ESSAYS ON MIGRATION AND REMITTANCES IN THE PHILIPPINES

CHRISTOPHER JAMES R. CABUAY

A THESIS SUBMITTED FOR THE
DEGREE OF DOCTOR OF PHILOSOPHY
AT THE AUSTRALIAN NATIONAL UNIVERSITY

FEBRUARY 2021

Declaration

Declaration

This thesis is my own work.

The data used in Chapter 2 was purchased by the De La Salle University Angelo King Institute for Economic and Business Studies (DLSU-AKIEBS) from the Philippine Statistics Authority (PSA) for use of their faculty members and students. The datasets used in Chapter 3 were taken from the Integrated Public Use Microdata Series – International (IPUMS-I) of the Minnesota Population Center, and the International Labour Organization's ILOSTAT. The survey dataset used in Chapter 4 was conducted by the Partnership for Economic Policy Community-Based Monitoring System (PEP-CBMS) and received from DLSU-AKIEBS. The views expressed in this thesis are my own and are not necessarily shared by the institutions mentioned above. All errors are my own.

CJCabuay

Christopher James R. Cabuay

June 2021

Acknowledgements

This PhD journey has been an interesting one. For many times I have been brought down to my knees crying as I was destroyed utterly. And yet, I could say at the very least – I was never bored. I struggled but I stepped up each time, and in many ways, I have changed. I have grown in many facets, not just academically, and now despite everything, I see the universe in all its splendor. I am truly grateful.

To God, for this beautiful world, and this marvelous experience. Call it fate or coincidence, everything unfolded as what was meant to be. Let me become an instrument of Your peace, glory and mercy.

To my supervisor, *Prof. Budy P. Resosudarmo*. I do not remember why you picked me, sir, but I can't thank you enough for your guidance. Everything I learned from you will stay with me for the rest of my life, and for that, I give you my eternal loyalty and respect. I hope that I was able to meet your expectations and that I could become half the economist you are. Here's to us working together in the future, Pak!

To my panelists, *Prof. Hal Hill* and *Prof. Tess Tiongco*. Thank you for the support and wonderful comments you gave me to improve my papers. It was truly an honor to have your guidance in my panel.

To my benefactors, the Australian National University, Crawford School of Public Policy, Australia Awards Scholarships (AAS), *Milalin*, *Nayra*, *Enna*, *Billie*, *Liz*, *Ngan*, *Aishah*, and *Ida*. Without whom none of this would be possible. Thank you for your support. Please know that you did not make a mistake in funding me. I will do all I can to give a bounteous return on your investment.

To the brilliant Professors of the Arndt-Corden Department of Economics and the Research School of Economics, *Chandra*, *Ross*, *Paul*, *Ryan*, *Arianto*, *Ligang*, *Sarah*, *Ruitian*, *Tim*, *Thomas*, *Xin Meng*, *Amir*, *Tina*, and *Dana*. It was truly an honor to learn from you all in both classes and seminars. Thank you for all the helpful comments and giving me the chance to work with you.

To the paragons that helped me in my stay here, *Fr. Laurie*, *Sandy*, *Heeok*, *Megan*, *Tracy*. For your invaluable help in a wide array of things, ranging from help with GIS, administrative matters, and funding, to refreshing my tired soul. In many ways you made my candidature easier.

To *Dr. Tullao*, the DLSU School of Economics, and DLSU-AKIEBS. For putting me and inspiring me to become an economist. I hope to be able to make a positive change wherever I may be.

To the *Asian and Australasian Society of Labour Economics* and two anonymous reviewers from *Labour Economics*. My first major conference and submission in a long time. I thank all involved for helping me gain confidence in presenting and submitting again. Thank you for the helpful comments for my first paper. They were undeniably devastating, but thanks to that, I have been tempered even more.

To *Mas Rus'an*, *Mbak Ruth*, *Phan*, and Oppa *Yim*. Geniuses and legends in the making. Thank you for discussing my papers in the PhD seminars. You truly inspire me to soar even greater heights.

To my colleagues, Oppa *Golf*, Mas *Yuventus*, Mas *Riswandi*, *Jose,* Mbak *Dika*, Mbak *Inggrid*, Mas *Nasir*, Mas *Krisna*, Mas *Wishnu*, Mbak *Martha*, Mbak *Anna*, Mbak *Umi*, and Mas *Agung*. I will never forget the times we spent together studying, cooking, struggling, discussing, and playing. I wish you all success in your respective careers. Let us work together to bring a positive change in the region!

To my AAS batchmates, *Charles*, *Sol*, *Sarah*, *Oli*, *Jerene*, and *Gab*. My friends – no, my family. What we shared in my earlier years in Australia fills a special place in my heart and will stay with me forever. With you I confirmed that family need not be related by blood. We will work together again, I know.

To the subtle group, *Albert*, *Mike*, *Rox*, *Eli*, *Alab*, *Epi*, *Aly*, *Sunny*, *Jason*, *Isabelle*, *Patricia*, *Lois*, *Belle*, *Tom*, *Bea*, *Doty*, and *Andy*. The universe conspired to bring us all together. It brings me great joy to have met you all, that we have stayed (clung) together up until the end of my program, and how our family has grown bigger. Dwell not on this parting, for we will meet again in brighter days, I am sure. I will always look back at our time together with fondness. Take care of each other.

To the assorted Filipinos in Canberra, *Reg*, *Ryan*, *Laya*, *Cy*, *Jayson*, *Iraya*, *Cherry*, *Bryan*, *Chichi*, *Joanna*, *Emer*, *Jennie*, and *Lem* and the Australian National University Filipino Association. Thank you for the (drunken) fun times, nature trips, and food. You have all given my family and I memories we will cherish forever. May our community of scholars grow even larger with you all as its pillars.

