAE, and 25 percent in other destinations.

Table 4.18: Human Capital Earnings Function by Country in US Dollars (Philippines as reference)

	Destination		Semi-elasticity		Dest*Schooling		Dest*Exper		Dest*ExperSq	
	Coef.	Std.Err.	Coef.	Std. Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
Australia	6.02***	0.761	305.94	203.48	-0.18***	0.045	-0.06	0.036	0.0000	0.001
Bahrain	2.25***	0.396	0.00	0.00	-0.04	0.025	-0.04	0.022	0.00*	0.001
Canada	4.28***	0.751	0.00	0.00	-0.05	0.050	-0.08*	0.033	0.00*	0.001
China	3.66***	0.823	26.64	19.39	-0.15**	0.056	-0.01	0.022	0.0000	0.000
Hongkong	1.08	0.600	0.00	0.00	0.09*	0.045	-0.06**	0.025	0.00*	0.001
Italy	5.97***	1.144	0.00	0.00	-0.29**	0.092	-0.03	0.044	0.0000	0.001
Korea	8.16*	4.136	-0.32	0.68	-0.76**	0.272	0.12	0.166	-0.01	0.005
Kuwait	2.73***	0.230	13.92	3.39	-0.11***	0.015	0.03**	0.011	0.0000	0.000
Japan	6.38***	1.916	93.46	93.25	-0.36**	0.138	-0.01	0.060	0.0000	0.001
Malaysia	1.16***	0.329	2.02*	0.97	-0.01	0.017	0.03	0.021	0.0000	0.000
Qatar	-0.68***	0.144	0.00	0.00	0.16***	0.010	-0.03***	0.006	0.00***	0.000
Saudi Arabia	0.34***	0.081	0.00	0.00	0.06***	0.006	-0.02***	0.003	0.00***	0.000
Singapore	0.56	0.414	0.61	0.64	0.08**	0.028	0.03**	0.011	-0.00*	0.000
Taiwan	3.57***	0.185	0.00	0.00	-0.04***	0.010	-0.02**	0.007	0.00**	0.000
UAE	0.85***	0.149	0.00	0.00	0.03**	0.011	0.01	0.005	-0.00*	0.000
Great Britain	1.69	1.264	0.00	0.00	0.03	0.083	0.02	0.047	0.0000	0.001
United States	3.65***	0.932	24.03	19.07	-0.05	0.054	-0.04	0.035	0.0000	0.001
Other	2.29***	0.477	7.82*	3.98	-0.23***	0.033	-0.05**	0.018	0.0000	0.000

legend: * p<.05; ** p<.01; *** p<.001

4.6.8 Individual major destinations by sex, in US Dollars

Table 4.19 shows the human capital earnings function by destination in US dollars for males. The monetary gains in earnings from the exchange rate range from one percent in Qatar, two percent in Taiwan, three percent in Hong Kong, Singapore, and UAE, to 24 percent in other destinations. On the other hand, there is an exchange rate loss of two percent in Saudi Arabia. There are exchange rate gains to returns to schooling of three percent in Saudi Arabia, four percent in Hongkong, but there is an exchange rate loss of two percent, in Taiwan and UAE, and three percent in Singapore. There remain no income gains for males in Australia, Bahrain, Italy, Japan, Malaysia, and USA.

For females, the human capital earnings function by destination in US dollars is shown in Table 4.20. Taking the ratio of returns in US dollars to those in PPP, the monetary gains from the exchange rate range from 2 percent in Taiwan, 7 percent in China and Hongkong, 8 percent in Malaysia, 12 percent in Japan, 14 percent in Italy, 15 percent in Great Britain, and 5 percent in other destinations. While there are no real income gains in Saudi Arabia and UAE, monetary gains are 25 percent and 62 percent, respectively. There are also exchange rate gains to returns to schooling ranging from 1 percent in Qatar, 2 percent in Saudi Arabia, 4 percent in Hongkong, 5 percent in Singapore, and 6 percent in UAE. On the other hand, there is a 2 percent exchange rate loss in Great Britain. However, there remain no gains to earnings and returns to schooling for female Filipino workers in Bahrain, Canada, and the US.

Table 4.19: Human Capital Earnings Function by Destination in USD: Males

	Destination		Schooling		Experience		Experience Squared	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Australia	1.69	1.40	-0.11	0.08	-0.06	0.12	0	0.0033
Bahrain	0.83	1.19	-0.04	0.07	-0.06	0.05	0	0.0013
Canada	1.32	1.88	-0.21	0.13	0.15*	0.06	0	0.0017
China	0.13	1.89	-0.08	0.13	0.11**	0.04	-0.00**	0.0009
Hongkong	-3.83**	1.18	0.20**	0.07	0.15	0.08	0	0.0016
Italy	0.27	1.84	-0.14	0.15	0.08	0.08	0	0.0017
Korea	41.93***	9.09	-2.94***	0.62	0.13	0.30	-0.01	0.0081
Kuwait	-2.91***	0.45	0.22***	0.03	-0.04	0.02	0.00**	0.0005
Japan	-0.6	4.41	0.26	0.33	-0.2	0.13	0	0.0030
Malaysia	0.31	0.67	-0.05	0.03	0.04	0.05	0	0.0012
Qatar	-1.04***	0.31	0.03	0.02	0.04*	0.02	0	0.0004
Saudi Arabia	0.33*	0.13	-0.04***	0.01	0	0.01	0	0.0001
Singapore	1.73*	0.82	-0.12*	0.06	-0.01	0.02	0	0.0007
Taiwan	-2.29***	0.35	0.15***	0.02	0.01	0.02	0	0.0005
UAE	0.70**	0.27	-0.08***	0.02	0	0.01	0	0.0003
Great Britain	-10.27***	2.42	0.76***	0.16	0.06	0.11	0	0.0023
USA	2.87	2.32	-0.19	0.15	-0.04	0.07	0	0.0015
Other	-3.29**	1.24	0.13	0.08	0.10*	0.05	0	0.0011