To the bois, *Mart*, *Dims*, *Pins*, *Vic*, *Dan*, *Kokoy*, and *Sol* You kept me sane while I was writing (hunting). Balancing everything was a challenge. There must have been an achievement there or something.

To the badminton boys and the John's choir. Whether through fitness or music, I grew in many ways thanks to our bond. Working with you helped me develop leadership and compassion.

To my mom, *Beth*, my dad, *Tony*, and my in-laws, *Robbie*, *JC*, and *Jocelyn*. Thank you for your support during our stay in Australia. We will be together again soon.

To this generous country, *Australia*, this wonderful city, *Canberra*, and our rustic apartment at Playfair. Not to mention the Florey house (Dubidubidapdap). I survived! Thank you for everything. Your majestic mountains, magnificent lakes, noble wildlife, and heartwarming people. Home is where the heart is, and even if it was only a short while, know that you will always have my heart.

I dedicate this thesis to my daughter, *Lucia*, and my wife (life), *Ket*. You both were with me from the start, and I would not be on this path if not for you. You were the necessary and sufficient conditions for the completion of this thesis, and our success here in this country. We have overcome a lot together, and for that, we have grown undeniably closer to our full potential. Let this be the proof that with the proper support, anything can be done. This is not just my success. This is ours. We will find our way back here for sure. For now, let us stay true to our calling. Become that which there is none, that which is needed.

I love you both, always.

To my country, I offer knowledge and wisdom. And to the world, I offer light.

"Behold, I am going to do something new; Now it will spring up; will you not be aware of it?
I will even make a way in the wilderness, rivers in the desert."
Isaiah 43:19

Abstract

This thesis compiles three essays on migration and remittances in the Philippines. The first essay investigates the role of remittances as an informal risk-coping mechanism for families during a disaster, and explores the interaction between remittances, relief, and a region's infrastructure and institutions. The study employs a unique identification strategy by tracking the regions that were directly lying on the path of Typhoon Haiyan, one of the most devastating typhoons in Philippine history. Using a difference-in-differences approach, the remittance response was found to be an increase in incidence but not necessarily in level. The extended analysis only provided suggestive evidence that remittances and relief generally act as substitutes but serve as complements during disasters. Moreover, remittances were higher in regions with good facilitators, but remittances tend to insure households against poor institutions during disasters. This study establishes remittances as both aid and insurance during times of disaster.

The second essay delves into how culture, migrant networks, and immigration policies may influence the labor market assimilation of Filipino immigrants. This study departs from the conventional framework used in studying assimilation by focusing only on immigrants from one sending country but in different host countries. This emphasizes the effects of the host country institutions on wage and employment assimilation. It was found that larger similarity in culture, a larger migrant network, and more selective immigration policies reduce the wage gap relative to natives and improves the transferability of human capital, thus facilitating assimilation. However, assimilation is hampered in countries with greater culture diversity and fractionalization.

The third essay estimates the spatial spillover effects of migration on education. This study uses a novel way in representing proximity and neighborhood effects by borrowing techniques from geography and spatial statistics. While causality is not argued, it is shown that the location of migrants and non-migrants within *purok* (district) is quasi-random after controlling for sorting and correlated effects. The distance to the nearest migrant is calculated for each non-migrant household, and interspatial autocorrelation was used to identify whether non-migrants are parts of migrant clusters (hotspots). The results show that closer proximity to a migrant and being identified as part of a migrant cluster is associated with higher tertiary enrolment. This suggests that the prospect of migration is enough to generate a brain gain for communities in general. Findings are only suggestive that community remittances may be a channel.

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List of Abbreviations

AKIEBS	Angelo King Institute for Economic and Business Studies
APIS	Annual Poverty Indicators Survey
ArcGIS	Arc Geographic Information System
BSP	*Bangko Sentral ng Pilipinas* (Central Bank of the Philippines)
CBMS	Community-Based Monitoring System
CEM	Coarsened Exact Matching
CFO	Commission on Filipinos Overseas
CMA	Centre for Migrant Advocacy
CPH	Census of Population and Housing
CS	Cross-section
DDD	Triple Difference
DID	Difference-in-Differences
DLSP	De La Salle Philippines
DLSU	De La Salle University
DPWH	Department of Public Workways and Highways
EA	Enumeration Area
ECIF	Ethnic Chinese-Invested Firms
FIES	Family Income and Expenditure Survey
GOGG	Getis-Ord General G
GOGi*	Getis-Ord Gi*
IPUMS-I	Integrated Public Use Microdata Series – International
LDI	Language Diversity Index
LINKAPIL	*Lingkod sa Kapwa Pilipino* (Philippine Development Program)
NDRRMC	National Disaster Risk Reduction Management Council
NER	Net Enrolment Rate
OFW	Overseas Filipino Worker
OLS	Ordinary Least Squares
PAR	Philippine Area of Responsibility
PDNA	Post-Disaster Needs Assessment
PEP	Partnership for Economic Policy
PSA	Philippine Statistics Authority
PSM	Propensity Score Matching
UNDESA	United Nations Department of Economic and Social Affairs

Chapter 1

Introduction

1.1 Migration and Remittances

International migration has become a global phenomenon given the substantial and rapid growth of migrants all over the world. In 2020, the global migrant stock reached 280.5 million, with the largest flows (around 45%) coming from less developed regions going to high-income countries (United Nations Department of Economic and Social Affairs [UNDESA], 2020). These people migrate either to reside in a new country, pursue economic opportunities, reunite with their families, or seek asylum from persecution or instability in their home countries. From earlier waves of migration came the rise of migration networks (or a “culture of migration”) which encouraged further migration. This drove the expansion of immigrant communities and the broadening of cultural diversity in many host countries. Great interest has then been garnered in learning about the impacts of migration on both home and host countries, particularly about debunking the “brain drain” (Stark, Helmenstein and Prskawetz, 1997), welfare impacts (Martey and Armah, 2020; Mergo, 2016), educational choice (Theoharides, 2018), and economic assimilation (Abramitzky, Boustan, and Eriksson, 2014).