legend: * $p<.05$; ** $p<.01$; *** $p<.001$

Table 4.20: Human Capital Earnings Function by Destination in USD: Females

	Destination		Schooling		Experience		Experience Squared	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Australia	4.75***	1.09	-0.11	0.06	0.01	0.12	0	0.0032
Bahrain	1.81	1.03	-0.02	0.06	0	0.05	0	0.0011
Canada	2.91	1.67	0.08	0.12	-0.13**	0.05	0.00*	0.0013
China	3.88***	1.17	-0.13	0.08	-0.07*	0.03	0	0.0007
Hongkong	3.38***	0.51	-0.08*	0.04	-0.08**	0.03	0.00**	0.0007
Italy	4.22***	0.92	-0.09	0.05	-0.09	0.05	0	0.0010
Korea	-19.31*	8.02	1.16*	0.55	-0.12	0.21	0.01	0.0060
Kuwait	3.72***	0.30	-0.19***	0.02	0.06***	0.01	-0.00***	0.0003
Japan	8.43*	3.43	-0.67*	0.26	0.13	0.09	0	0.0018
Malaysia	1.14*	0.49	0.01	0.02	0.01	0.04	0	0.0011
Qatar	0.13	0.27	0.13***	0.02	-0.06***	0.02	0.00**	0.0004
Saudi Arabia	0.25*	0.12	0.08***	0.01	-0.01**	0.00	0.00**	0.0001
Singapore	0.27	0.57	0.10*	0.04	0.04*	0.02	0	0.0006
Taiwan	5.53***	0.19	-0.17***	0.01	-0.04***	0.01	0.00***	0.0001
UAE	0.62**	0.19	0.06***	0.01	0.01	0.01	-0.00*	0.0002
Great Britain	5.47***	1.40	-0.23**	0.09	-0.03	0.06	0	0.0014
USA	1.06	2.03	0.12	0.13	0	0.06	0	0.0013
Other	4.82***	1.14	-0.35***	0.08	-0.11*	0.05	0	0.0011

legend: * p<.05; ** p<.01; *** p<.001

4.6.9 Returns by Region

The first part of this dissertation compared returns to education across regions in the Philippines in 2007-2010. That study found that returns to education in the national capital region are higher than in the rest of the regions in the country, using standard least squares estimation and the fixed-effects estimation. These estimates may be biased as they do not account for migration. If the more able migrate from the periphery to the capital or abroad, the returns to education in the peripheral regions may be underestimated while those in the capital may be overestimated. Table 4.21 shows the regression results of the human capital earnings function for domestic and overseas workers by region for 2011. Similar to the earlier results, the average return to schooling for local workers in the national capital region is higher than in most other regions, except Central Visayas (the economic hub of central Philippines) and surprisingly Bicol. Average earnings for local workers in the capital are also higher than those in most other regions, except CaLaBaRZon, adjacent to the capital and home to the export processing zone. To address the suspected bias in domestic returns to education across regions, returns to education for overseas workers from different regions are compared, controlling for sex, civil status, occupation and destination country. If the relative returns are similar to those for domestic workers, then the domestic returns may be deemed unbiased. Otherwise, domestic returns are unbiased. Unlike earnings for domestic workers, earnings of overseas Filipino workers from most regions are not significantly different from those from the national capital. Only the earnings of those from Ilocos, Central Luzon, Zamboanga, and Northern Mindanao are lower than the earnings of those from the capital region. Conversely, returns to schooling for overseas workers from Ilocos, Central Luzon, Central Visayas, Zamboanga, and Northern Mindanao are higher than the returns for those from the capital region, while returns to schooling for those from the rest of the regions are not significantly different from returns for those in the capital. This confirms the hypothesis that the higher returns for domestic workers in the capital are due to the migration of workers with higher ability, and not to superior quality of education in the national capital.

Table 4.21: Human Capital Earnings Function, Domestic and Overseas Workers by Region

	Intercept	Schooling	Experience	Exper.Sq.	OCW	OCW*Schooling	OCW*Exper.	OCW*Exper.Sq.
	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)	coef (se)
NCR (base)	-0.350***	0.080***	0.015***	-0.000***	-1.542***	-0.010	-0.009	0.000*
	(0.055)	(0.003)	(0.002)	(0.000)	(0.148)	(0.010)	(0.006)	(0.000)
1.Ilocos	-0.196***	-0.017***	0.007**	-0.000	-0.749**	0.076***	0.010	-0.000
	(0.068)	(0.005)	(0.004)	(0.000)	(0.356)	(0.023)	(0.015)	(0.000)
2.Cagayan	-0.177***	-0.021***	0.003	-0.000	-0.039	0.042	-0.017	0.000
	(0.059)	(0.004)	(0.003)	(0.000)	(0.398)	(0.026)	(0.017)	(0.000)
3.C.Luzon	-0.110*	-0.014***	0.007**	-0.000	-0.573***	0.056***	-0.009	0.000
	(0.058)	(0.004)	(0.003)	(0.000)	(0.212)	(0.014)	(0.009)	(0.000)
5.Bicol	-0.521***	-0.003	0.017***	-0.000***	-0.354	0.053*	0.019	-0.001**
	(0.075)	(0.005)	(0.004)	(0.000)	(0.461)	(0.030)	(0.019)	(0.000)
6.W.Visayas	-0.456***	-0.013***	0.011***	-0.000*	0.558	-0.011	-0.009	-0.000
	(0.059)	(0.004)	(0.004)	(0.000)	(0.526)	(0.033)	(0.023)	(0.001)
7.C.Viasayas	-0.465***	-0.006	0.016***	-0.000***	-0.525	0.092**	-0.074***	0.002***
	(0.063)	(0.004)	(0.004)	(0.000)	(0.629)	(0.042)	(0.026)	(0.001)
8.E.Visayas	-0.444***	-0.020***	0.023***	-0.000***	0.395	0.010	-0.016	0.000
	(0.067)	(0.005)	(0.004)	(0.000)	(0.595)	(0.039)	(0.023)	(0.001)
9.Zamboanga	-0.169***	-0.035***	0.003	0.000	-3.279***	0.211***	0.147***	-0.004***
	(0.062)	(0.004)	(0.004)	(0.000)	(0.761)	(0.045)	(0.036)	(0.001)
10.N.Mindanao	-0.501***	-0.013***	0.019***	-0.000***	-3.066***	0.209***	0.052*	-0.001
	(0.066)	(0.005)	(0.004)	(0.000)	(0.705)	(0.046)	(0.027)	(0.001)
11.Davao	-0.152**	-0.022***	0.006*	-0.000	2.908***	-0.126**	-0.156***	0.004***
	(0.061)	(0.004)	(0.004)	(0.000)	(0.972)	(0.060)	(0.052)	(0.001)
12.SoCCSKSarGen	-0.406***	-0.021***	0.014***	-0.000	-0.409	0.062	0.034	-0.001*
	(0.068)	(0.005)	(0.004)	(0.000)	(0.753)	(0.048)	(0.035)	(0.001)
14.Cordillera	-0.218***	-0.022***	0.025***	-0.000***	-0.475	0.087	-0.049	0.001
	(0.076)	(0.005)	(0.005)	(0.000)	(0.750)	(0.056)	(0.031)	(0.001)
15.ARMM	-0.290***	-0.014*	0.001	0.000	-0.802	0.057	0.057	-0.002*
	(0.106)	(0.007)	(0.007)	(0.000)	(0.690)	(0.045)	(0.036)	(0.001)
16.Caraga	-0.214***	-0.036***	0.019***	-0.000***	-0.492	0.041	0.013	-0.001
	(0.069)	(0.005)	(0.004)	(0.000)	(0.941)	(0.060)	(0.043)	(0.001)
41.CaLaBaRZon	0.042	-0.017***	0.004	-0.000	0.281	-0.007	-0.007	0.000
	(0.059)	(0.004)	(0.003)	(0.000)	(0.208)	(0.014)	(0.009)	(0.000)
42.MiMaRoPa	-0.253***	-0.031***	0.017***	-0.000**	0.158	0.024	0.017	-0.001
	(0.075)	(0.005)	(0.004)	(0.000)	(0.590)	(0.042)	(0.022)	(0.001)