The phenomenon of migration is almost always accompanied by remittances sent to the home country. Global remittance inflows soared to approximately USD 717 billion in 2019 and stayed afloat at an estimated USD 666 billion in 2020 despite the Coronavirus Pandemic (World Bank, 2020). In both years, around 76% of these inflows were directed towards low- and middle-income countries. The motivations for sending remittances are incredibly nuanced (Stark, 2009). Migrants send remittances to convey their love for their family, to purchase assets in the home country, to repay loans for migration, to prevent the migration of lower-skilled workers and the saturation of the host country labor market, or to cushion their families from adverse economic shocks. While remittances have been stigmatized to foster a culture of laziness and dependence, used only for leisure items and vices, and not contributive towards nation building, many studies have come forth showing its myriad developmental impacts. Remittances may reduce poverty (Lokshin, Bontch-Osmolovski and Glinskaya, 2010), improve health outcomes

(Hildebrandt and McKenzie, 2005), increase human capital formation (Yang, 2008a), and induce productive investments (Adams and Cuecuecha, 2010).

This thesis contributes to the growing literature of migration and remittances with a strong focus on the Philippines. While falling under the same overarching theme, each major chapter stands alone with different topics revolving around the motivations, roles, impacts, and implications of migration and remittances. The topics include the role of remittances as aid and insurance during disasters (Chapter 2), the role of host country institutions in the labor market assimilation of Filipinos in different countries (Chapter 3), and the spatial spillovers of migration on education (Chapter 4). Chapter 2 innovates in developing an identification strategy by utilizing a natural experiment that uniquely exploits the randomness of a disaster. Chapter 3 offers an alternative perspective in studying assimilation by changing the usual setting of single host country with immigrants from multiple home countries, to a setting with immigrants from a single sending country with multiple host countries. Chapter 4 borrows techniques from spatial statistics to develop a distinct approach in estimating proximity and neighborhood spillover effects based on geographical proximity and clustering of migrants.

1.2 Focus on the Philippines

This thesis takes the Philippines for its case study primarily because it is known to have a prolific culture of migration. The Philippines has a strong history of labor migration occurring in waves dating back to 1906 where approximately 100,000 Filipinos migrated to Hawaii to work in sugar plantations and to Alaska to work in fish canneries (Center for Migrant Advocacy [CMA], 2020). Filipinos worked in logging camps in Sabah and Sarawak and American army bases in Guam, Thailand, and Vietnam in the 1950s, and they worked as technicians and engineers in Iran and Iraq in the 1970s (CMA, 2020). It was the Marcos government then that recognized the potential of temporary labor migration to stimulate the economy and allow it to recover from the 1973 oil crisis, formalizing the support for overseas employment under the Labor Code in 1974 (Asis, 2006). The growing demand for Philippine workers across the world enabled migration to grow further, leading to the Overseas Filipino Worker (OFW) phenomenon observed today. OFWs are temporary labor migrants usually working casual jobs in domestic help, hospitality, retail and trade, or production and are known to usually undertake migration and send remittances to alleviate their families' financial hardship out of altruism (Basa, Harcourt, and Zarro, 2011). While international migration from the Philippines is mostly temporary, distinction between temporary and permanent migrants is not permitted due to limitations of the datasets used. In Chapter 3 however, I exert some effort in my analysis to distinguish between destination countries with larger shares of permanent migrants and those with more temporary migrants.

In 2020, with an international migrant stock estimated at 6 million, the Philippines was the ninth largest migrant-sending country in the world (UNDESA, 2020). Remittances into the country were estimated at USD 33 billion, making up 8.8% of GDP (World Bank, 2020a) whereas other international flows such as official development assistance only amounted to USD 540 million in 2018, and foreign direct investment only amounted to USD 7 million in 2019 (World Bank, 2020b). The country identifies international migration and remittances as key drivers of growth and development, cementing their roles in the economy, and justifying the Philippines as the stage for this thesis.

In Chapter 2, the Philippines was recently hit by one of the strongest typhoons in its history - Typhoon Haiyan, allowing the assessment of remittances as informal aid and insurance. In Chapter 3, the extent of Filipino migrant networks across the world enables the study of how the heterogeneities in the institutions of different countries may impact the assimilation of migrants. In Chapter 4, the prevalence and popularity of migrants gives everyone in the community a prospect and aspiration to migrate, warranting an inquiry into the presence of spillover effects on human capital formation.

1.3 Summary of objectives, contributions, methods, and results

1.3.1 Chapter 2

This chapter investigates how remittances served as a risk-coping mechanism for families, insuring them against a disaster and the deficiencies in their region's infrastructure and institutions (facilitators). This chapter also explores the interaction of remittances with formal relief and a region's facilitators. The distinct contributions of this chapter are the unique identification strategy based on distinguishing regions along the path of a single, destructive typhoon, and the first attempt to empirically link remittances with formal aid and a region's facilitators in the context of a disaster. The study combines the 2013 and 2014 Annual Poverty Indicators Survey (APIS) into a pooled cross-section and implements a difference-in-differences (DID) approach to capture the remittance response to Typhoon Haiyan. The identification strategy involves a natural experiment treating the regions along the path of Typhoon Haiyan as "affected". The results revealed that the remittance response to the typhoon is in terms of higher remittance incidence (more households receiving remittances) but not necessarily higher remittance levels. This result holds true for poorer households, particularly those in the third- and fourth-income deciles, house and lot renters, and household heads with lower educational attainment. There is only suggestive evidence that remittances and relief generally act as substitutes, but they complement each other during disasters. Likewise, remittance incidence is higher in regions with good facilitators, but evidence shows that this increases during crises especially when a region's facilitators are poor. This chapter paints remittances as a resilient, risk-coping mechanism for households.

1.3.2 Chapter 3

This chapter explores how cultural similarity and diversity, migration networks, and immigration policies in different host countries may affect the labor market assimilation of Filipinos. This chapter primarily contributes to the literature on immigrant assimilation by developing a unique framework observing immigrants from a single origin but in different host countries with varying institutions. The value added in this approach is the emphasis on the heterogeneity of institutional factors and how they may assist or hamper assimilation. The study pools the census data of Canada, Greece, Malaysia, Spain and the US from the Integrated Public Use Microdata Series International (IPUMS-I), making it one of the broadest comparative studies on assimilation to date. The study builds on the wage and employment assimilation models of Borjas (1995; 1985) and Abramitzky et al (2014). The assimilation profile is developed by observing how wage and employment rates of Filipinos relative to natives in each host country change over years since migration (YSM). The assimilation profiles of Filipinos are then compared according to how their host countries are classified in terms of culture, migration network, and immigration policy. The results show that migrating to a country of similar culture (language, religion), extensive migration history, and selective immigration policies, is associated with lower wage gaps and better transferability of human capital, thus encouraging assimilation. On the contrary, cultural diversity hampers assimilation and transferability.

1.3.3 Chapter 4

This chapter examines whether the prospect of migration can generate brain gain, focusing on the less-studied spatial spillover effects of migration on the education choices of non-migrant households. This chapter estimates the migrant proximity and clustering spillover effects on enrolment of school-aged household members. The distinctive contribution of this chapter is the innovative use of techniques borrowed from geography and spatial statistics to estimate proximity and neighborhood effects. Using the Community Based Monitoring System (CBMS) 2015 dataset and ArcGIS, the study measures the proximity to the nearest migrant, determines a critical distance using interspatial autocorrelation indicated by the Getis-Ord General G (GOGG), and identifies migrant clusters with Hot Spot Analysis based on the Getis-Ord Gi* (GOGi*). While the study does not argue for causality, it is shown that after controlling for sorting and correlated effects at the *purok* (district) level, the location of migrants and non-migrants are deemed quasi-random. The results indicate that closer proximity to a migrant and living in a migrant hotspot increases the likelihood of enrolment, but only for tertiary enrolment. Furthermore, there is only suggestive evidence that community remittances may be a channel through which having a migrant household within an area may affect a non-migrant household's decision to enroll their children.

1.4 Thesis Structure

The remainder of this thesis is as follows: Chapters 2-4 present the three standalone essays on migration and remittances, and Chapter 5 concludes. Chapter 2 investigates the remittance response during Typhoon Haiyan in the Philippines and attempts to link remittances with relief and a region's facilitators. Chapter 3 studies the impacts of cultural similarity and diversity, migrant networks, and immigration policies of host countries on the labor market assimilation of Filipino immigrants. Chapter 4 explores the proximity and neighborhood spillover effects of migration on the education of non-migrant households. Lastly, Chapter 5 presents highlights of the results and contributions of each paper, then gives comments for policy implications and future avenues of continuing research.

Chapter 2

Remittances as aid and insurance during disasters[1]

Abstract

Aggregate international remittances have been documented to increase as an ex-post response to a disaster, but subtle nuances may be present when looking at household level behavior. This study looks at the role of remittances as informal aid and insurance during disasters. I look at the response of remittance incidence and levels to a disaster using a natural experiment exploiting the randomness of the path of Typhoon Haiyan, one of the strongest typhoons in Philippine history. I combine the 2013 and 2014 APIS into a pooled cross-section and use a difference-in-differences approach. Upper-bound estimates reveal a 3.8% higher remittance incidence but no statistically significant increase in remittance levels. Households also incurred income losses but spending in general and particularly on food was not lower. Heterogeneity of the remittance response is observable only for third- and fourth- income decile households, as well as those renting their house and lot and with lower educational attainment. I attempt to empirically link remittances with relief and a region's infrastructure and institutions. I find suggestive evidence that remittances and relief substitute each other on average but may exhibit complementation during disasters. Remittances are generally higher with better facilitators, but remittances are also found to insure families against poor infrastructure and institutions following a disaster. The results paint remittances as a resilient, risk-coping mechanism for households during disasters.

[1] Paper title: "Insuring against disasters and poor institutions: Remittances as aid and informal family insurance during Typhoon Haiyan in the Philippines". This paper was presented at the 2019 Asian and Australasian Society of Labour Economics Conference. I am grateful to the two anonymous reviewers of *Labour Economics* for comments and suggestions that helped me improve the paper.

2.1. Introduction

In recent years, migration from and remittances to developing countries have been growing at an outstanding pace. In 2017, the global migrant stock reached an estimated 266 million and global remittances amounted to USD 613 billion with 76% of remittances (USD 466 billion) directed toward low- and middle-income countries (Ratha, De, Kim, Plaza, Schuettler, Seshan, and Yameogo, 2018). This unprecedented growth led to the departure from the usual role that migration and remittances had played in smoothing household consumption. In developing countries, several households (particularly in agriculture) are exposed to various risks and incur losses in income whenever they experience shocks. Migration has been found to be a response to vulnerability to disasters in the home country (Mahajan and Yang, 2020) and a substitute for informal risk sharing (Morten, 2019). Migrants have sent remittances to insure their families against these shocks (Stark, 2009; Rapoport and Docquier, 2006), and a growing body of literature have found remittances to increase particularly in times of crises and even serve as informal aid during disasters (Bettin and Zazzaro, 2018; Mohapatra, Joseph, and Ratha, 2012; Savage and Harvey, 2007).