Controls: sex, civil status, occupation, destination country

4.6.10 Income gains through occupational choice

Interpreting the estimated returns to education of migrants as causal effects using the foregoing approach relies on assumptions that may not always be realistic. For this reason, an alternative approach is also employed. Using equations 4.6 - 4.8, the following analysis relates wages to level of schooling indirectly through occupation. Overseas workers take on particular occupations depending on their level of schooling and earn different wages depending on their occupation.

4.6.11 Returns to migration (Purchasing Power Parity)

Table 4.22 shows the relative wages for various occupations across countries. The second column shows the wages for various occupations in the Philippines relative to those of laborers and unskilled workers. Professionals have the highest wages relative to laborers, earning 1.4 times more on average, followed by officials, managers and executive with 1.3 times more. Technicians earn 92 percent, those in special occupations 84 percent, clerks 83 percent, plant and machine operators 44 percent, traders 38 percent, and service workers 23 percent - more than laborers. Farmers, fishermen and forestry workers do not earn differently from laborers.

The rest of the columns in Table 4.22 show wages in destination countries by occupation relative to those of the same occupation in the Philippines in purchasing power parity. Earnings for officials, managers and executives are between 1.44 to 3.81 times higher in most top destinations than in the Philippines, except for Korea with lower earnings. Professionals in top destinations earn 1.67 to 4.45 times more than in the Philippines, except in Korea with lower earnings. Professionals in other destinations earn less than in the Philippines. Technicians earn between 1.44 to 3.71 times higher in top destinations than in the Philippines except in Korea. Even those in other destinations earn 17 percent more than in the Philippines. Clerks in top destinations earn from 1.26 to 3.83 times more than in the Philippines, except in Korea and Great Britain with the same earnings as in the Philippines. Service workers in top destinations earn between 92 percent to 3.9 times more than in the Philippines. Farmers earn from 50 percent to 4.13 times more in top destinations than in the Philippines, except in Great Britain and Kuwait with the same earnings. Trade workers in top destinations earn 38 percent to 3.81 times more than in the Philippines. Plant operators earn between 1.13 to 4.98 times more. Trade workers and plant operators in other destinations earn less. Laborers earn 49 percent to 3.69 times more, except in Korea with same earnings as in the Philippines. Laborers in other destinations also 68 percent more than in the Philippines. Workers in special occupation earn 1.26 to 3.79 times higher in top destinations, except in Canada where they earn the same as in the Philippines. Those in other destinations also earn the same.

4.6.12 Returns to migration (U.S. Dollars)

Apart from real income gains from working overseas, there are monetary gains from currency conversions. Table 4.23 shows the wage ratios in US Dollars. Officials, managers and executives earn between 1.87 to 4.59 times more in top destinations than in the Philippines, except in Korea with lower earnings. Professionals overseas in top destinations have between 1.4 to 4.6 times higher earnings than local professionals, also except Korea. Professional earnings in other destinations are not significantly different from that in the Philippines. Technicians in top destinations earn between 2.03 to 4.35 times higher than those in the Philippines, again except in Korea. Technicians in other destinations earn 38 percent more than in the Philippines. Clerks earn from 1.06 to 4.07 times more in top destinations, except in Japan where they have the same earnings as in the Philippines. Clerks in other destinations earn less than in the Philippines. Trade workers in top destinations except Italy earn between 1.06 to 4.18 times more than in the Philippines. Those in other destinations earn less.

Depending on the occupation, the income gains of Filipino workers in Australia rise by 24 to 33 percent when using the official exchange rate (USD). In Bahrain, the gains rise by 16 to 38 percent; in Canada, 19 to 26 percent; China 4 to 8 percent, Hongkong 5 to 8 percent. In Italy, the gains rise by 15 to 43 percent when using the official exchange rate, in Korea 9 to 36 percent, Kuwait 33 to 77 percent, Japan 17 to 69 percent. In Malaysia, the gains from the exchange rate are 3 to 9 percent, in Qatar 27 to 130 percent, Saudi 18 to 55 percent, Singapore 13 to 31 percent, and Taiwan 3 to 4 percent. In UAE, the exchange rate gains are 23 to 56 percent, in UK 21 to 186 percent, and in the US 15 to 22 percent. In other destinations, the exchange rate gains are between 80 to 224 percent.