This study investigates the role of remittances as a risk-coping mechanism (insurance) for families following a disaster. This study is one of the few that provide empirical evidence at a microeconomic (household) level. This is done by implementing a DID approach employing a natural experiment that uniquely utilizes the randomness of the path of a single, yet large and extremely devastating disaster – Typhoon Haiyan. I also look at the impact of the typhoon on other household outcomes which may have pushed migrants to insure their families with remittances, and investigate whether heterogeneities in the remittance response occurs among households according to various characteristics.

In the wake of Typhoon Haiyan, Su and Mangada (2018) noted issues particularly for remittance-receiving households in the targeting formula used by international humanitarian agencies to administer formal aid (relief), particularly how receiving remittances lowers a person's prioritization. They also highlight that not all households who regularly have access to remittances are able to mobilize remittances during disasters, and this is driven by class-based inequality. This is discussed in greater detail in Appendix 2.A.6. Considering this, I extend my analysis of the remittance response by looking at the correlation between remittances and relief. I also test for the correlation between remittances and the extent of a region's infrastructure and institutions (facilitators), potentially revealing how these factors may facilitate remittances. Despite this a-priori expectation, surprisingly, it may be that remittances insure against low levels of facilitators and development as well. While endogeneity problems may confound the estimates of the extended analyses, with scant literature on the relationship of remittances, relief, and regional infrastructure and institutions, even an exploratory inquiry using correlations may be a considerably significant contribution to our understanding.

This study focuses on the Philippines because it has one of the largest migrant diasporas in the world. It had approximately 6 million international migrants in 2017 comprised of permanent and temporary migrants (OFWs). Permanent migrants are those migrants in the traditional sense, whereas OFWs are those that seek contract work with prospect of return migration at the end of the contract. The country received USD33 billion in remittances making it one of the highest remittance-receiving countries (Ratha et al, 2018). With its size accounting for about 14.3% of GDP, remittances have been identified as a key driver of growth for the country. While OFWs account for a large proportion of migrants, amounting to nearly 2.4 million workers sent in 2012-2017 (Bersales, 2018), this study looks at \both permanent migrants and OFWs as the dataset does not distinguish these two classifications.

The Philippines lies on the Pacific Ring of Fire making it susceptible to various natural disasters such as volcanic eruptions and earthquakes. It is also frequently visited by typhoons (20 each year on average; see Figure 2.2). In November 2013, Typhoon Haiyan (locally named "Yolanda") crossed the Philippines and tested the resilience of affected families and the remittances sent by OFWs. The Typhoon affected approximately 3.4 million families, left approximately 6.3 thousand dead, 28.7 thousand injured, and a thousand people missing (National Disaster Risk Reduction and Management Center [NDRRMC], 2014a), and caused around USD 904 million in damage (Su and Mangada, 2018). The first, and heaviest hit was Tacloban City, the center of the Eastern Visayas region (Region 8). With its large migrant diaspora, the Philippines received a surge of remittances. Comparing the three months directly after the typhoon (November, December, and January of the next year), total remittances were approximately USD 537.84 million higher in 2013-2014 compared to 2012-2013 (Bangko Sentral ng Pilipinas [BSP], 2020). This is suggestive of the role that remittances play as a safety net in times of disasters.

This study finds that the upper-bound remittance response was a 3.8% higher incidence in affected regions during the typhoon. Although small, this figure may turn out to be crucial to the survivability of a community during crises. However, the level of remittances does not increase during the typhoon year. More people receiving remittances without an increase in the average level of remittances characterizes remittances as an informal form of aid. Households were found to incur losses in income due to the typhoon, but it was found that their spending, particularly on food, was not statistically lower, suggestively thanks to remittance transfers.

Heterogeneity is found across income deciles, with only households from the third and fourth deciles experiencing increases in both remittance incidence and levels. This may indicate that only lower income, non-poor households have the incentive to mobilize remittances during crises and reflects the fact that affected regions have a slightly higher concentration of households from the second to the fourth income deciles. The same trend is found for households that are only renting their current dwelling. Furthermore, higher remittance incidence is seen for household heads with lower or unfinished educational attainment as well as households that receive domestic remittances.

I find only suggestive evidence from coefficients that remittances and relief play as substitutes on average, and that there may be some complementation between the two following a disaster, but the estimates lack the statistical significance to fully confirm these relationships. Results may also imply that remittances act autonomously during crises, regardless of whether relief is administered. Remittances have a negative correlation with comparatively good communication infrastructure and positive correlations with good transportation infrastructure, and governance and banking institutions. Moreover, although not completely surprising, the likelihood of receiving remittances may be lower during crises when infrastructure and institutions are comparatively good, suggesting that remittances may insure against poor regional facilitators. In both cases, this reinforces the role that remittances play during crises: a potentially powerful and resilient risk-coping mechanism for households.

While the results only reinforce the findings of existing studies in that remittances increase in times of disasters, the main innovation lies in the new, unique identification strategy distinguishing affected regions along the path of a single, destructive typhoon. With improvements in the collection of geospatial and disaster data, this strategy paves the way for single-event identification strategies which may help determine the localized effects of specific disasters. Furthermore, while it does not argue for causality, this study represents the first attempt to empirically link remittances with formal aid and a region's facilitators in the context of a disaster.

The chapter is organized as follows: Section 2.2 reviews the literature on remittances and disasters, relief, and remittance facilitators. Section 2.3 describes the data sources. Section 2.4 summarizes the Typhoon Haiyan story in the Philippines, elaborates on the identification and empirical strategies, and threats to identification. Section 2.5 presents supporting descriptive statistics, reports the results of the main empirical model, presents a placebo test, inspects alternative outcomes and channels, and investigates heterogeneities by different household characteristics. Section 2.6 probes into the correlations among remittances, relief, and the level of a region's facilitators. Section 2.7 concludes.

2.2 Review of Literature

Migrants send remittances under the enforcement of intertemporal contractual arrangements (Stark and Lucas, 1988) driven by altruism, self-interest, or a combination of both (Carling, 2008). In truth, the motivations for remitting are much more nuanced and remittances may be modeled as a household decision or an interaction between migrant and family. Remittances may be viewed as insurance – a mutual risk-sharing move where the migrant typically insures the family when they are made vulnerable due to adverse economic shocks (usually in agriculture) (Stark, 2009; Rapoport and Docquier, 2006).

Several macroeconomic studies document the insurance motive, highlighting that remittances move countercyclically to output changes in the home country, often increasing in response to negative output fluctuations (i.e. disasters). Country-level remittances respond positively to greater storm exposure (Yang, 2008b) and other climatic disasters[2] (Bettin and Zazzaro, 2018; Mohapatra, Joseph, and Ratha, 2012; David, 2011; Amuedo-Dorantes, Pozo, and Vargas-Silva, 2010). However, Bragg, Gibson, King, Lefler, and Ntoubandi (2018) find qualitative evidence that this surge occurs only a few months right after a disaster and may persist up to a quarter, but this is offset by decreases in transfers in succeeding months, so average remittances for the year may not increase. Remittances also decrease with foreign aid and exchange rate appreciations (Amuedo-Dorantes et al, 2010) and do not respond to man-made disasters e.g. famine, epidemics, conflict, financial crises (Naude and Bezuidenhout, 2014; David, 2011). Furthermore, Arezki and Bruckner (2012) find that the receipt of remittances in response to rainfall is strongly positive for the bottom 25% and decreases as the level of remittances decrease, which may suggest heterogeneity across income deciles.

On the other hand, there is a scarcity of micro-level evidence. Among the few that provide household-level empirical evidence are Brown, Leeves and Prayaga (2014) and Koczan (2016). Brown et al (2014) used the cyclone (Cyclone Pat) that hit the Cook Islands in February 2010 as a natural experiment and found that Pacific Island migrants to Australia were more likely to remit but did not remit more. Koczan (2016) tested for structural change caused by conflict and instability and found that for migrants from ex-Yugoslavia to Germany, remittances had no response. In the Philippines, Yang and Choi (2007) used

[2] Climatic disasters include meteorological disasters e.g. storms and hurricanes; hydrological disasters i.e. flood; and wet mass movements e.g. tsunamis, drought, extreme temperature, wildfires) and geophysical disasters (e.g. volcanic eruptions, earthquakes, landslides)

household survey data to explore the role of remittances as insurance. Using monthly variations in rainfall to instrument for income shocks, they find that household remittances decrease when income increases. Licuanan, Mahmoud, and Steinmayr (2014) look at the drivers of donations coming from migrant diasporas channeled to the Link for Philippine Development Program (LINKAPIL) of the Commission on Filipinos Overseas (CFO). Like Yang (2008b), they find that the likelihood and size of migrant donations increase with a province's exposure to typhoons.

A group of humanitarian case studies (Savage and Harvey, 2007; Deshingkar and Aheeyar, 2006; Fagen, 2006; Lindley, 2006; Suleri and Savage, 2006; Wu, 2006; Young, 2006) document how remittances served as aid during various debilitating disasters particularly in Sri Lanka, Haiti, Somalia, Pakistan, Indonesia, and Sudan. Remittances come often in lieu of, and later in complementation with formal aid which is mobilized slowly in most developing countries. In the case of Tacloban city during Typhoon Haiyan, Su and Mangada (2018) found that there are significant heterogeneities when it comes to the households receiving remittances. They highlight the difference between access to remittances and the mobility of remittances. Access pertains to the regular receipt of remittances, whereas mobility covers the channels through which remittances are received. They find that among those affected by the disaster, middle-class households were more likely to mobilize remittances compared to lower-class households who lack the resources to do so. They also mention that the remittances received by lower-class households tend to be only one-time forms of support and that structural barriers such as poverty, social inequality and class status hinder the mobilization of remittances during crises. Furthermore, they observed that receiving remittances of any amount lowers the priority of a household in receiving aid from international agencies.

The usual channels of remittances can be classified into formal and informal channels. Formal channels include bank-to-bank transfers, post, and money transfer companies (e.g. Western Union, MoneyGram), whereas informal channels are mainly friends or relatives, or migrants themselves that go home. Often when faced with high costs of formal transfers migrants opt to send money via informal channels. But what ensures the strength and reliability of remittance channels? Communication and transportation maintain connectedness and improve the reliability that remittances reach their intended beneficiaries (Elmi and Ngwenyama, 2020). The local government aids communities in preparedness, evacuation, relief, and recovery. In general, good governance helps facilitate remittances but Effiong and Asuquo (2017) conclude that this is not always the case and that poor governance quality may induce outmigration thereby increasing remittances. Banks are the primary channel through which remittances are funneled and can provide alternative risk-coping mechanisms (e.g. loans). In general, the greater the level of development in the banking sector – increased competition, more branches and ATMs, the lower the cost of and the greater the access to remittance transfers (Endo and Afram, 2011).

The contribution sought by this study is two-fold. First, while the study simply reaffirms the findings of other studies about the remittance response during disasters, it is one of few micro studies and the first to employ a unique natural experiment exploiting the randomness of the path of a single, debilitating typhoon. Second, to my knowledge, this study is the first to empirically determine how remittances may be linked with formal aid and the quality of remittance facilitators (infrastructure and institutions) in a region managing the impacts of a disaster.

2.3 Data Sources

I use the 2013 and 2014 APIS household profile datasets published by the Philippine Statistics Authority (PSA). These survey rounds are close enough to be able to capture the impact of Typhoon Haiyan which occurred November 2013. The survey is collected June of each year not covered by the PSA's Family Income and Expenditure Survey (FIES). However, the dataset does not contain panel information; hence, the 2013 and 2014 APIS are combined into a pooled cross-sectional dataset. Furthermore, due to sampling, the survey is unable to disaggregate observations lower than the regional level, and that remittance information is recorded without knowledge if households themselves have OFWs. The pooled dataset contains information on 21,333 households (10,864 in 2013 and 10,469 in 2014) across 17 regions (see Table 2.A.1.1 in the Appendix). The list of variables used in the analysis is in Table 2.A.1.2 in the Appendix. More information on the survey and the sampling procedure is available in Appendix 2.A.2.