Table 4.22: Return on Occupation by Country in PPP (laborers and unskilled workers as reference)

	PHL	AUS	BHR	CAN	CHN	HKG	ITA	KOR	KWT	JPN
Officials	1.27***	3.45***	2.10***	3.81***	2.52***	3.63***	2.16***	-3.84***	1.44***	1.52***
Professionals	1.39***	3.46***	2.53***	4.07***	2.65***	3.85***	3.60***	-2.98***	2.11***	1.69***
Technicians	0.92***	3.36***	2.05***	3.36***	2.56***	4.11***	(empty)	-3.46***	1.46***	1.67***
Clerks	0.83***	3.08***	1.75***	3.09***	1.77***	(empty)	1.27*	0.78	1.26***	-0.17
Service Workers	0.23***	3.02***	1.49***	3.29***	1.47**	(empty)	2.22***	-3.62**	0.92***	2.31***
Farmers	-0.03	4.13***	(empty)	2.99***	(empty)	(empty)	(empty)	(empty)	0.5	(empty)
Trades	0.38***	3.16***	1.75***	3.41***	1.50***	(empty)	1.71	1.04*	1.21***	2.19***
Plant Operaters	0.44***	3.77***	1.46**	3.65***	2.60***	(empty)	(empty)	1.85**	1.38***	4.98***
Laborers		2.99***	1.46***	3.63***	1.70***	2.38***	2.11***	0.86	1.51***	1.56***
Special Occupation	0.84***	3.79***	3.34**	0.56	3.20***	2.47***	(empty)	(empty)	1.73**	1.26*

	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	OTHER	
Officials	2.25***	1.54***	1.48***	2.65***	3.35***	1.69***	1.98**	3.79***	-0.49***	
Professionals	2.50***	2.19***	2.19***	2.46***	4.45***	2.22***	2.59***	3.63***	-0.30***	
Technicians	2.39***	1.44***	1.64***	2.45***	3.71***	1.68***	3.11***	3.23***	0.17*	
Clerks	1.92***	1.44***	1.51***	2.45***	3.83***	1.58***	2.22	3.56***	-0.71***	
Service Workers	1.55***	1.38***	1.19***	2.26***	3.90***	1.20***	1.29*	2.63***	0.04	
Farmers	(empty)	(empty)	1.20***	1.58**	(empty)	1.81***	-0.76	(empty)	2.54***	
Trades	1.79***	0.46***	1.02***	2.05***	3.81***	1.12***	2.66***	3.05***	-0.83***	
Plant Operaters	1.80**	1.28***	1.13***	2.35***	3.91***	1.33***	2.14*	2.72*	-0.75***	
Laborers	0.91**	0.49***	0.71***	1.26***	3.69***	0.91***	1.81**	2.59***	0.68***	
Special Occupation	2.90***	2.16***	1.99***	2.83***	(empty)	2.01***	2.22*	(empty)	0.33	

legend: * p<.05; ** p<.01; *** p<.001

Table 4.23: Return on Occupation by Country in US Dollars (laborers and unskilled workers as reference)

	PHL	AUS	BHR	CAN	CHN	HKG	ITA	KOR	KWT	JPN
Officials	1.27***	4.43***	2.66***	4.59***	2.65***	3.82***	2.71***	-3.56***	2.14***	2.39***
Professionals	1.39***	4.44***	3.09***	4.85***	2.78***	4.04***	4.15***	-2.70***	2.81***	2.55***
Technicians	0.92***	4.35***	2.61***	4.14***	2.68***	4.30***	(empty)	-3.19***	2.16***	2.54***
Clerks	0.83***	4.07***	2.31***	3.87***	1.90***	(empty)	1.82**	1.06*	1.96***	0.7
Service Workers	0.23***	4.00***	2.05***	4.07***	1.59**	(empty)	2.77***	-3.34**	1.63***	3.18***
Farmers	-0.03	5.12***	(empty)	3.76***	(empty)	(empty)	(empty)	(empty)	1.2	(empty)
Trades	0.38***	4.14***	2.30***	4.18***	1.62***	(empty)	2.26	1.31**	1.91***	3.05***
Plant Operaters	0.44***	4.75***	2.02***	4.43***	2.72***	(empty)	(empty)	2.12***	2.08***	5.85***
Laborers		3.97***	2.02***	4.40***	1.82***	2.58***	2.66***	1.14*	2.21***	2.43***
Special Occupation	0.84***	4.77***	3.89**	1.33	3.33***	2.66***	(empty)	(empty)	2.43***	2.13***
	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	OTHER	
Officials	2.33***	2.14***	1.87***	3.03***	3.48***	2.20***	2.62***	4.35***	-0.32***	
Professionals	2.58***	2.79***	2.58***	2.84***	4.58***	2.73***	3.24***	4.19***	-0.06	
Technicians	2.47***	2.04***	2.03***	2.84***	3.83***	2.19***	3.75***	3.79***	0.38***	
Clerks	2.00***	2.05***	1.90***	2.84***	3.95***	2.09***	2.86*	4.12***	-0.52***	
Service Workers	1.63***	1.98***	1.58***	2.65***	4.03***	1.71***	1.93**	3.18***	0.33***	
Farmers	(empty)	(empty)	1.59***	1.96***	(empty)	2.32***	-0.12	(empty)	2.97***	
Trades	1.87***	1.06***	1.41***	2.43***	3.94***	1.63***	3.30***	3.61***	-0.40***	
Plant Operaters	1.88***	1.89***	1.51***	2.73***	4.04***	1.84***	2.78**	3.27**	-0.43***	
Laborers	0.99**	1.09***	1.10***	1.65***	3.82***	1.42***	2.46***	3.15***	1.05***	
Special Occupation	2.98***	2.76***	2.38***	3.21***	(empty)	2.52***	2.86**	(empty)	0.44*	

legend: * p<.05; ** p<.01; *** p<.001

4.6.13 Probability of Employment

The effective returns to migration are affected by the probability of employment in the destination. Table 4.24 shows the results of multinomial logistic regression of destination on occupation. The figures show the percentage change in the odds of working in a major destination relative to minor destinations with respect to working in a particular skilled occupation (relative to being a laborer or unskilled worker). Being a trade worker increases the odds of working in Australia by over 6 times; being a professional increases the odds by almost 4 times. Being a service worker raises the odds of working in Canada by 2.8 times. Being a technician increases the odds of working in China by 2.7 times. Being a technician and plant operator raises the odds of working in Korea by 2.9 times and 3.2 times, respectively. Being a technician and plant operator increases the chance of working in Japan by 2.3 and 2.4 times, respectively. Being a clerk raises the odds of working in Qatar by 2.2 times. Being a clerk, trade worker and professional increases the odds of working in Saudi Arabia, by 2, 1.9 and 1.4 times, respectively. Being a clerk and service worker raises the odds of working in the UK by 5 and 3 times, respectively. Being a clerk, service worker, professional and technician raises the odds of working in the US by 9, 7.3, 4.30 and 4.33 times, respectively.

Table 4.24: Multi-nomial Logit: Destination on Occupation (Odds Ratio)

	AUS	BHR	CAN	CHN	HKG	ITA	KOR	KWT	JPN
Officials	2.85	0.3	1.02	0.00***	0.07***	0.00***	0.52	0.30**	0.19
Professionals	3.76*	0.34	0.77	0.57	0.01***	0.19*	0.78	0.16***	0.43
Technicians	2.98	0.21	0.43	2.65*	0.02***	0.17	2.89*	0.12***	2.25*
Clerks	0.00***	1.72	1.95	1.46	0.14**	0.95	0.00***	0.33	1.46
Service Workers	2.52	0.8	2.82***	1.23	0.11***	1.39	1.22	0.30***	1.12
Farmers	8.18	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	3.28
Trades	6.14**	0.54	0.44	0.82	0.03***	0.53	1.67	0.14***	1.91*
Plant Operaters	2.2	0.13**	0.45*	0.84	0.03***	0.55	3.21**	0.07***	2.39***
Constant	0.03***	0.15***	0.21***	0.11***	1.81***	0.18***	0.08***	1.02	0.23***

	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	
Officials	0.27	0.51	0.95	0.38*	0.28*	0.43*	1.55	1.55	
Professionals	0.10**	0.45**	1.44*	0.45**	0.14***	0.79	2.34	4.30***	
Technicians	0.47	0.47*	0.82	0.54*	0.33*	0.78	1.08	4.33**	
Clerks	1.04	2.16*	2.00*	0.66	0.54	4.16***	4.96**	8.93***	
Service Workers	0.48*	0.72	0.58**	0.20***	0.47*	0.94	3.05**	7.33***	
Farmers	0.00***	0.32	0.27	0.22	1.61	0.16	2.98	0.00***	
Trades	0.15**	1.24	1.87***	0.15***	0.44*	0.61*	0.93	1.12	
Plant Operaters	0.12***	0.22***	0.72*	0.19***	1.16	0.21***	1.03	3.78***	
Constant	0.32***	0.77*	1.88***	1.13	0.47***	1.60***	0.08***	0.08***	

legend: * p<.05; ** p<.01; *** p<.001

4.6.14 Skilled employment by years of schooling

Table 4.25 shows the results of multinomial logistic regression of occupation on schooling using the SOF data.[6] This complements the information on years of schooling by occupation across destinations in Table 4.9. The odds (relative risk) ratios reported show the percentage change in the odds of taking on a particular occupation relative to laborers and unskilled workers for each year of schooling. In the US, the effects of schooling on employment are higher for professionals, service workers and plant and machine operators. These reinforce the positive earnings differentials for these occupations. In Japan, the effects are higher for plant operators, lower for officials, professionals, and clerks, but the same for the rest. In Australia, each year of schooling increases the odds of taking on any particular occupation by as much as that for being a laborer or unskilled worker. This is consistent with high levels of education across occupations meaning that Filipino workers with different schooling have the same chance of employment in all occupations in Australia. In the UK, the effect of schooling on the odds are the same for most occupations but lower for farmers. This is consistent with the fact that while education levels are high across most occupations, education level in agriculture is quite low. In China, the effects on the odds are surprisingly lower for professionals and clerks than laborers. In Korea, the effect is higher for plant operators and lower for officials. In most major destinations, schooling decreases the odds of all or most skilled employment. In Singapore, Kuwait, Qatar, and the UAE, the effects are unexpectedly lower for all occupations compared to laborers. In Canada, Hongkong, and Malaysia, the effects are lower for all occupations excluding farmers, but higher for service workers in Canada. In Saudi Arabia, the odds are lower for all except professionals and trade workers. In Bahrain, the effects are lower for all occupations except service workers. In Taiwan, the effects are lower for all occupations except plant and machine operators. In Italy, the effects are lower for most occupations except for service workers. The negative effect of schooling on skilled employment is consistent with lower returns to schooling in most of these destinations compared to the Philippines.

[6] Due to the difficulty in achieving convergence with multi-variate regression, the reported estimates are from a simple regression of occupation on schooling.

Table 4.25: Odds ratio: Occupation on Schooling (Laborers and unskilled workers as base outcome) - Multi-nomial Logit

	AUS	BHR	CAN	CHN	HKG	ITA	KOR	KWT	JPN
Officials	0.96	0.80**	0.88***		0.69***		0.82*	0.79***	0.77**
Professionals	1.05	0.88*	0.93**	0.91*	0.63***	0.83**	0.94	0.82***	0.89**
Technicians	0.99	0.80**	0.85***	0.97	0.63***	0.77**	0.98	0.75***	0.96
Service Workers	1.04	0.95	1.04*	0.98	0.79***	0.99	0.97	0.87***	0.97
Farmers	0.88							0.82***	
Trades	1.08	0.89*	0.89***	0.94	0.68***	0.89**	0.99	0.79***	1.00
Plant Operators	1.05	0.84**	0.92**	0.98	0.72***	0.94*	1.08**	0.77***	1.06***
Clerks		0.87**	0.88***	0.87*	0.69***	0.83**		0.75***	0.87***
	MYS	QAT	SAU	SGP	TWN	ARE	GBR	USA	OTHER
Officials	0.78***	0.82***	0.88***	0.82***	0.79***	0.82***	0.91	0.92	0.88***
Professionals	0.79***	0.90***	0.99	0.90***	0.80***	0.94***	1.02	1.07*	0.96***
Technicians	0.84***	0.85***	0.89***	0.87***	0.81***	0.89***	0.92	1.02	0.91***
Service Workers	0.91**	0.94***	0.92***	0.86***	0.90***	0.96***	1.05	1.13***	0.96**
Farmers		0.68***	0.65***	0.64***	0.77***	0.62***	0.81*		0.73***
Trades	0.79***	0.96**	1	0.82***	0.87***	0.91***	0.95	0.96	0.94***
Plant Operators	0.84***	0.86***	0.96***	0.87***	0.99	0.87***	1	1.10***	0.99
Clerks	0.83***	0.88***	0.89***	0.81***	0.79***	0.94***	0.95	1	0.84***