Various infrastructure and institution data were collected from the 2015 Philippine Statistical Yearbook (PSY) (PSA, 2015a) and the *Bangko Sentral ng Pilipinas* (Central Bank of the Philippines, [BSP]). Data for communication infrastructure (i.e. telephone density, radio stations, broadcast TV stations, cable TV network) was sourced from the National Telecommunications Commission. Data on transport infrastructure (i.e. aircraft movement, air passenger movement, airports) came from the Civil Aviation Authority of the Philippines. Data on governance indicators (i.e. calamity funds, internal revenue allotment, revenue collection) came from the NDRRMC, Department of Budget and Management, and Department of Internal Revenue. Data on banking infrastructure (i.e. ATM and electronic banking facilities, banking offices) were taken directly from the BSP. The list of gathered infrastructure and institution data may be seen in Table 2.A.1.3 in the Appendix.

2.4 Methodology

2.4.1 Typhoon Haiyan

Typhoon Haiyan (Philippine name: Yolanda) is known to be one of the strongest, most disastrous tropical cyclones. It registered maximum sustained winds of 195kph near the center and gustiness of 230kph as it entered the Philippine area of responsibility (PAR), moved West-Northwest at a speed of 30kph, (NDRRMC, 2014a) and had a diameter of 600km (Lagmay, Agaton, Bahala, Briones, Cabacaba, Caro, Dasallas, Gonzalo, Ladiero, Lapidez, Mungcal, Puno, Ramos, Santiago, Suarez and Tabalzon, 2014). Despite warnings and preparations made by the local government of Tacloban and the Department of Public Works and Highways (DPWH), the typhoon and the storm surge that followed levelled several communities (Lagmay et al, 2014). Tacloban's location and geography (coastal city, low elevation, urbanization, dense population, and being caught in between mountains) made it even more susceptible to storm surges (Lagmay et al, 2014).

Figure 2.1 shows the path of the typhoon through the Philippines. The typhoon entered the PAR on November 6, 2013 (NDRRMC, 2014a). Landfall occurred on November 8, 2013 over the provinces Eastern Samar then Leyte in Region 8, then moved towards Cebu in Region 7. The path of the typhoon went through Region 8 (Eastern Visayas), Region 7 (Central Visayas), Region 6 (Western Visayas), and Region 4b (MIMAROPA). It exited the PAR on November 9, 2013.

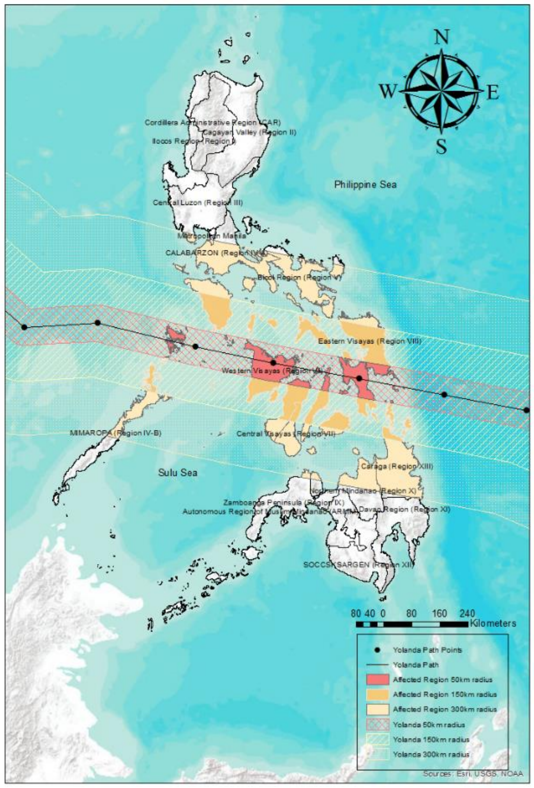

Figure 2.1. Path of Typhoon Haiyan

Note: Regional boundaries in the map are boundaries between regions in the Philippines.

50km, 150km, and 300km buffer radii are presented.

Source: NDRRMC (2014a)

Table 2.1 summarizes the damage caused by Haiyan across the affected regions according to the NDRRMC's (2014a) final report and their Post-Disaster Needs Assessment (PDNA). Haiyan affected 3,424,593 families (16,078,181 persons), causing the death of 6,300, and leaving 28,688 injured and 1,062 missing (NDRRMC, 2014a). 93.68% of the deaths, 91.28% of the injured, and 94.72% of the missing came from Region 8, where Tacloban is located (NDRRMC, 2014a). Notably the heaviest hit regions were the regions along the path of the typhoon: Eastern Visayas, Central Visayas, Western Visayas, and MIMAROPA. Eastern Visayas, which has Tacloban, has the highest casualties, 33,093, where 5,902 were dead, 1,005 missing, and 26, 186 injured. Western Visayas followed with 2,389 (294 dead, 28, missing, 2,067 injured) and Central Visayas with 427 (74 dead, 5 missing, 348 injured). The damage to houses in Eastern Visayas reached USD 1.577 billion, followed by severe damages to it social sector (Education, Health, and Housing) amounting to USD440.27 million, and its productive sector (agriculture, fisheries, mining, trade, industry, services and tourism). Although, smaller, Eastern Visayas had the highest damage to infrastructure (roads, bridges, seaports, airports, flood control, utilities, and state-owned buildings). This is closely followed by Western Visayas which appeared to have larger damage to its social sector relative to the damage to houses. Apart from the damage reported in the PDNA, there is also additional reported infrastructural and productive sector damages to CALABARZON, Bicol and CARAGA (NDRRMC, 2014a). Appendix 2.A.3 gives an additional glimpse of more challenges met by the victims of the typhoon.