legend: * p<.05; ** p<.01; *** p<.001

4.6.15 Migration Selection

If migration were random, least squares estimates of returns to migration and education of migrants would be unbiased. However, if migrants self-select based on observed and unobserved characteristics, migration will be correlated with the error term and estimates of returns to migration and education would be biased. To account for selection bias, I employ the Heckman selection model on 2003 data from the combined Labor Force Survey and Survey of Overseas Filipinos. Table 4.26 shows the results of the human capital earnings function for migrants and non-migrants using the Heckman model in comparison with the ordinary least squares. The selection equation and the SOF data allows the modeling of migration as a function of age, marital status and family size (this last variable is not available in the POEA dataset). The hypotheses are that younger individuals are more likely to migrate as they have more energy and enthusiasm, married individuals are less likely to migrate due to the psychic costs of being away from their partners, and individuals from bigger families are more likely to migrate to help support the huge household consumption. The results indicate that older individuals are actually more likely to migrate. Married individuals are less likely to migrate as expected. Individuals from larger families are actually less likely to migrate. Accounting for selection bias increases the returns to schooling for non-migrant workers by 1 percentage point. While the marginal increase for migrant workers is small, only 0.1 percentage point, returns to schooling effectively increases by 1.1 percentage points. The change in the returns to schooling suggest selection bias and this is confirmed by the significance of the inverse Mill's ratio (lambda). However, selection is not limited to migrants; both migrants and non-migrants appear to be negatively selected. The negative selection of migrants is confirmed by the negative coefficient of schooling in the selection equation. As explained in the data section, however, remittance data is used as a proxy for migrant wages. Other ways of addressing migration selection are explained in the appendix.

4.7 Summary

In 2011, the Philippine Overseas Employment Administration deployed 131,148 overseas Filipino workers on return contracts. Two-thirds of those deployed are males. Seven out of ten were deployed in the Middle East, four in Saudi Arabia. There are more males in most destinations, concentrated in certain jobs in some countries like trade in Australia and Qatar and clerical work in Korea. In some destinations,

Table 4.26: Migration Selection

	OLS		HECKMAN			
	LN Wage		LN Wage		Overseas Worker	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Constant	3.1352***	0.0384	2.8595***	0.0556	-2.5230***	0.2946
Schooling	0.0510***	0.0011	0.0612***	0.0017	-0.5384***	0.0464
Experience	0.0201***	0.0007	0.0303***	0.0014	-0.5384***	0.0464
Experience^2	-0.0002***	0.0000	-0.0005***	0.0000	-0.0006***	0.0000
OFW	0.0202	0.0812	0.0026	0.0753		
OFW $\times$ Schooling	0.0287***	0.0056	0.0297***	0.0052		
OFW $\times$ Experience	0.0115**	0.0039	0.0129***	0.0035		
OFW $\times$ Experience^2	0.0000	0.0001	-0.0000	0.0001		
Age					0.5689***	0.0463
Married					-0.0352**	0.0121
Family Size					-0.0041**	0.0014
lambda			0.5545***	0.0623		
Adjusted R^2	0.4855					
Observations	37949		183817			

Controls: Region, Occupation

there are more females, mostly laborers and unskilled workers in Hong Kong, Italy and Kuwait; service and sales workers in Canada; and service and sales workers and clerks in Taiwan.

Overseas workers on average have more years of schooling than local workers: 12.2 years for males compared to 8.4 years for their local counterparts; and 11.6 years for females compared to 8.9 years for their local counterparts. Overseas workers in Canada, Australia and USA have the highest educational attainment at over 13 years. Across occupations, professional overseas workers have the highest schooling, followed by technicians and associate professionals, and officials, managers and executives.

On average, overseas workers earn 3.1 times more than their counterpart in the Philippines. However, returns to education are generally lower than that in the Philippines. Nevertheless, it appears that income gains are sufficient to attract Filipino workers. Gains from migration accrue to both sexes, with females earning over twice more than their local counterparts and males 73 percent more. However, returns to schooling for females overseas are no different from those in the Philippines. For males, returns to schooling are even lower than those of their local counterparts.

Among the top destinations, earnings of Filipino workers in Australia, Italy, Japan, Canada, China, Taiwan and USA are higher than in the Philippines. Returns to schooling is higher in the UAE, but lower in Australia, China, Italy, Korea, Kuwait, Japan, Malaysia and Taiwan. Returns to schooling in Bahrain, Canada, Malaysia and USA are no different from that in the Philippines. Nevertheless, higher labor returns still explain the temporary migration. While the return to labor is lower in Qatar, the return to schooling is higher than in the Philippines. Although returns to labor in Hong-Kong, Korea, Saudi Arabia, Singapore, and the UK is the same as in the Philippines, returns to schooling is higher in Saudi Arabia, Singapore, and Hong-Kong. However, the return to schooling in the UK is not different from that in the Philippines, and they are even lower in Korea. This raises a question on the motivation for temporary migration, given no apparent gains to either labor or human capital.

The trade-off between earnings and returns to schooling plays out across sexes. Earnings for female overseas workers in Australia, China, Hong-Kong, Italy, Japan, Kuwait, and Malaysia are higher than in the Philippines. However, returns to schooling are lower in Hong-Kong, Kuwait, Japan, Taiwan, and UK, and not significantly different in Australia, China, Italy, and Malaysia. Earnings for females in Korea is lower but return to schooling higher. Although returns on female labor in Bahrain, Canada, Qatar, Saudi Arabia, Singapore, UAE and USA are not significantly different from that in the Philippines, return to female schooling is higher in Qatar, Saudi Arabia, Singapore, and UAE. However, returns to female schooling in Bahrain, Canada, and USA are not significantly different from that in the Philippines.

For males, returns to labor are higher in Korea, Saudi Arabia, Singapore, and UAE and returns to schooling are higher for Singapore but lower in Korea, Saudi Arabia, and UAE. Although returns to labor are lower in Hong Kong, Kuwait, Qatar, Taiwan, and the UK, returns to schooling are higher in Hong-Kong, Kuwait, Taiwan and the UK, but not significantly different in Qatar. However, apart from returns to male labor in Australia, Bahrain, Canada, China, Italy, Japan, Malaysia, and the USA not being significantly different from that in the Philippines, returns to schooling are also no better in Australia, Bahrain, Canada, China, Italy, Japan, Malaysia, and USA. Some gains accrue from experience, as in Canada and China, but for the rest, the puzzle remains.

Apart from real income gains for overseas workers, there are monetary gains from currency conversions. Income gains in US dollars are between 3 percent to 117 percent higher than gains in purchasing power parity in most top destinations. Without apparent real income gains for some overseas workers to their labor or human capital in purchasing power parity terms, gains may be realized through the exchange rate as remittances sent or brought home are converted to the local currency. While there are no real income gains in Korea and Saudi Arabia, there are indeed exchange rate gains. There are also exchange rate gains in returns to schooling in a third of the top destinations.

This paper provides the only known estimates of the impact of migration on the earnings of workers for the most number of destination countries for a single origin country with this level of disaggregation (including by sex). It is also the only paper to estimate returns to schooling for migrants by destination country and sex. With the foregoing estimates of gains to migration for most overseas workers, the problem of accounting for migration selection and deriving unbiased estimates of the returns to labor and human capital remains.

The estimation of earnings and returns to schooling for overseas workers from various regions aims to correct for the bias in estimates of returns to schooling for domestic workers across regions. The results show that returns to schooling for overseas workers from the capital are not necessarily higher and may be lower than the returns for those from other regions. This confirms that returns to education in the capital are overestimated due to the in-migration of workers with higher ability, and those in other regions are underestimated due to their out-migration.

With wage and education data contained in separate sources, estimating returns to education relies on strong assumptions. An alternative approach is employed by separately relating earnings and destination to occupation using the POEA data-set and occupation to schooling using the SOF data-set. The probability of working in a particular destination depends on the worker's occupation. Professionals and trade workers have the highest odds of working in Australia, service workers in Canada, technicians in China, professionals in Italy, plant operators in Korea, managers and executives, and services workers in Kuwait, technicians in Japan, service workers in Malaysia, clerks in Qatar, trade workers and clerks in Saudi Arabia, professionals and technicians in Singapore, service workers in Taiwan and UAE, clerks and service workers in the UK and the US.

Consequently, earnings of professionals and trade workers in Australia are 3.46 times and 3.16 times higher than counterparts in the Philippines, respectively. Service workers in Canada earn 3.3 times more, technicians in China earn 2.6 times more, and professionals in Italy earn 3.6 times more, than in the Philippines. Plant operators in Korea earn 1.9 times more, managers and executives earn 1.44 times more and service workers earn 92 percent more in Kuwait, and technicians in Japan earn 1.7 times more, than their counterparts in the Philippines. Service workers in Malaysia earn 55 percent more, clerks in Qatar earn 1.4 times more, and clerks in Saudi Arabia earn 51 percent more, than their local counterparts. Professionals and technicians in Singapore earn 2.5 times more, service workers in Taiwan earn 3.9 times more, clerks earn 3.6 times more and service workers earn 2.6 times more in the US, than in the Philippines.

Relating occupation to schooling shows that the likelihood of skilled employment increases with schooling in a few destinations. The odds of working as a professional, service worker, and plant and machine operator in the US and as a plant operator in Japan increases with schooling. On the other hand, the odds of all skilled employment in Australia and most skilled employment in the UK do not rise with schooling. In most major destinations, schooling decreases the likelihood of all or most skilled employment, contrary to expectation.

Appendix: Addressing Migration Selection[7]

If migration were random, this variable would be uncorrelated with the error term and its coefficient unbiased. However, if migrants self-select based on observed and unobserved characteristics, migration will be correlated with the error term and its coefficient would be biased.

Propensity Score Matching

If migrants self-select on observed characteristics, the bias can be corrected using propensity score matching. The first step is to estimate a probit/logit model of migration on observed characteristics (i.e. age/experience, schooling, sex, marital status, etc.).

$$Pr(M_i = 1|x_i) = \Phi(\alpha_i + \beta S_i + X_i'\theta + \varepsilon_i) \tag{4.10}$$

The predicted values $\hat{M}_i$ of the probability model are derived, representing the estimated probability of migration or propensity score. The propensity score can be estimated using the Stata estimation command *pscore.ado* developed by Becker and Ichino (2002). The second step is to identify the overlap in propensity scores between migrants and non-migrants. The third is to match migrants M to a non-migrant comparison group C based on the propensity score. Finally, the average

[7] Adapted from the theory of impact evaluation (Khandker et al., 2010)

effect of migration is calculated as follows:

$$TOT_{PSM} = \frac{1}{N_M}[\sum_{i\epsilon M} W_i^M - \sum_{j\epsilon C} \omega(i,j)Y_j^C]. \tag{4.11}$$

The nearest neighbor and stratification criteria are used to match migrants and non-migrants and compute the average migration effect.

Double-Difference

As migration may be affected by unobserved characteristics such as ability, propensity score matching estimates may still be biased. To account for unobserved characteristics, a double-difference method is used, as it assumes the presence of unobserved heterogeneity affecting migration. Assuming that these unobserved characteristics, α_i, are time-invariant, they can be differenced out. Using panel data, the model becomes:

$$\begin{aligned} ln(W_{it}) - ln(W_{it-1}) = (\alpha_i - \alpha_i) + \beta(S_{it} - S_{it-1}) + \gamma(M_{it} - M_{it-1}) \\ + \delta(S_{it} * M_{it} - S_{it-1} * M_{it-1}) + (X'_{it} - X'_{it-1})\theta + (\varepsilon_{it} - \varepsilon_{it-1}) \end{aligned} \tag{4.12}$$

Instrumental Variable Regression

If unobserved characteristics are time-varying, the double difference method estimates may still be biased. To allow for time-varying unobserved heterogeneity, instrumental variable regression can be used. It involves finding an instrument that is highly correlated with migration, but not correlated with unobserved characteristics affecting earnings ($\gamma \neq 0$). Instrumental variable regression is done using two-stage least squares. The first stage is a probit regression of the Migration dummy on the instrument Z, the other covariates X and a disturbance u:

$$Pr(M_i = 1|x_i) = \Phi(\alpha_i + \gamma Z_i + \beta S_i + X'_i\theta + u_i) \tag{4.13}$$

where the instrument Z is the number of members of the family / household. The idea is that a larger dependency ratio would motivate a worker to migrate to earn more for his/her family, but would not affect his wage directly. The second stage involves substituting the predicted value of the migration model into the wage model as follows:

$$ln(W_i) = \alpha_i + \beta S_i + \gamma \hat{M}_i + \delta(S_i * \hat{M}_i) + X'_i\theta + \varepsilon_i \tag{4.14}$$

To test for endogeneity, a regression-based Hausman test is used. The error term ε_i is regress on u_i; endogeneity is rule out if the coefficient of u_i is not significant.

Chapter 5

Conclusion

In the first part of this dissertation, I aimed to account for education quality and ability in returns to education in the Philippines. This was done by considering primary and secondary test scores and sibling fixed-effects in human capital earnings functions. The results confirm the importance of ability and indicate that standard estimates of returns to education are overestimated as they capture the effects mainly of sector, occupation, region and ability. Most of what have hitherto been considered as returns to education are actually due to ability. Contrary to earlier findings of high returns to primary education and decreasing returns to education (e.g. Hossain and Psacharopoulos (1994)), there are no significant returns to primary and secondary education. Earnings of workers with only basic education are due not to its productive content but to the ability signaled by its completion, consistent with the signaling hypothesis (Spence, 1973). On the other hand, there are clear returns to tertiary and higher education, and these entail even higher abilities. These suggests that reducing social inequalities that underlie differences in ability and learning outcomes may have the most impact on increasing worker productivity and earnings.

Education quality is insignificant to wages when controlling for province and key city fixed effects, the level at which education quality data are available. Several points are noteworthy in this light. The first is the reliability of the test scores. It is important to determine the integrity of testing from question formulation, through to implementation and evaluation. Second, the insignificance of test scores may be due to migration of the best among the test cohorts. Third, individual level achievement is best related to individual wages. This requires a tracing individual outcomes over time, something that should be considered by the Department of Education or the National Statistics Office. If the measures of education quality are reliable but insignificant to wages, there remains a case for increasing the quantity of education as the government thrust is. The Philippine government has just embarked on the K-12 program which includes adding senior high school to secondary education, effectively increasing the quantity of basic education from 10 to 12 years. It remains to be seen whether the additional years of schooling would increase worker productivity and wages. As this has shown, education completion and certification matter more than additional schooling. Enhancing education quality may be as (more) important and efficient as (than) increasing the quantity of schooling.

Uneven development across regions in the country accounts for inequalities in earnings and returns to education. Greater economic development in certain regions, especially the capital and other economic centers, creates advantages in earnings. This drives migration into richer regions especially of the best from the poorer regions, or a positive selection of migrants in terms of ability. This raises productivity further in richer regions and decreases that in poorer regions, worsening inequality.

International labor migration has long been an alternative to internal migration, and brain drain or the migration of more skilled workers has been a concern for some. This concern seems warranted considering the findings in the second part of this dissertation. In particular, permanent migrants are positively selected from the local labor force, much like internal migrants. Permanent migration increases despite increasing domestic employment as they have higher reservation wages relative to the equilibrium wage. On the other hand, temporary migrants are negatively selected in the destination labor force. Temporary migration increases despite increasing labor supply in Saudi Arabia as Filipino workers accept jobs at the lower wages which Saudi nationals are unwilling to accept. The negative selection of temporary migrants is confirmed in the third study in this dissertation showing higher earnings and lower returns to schooling for overseas workers compared to local workers and confirmed by a Heckman selection model.

Permanent and temporary migration are positively related to domestic wages, controlling for income. Migration increases if wages increase without economic growth. This means that poor employment rather than low wages is driving migration. However, permanent migration is positively related to domestic employment, controlling for wages. Higher employment does not necessarily reduce permanent migration and may in fact increase it, as this decreases what employers are willing to pay and increases what additional workers are willing to accept. This makes permanent migrants positively selected from the local labor force. These findings imply that changes in wages and employment should be consistent with changes in labor demand and supply.

On the other hand, temporary migration is not significantly related to domestic employment. Permanent migration is negatively related to remittances as remittances complement national income, increasing labor demand at home. On the other hand, temporary migration is positively related to remittances as these serve defray the costs of migration. Domestic employment increases if wages increase proportionately to labor demand. Otherwise, additional workers would migrate instead.

Permanent and temporary migration are negatively related to domestic income per capita, controlling for labor force, wages and employment. This confirms the hypothesis that poverty drives migration (Lewis, 1954; Harris and Todaro, 1970) and that migration decreases with economic development. However, economic growth does not mitigate migration if employment does not increase proportionately. This implies the imperative for broad-based development benefiting not just capital, but more importantly labor. This also implies that migration may be inevitable during economic downturns as both wages and employment fall, unless workers are willing to accept even lower wages to keep their local employment. Permanent and temporary migration are also negatively related to the labor force. The economy can accommodate returning migrants despite an increasing labor force if employers can pay their reservation wage.

Permanent and temporary migration are positively related to destination wages. The quantity of destination labor demanded decreases as wages increase. If migrants can be paid lower than the destination labor, they can fill the decrease in destination labor. This implies that Filipinos may have to accept wages lower than those of natives in the destination country to be employed. Permanent and temporary migration are also positively related to destination income; destination economic growth increases labor demand. Permanent migration is negatively related to destination labor force; an increase in destination labor supply at existing wages creates excess labor supply. On the other hand, temporary migration is positively related to destination labor force. Filipino workers can take the additional employment at lower wages if destination workers cannot accept lower wages. This makes temporary migrants negatively selected in the destination labor force.

Temporary migration responds positively to destination wages, although these wages may be lower than what natives in destination countries earn. The third part of this dissertation estimated returns to migration and education of overseas

Filipino workers. This was done by comparing earnings of overseas Filipino workers with those of local workers with the same observable characteristics. It uses an augmented human capital earnings function, relating wages to schooling, experience and its square, migration and its interactions with the first three variables, with sex, civil status, occupation, and region of origin in the Philippines as controls. It also estimates the human capital earnings function by sex, for top destination countries as a group, and by each destination country.

Results show that overseas workers earn more than local workers. This is consistent with the model relating migration positively to destination wages and negatively to origin wages (Borjas, 1987) and to the fact that labor is more abundant in the Philippines. However, returns to predicted schooling of overseas workers are lower than actual returns for local workers. While this is constrained by the imputation of schooling for migrants, this may well reflect the relative scarcity of human capital in the Philippines. While earnings of overseas workers in top destinations as a group are lower than those of local workers, earnings in most top destinations are higher. Returns to schooling in top destinations as a group are higher than in the Philippines. This is consistent with the fact that overseas workers in top destinations have more schooling than local workers (Borjas, 1999). However, returns to schooling of Filipino workers in most top destinations are not significantly different from or even lower than those for local workers. The higher earnings and lower returns to schooling together suggest high relative equality in the corresponding countries. This indicates that overseas workers are negatively selected; if income inequality is higher in the home country, the less able migrate and earn less than the average worker in the destination country (Borjas, 1987). This is confirmed by the Heckman selection model and consistent with the negative selection noted in the study on determinants of migration. There appears to be a general trade off between earnings and returns to schooling. This applies to both male and female overseas workers. Nevertheless, there are further gains from the conversion of earnings from the destination currency to the Philippine currency through the official exchange rate (US dollars). Earnings sent home as remittances also yield gains through differences in costs of living. However, there are no apparent gains in earnings and returns to schooling in general for a few countries, and particularly for males and females in several countries.

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