Table 2.1. Summary of damages based on PDNA (damages in USD millions).

	Region	Casualties (Dead, Missing, Injured)	Damaged Houses	Cost of Damage to Houses	Infra. Damage	Social Sector Damage	Productive Sector Damage	Cross Sectoral Damage
4A	**CALABARZON**	7	840	1.50				
4B	**MIMAROPA**	104	33,813	48.90	7.96	6.56	5.58	1.08
5	**Bicol**	27	12,412	20.00				
6	**Western Visayas**	2,389	482,349	409.34	76.29	449.92	98.01	2.78
7	**Central Visayas**	427	111,319	130.54	21.07	90.38	50.65	0.00
8	**Eastern Visayas**	33,093	492,856	1,577.98	114.80	440.27	406.85	66.62
10	**Northern Mindanao**		20					
11	**Davao**		19					
16	**CARAGA**	1	6704	4.67				
	Total		1,140,332	2,192.92	220.13	987.14	561.10	70.49

Source: NDRRMC, (2014a)

2.4.2 Identification Strategy

The identification strategy of this study takes inspiration from Brown et al. (2014) who used cyclone Pat as a natural experiment and introduced a DID term for the affected country and the location where the migrants lived. Utilizing the timing of the APIS rounds to the onslaught of Typhoon Haiyan, I introduce a DID term indicating affected regions in the post-typhoon survey year. In identifying whether a region is considered affected, I identify regions directly along the typhoon path: regions 8 (Eastern Visayas), 7 (Central Visayas), 6 (Western Visayas), then 4B (MIMAROPA) (Figure 2.1).

Using any positive level of affected persons, damage cost, or infrastructural damage enumerated in Table 2.1 may indicate the impact of the typhoon, but factors such as building age, resilience (or lack thereof), and household wealth may confound identification. Looking at casualties and damages, not all regions with reported affected persons or damaged houses experienced infrastructural damage, and not all regions that experienced infrastructural damage experienced damage in different sectors. Only regions directly along the path of the typhoon were recorded to have all provinces affected and experienced cross-cutting, multi-sectoral damage. Therefore, I make the identifying assumption that the typhoon fully impacts all households in a region in its path and statistically has no spillover effects on regions not lying on the typhoon path.

I argue that the typhoon path is random, and when looking at the path of all tropical storms in the Philippines from 1956 to 2017 (Figure 2.2), it may be seen that all regions in the country have a chance to be impacted by a storm. The typhoon path will also have the strongest winds and rainfall causing significant damage to households and disrupt infrastructure, remittance channels, production, and government institutions. Yang and Choi (2007) comment on the value of a collective shock relative to an idiosyncratic/household-specific shock. Collective shocks (e.g., typhoons) may deny household access to alternative risk-pooling arrangements. Whereas for idiosyncratic shocks (e.g., self-reported flooding or crime), households may still have the means to insure themselves (e.g., domestic/local borrowing). In addition, idiosyncratic shocks may not be exogenous because this may be driven by a household's decision to reside in the location and other unobserved factors.

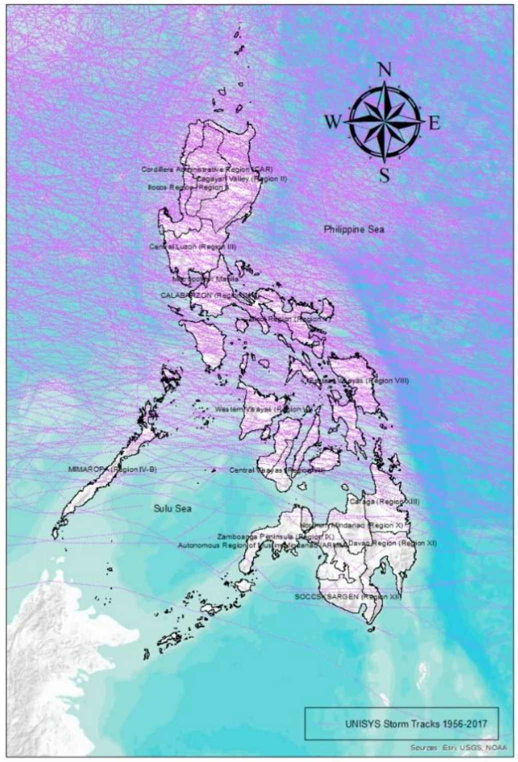

Figure 2.2 Tracks of all tropical storms, 1956-2017.

Source: Humanitarian Data Exchange. Basemap from Esri, USGS, NOAA, in the Geographic Information System (GIS) in Arcmap.

2.4.3. Empirical Strategy

The core result will be estimated through the following equation:

$$\boldsymbol{R_{ijt}} = \beta_0 + \beta_1 Affected_i + \beta_2 Year_t + \beta_3 Affected_i * Year_t + \boldsymbol{\pi X_{it}} + \boldsymbol{\delta_j} * Year_t + u_{ijt} \quad (2.1)$$

$\boldsymbol{R_{ijt}}$ includes both remittance participation (a binary variable = 1 if the *i*th household in region *j* receives remittances at time *t* = 2013, 2014 and = 0 otherwise) and remittance levels (a continuous variable representing the total remittances received during the survey period). Remittances are measured in nominal terms (based on amounts reported by households). While inflation may be a concern, this is addressed with the inclusion of a time trend variable and region-specific time trends. $Affected_i$ equals 1 indicating the household is in an affected region and β_1 captures the socioeconomic differences between affected and unaffected regions. $Year_t$ equals 1 for the year 2014 indicating the post-typhoon year, and captures time trend effects. The main coefficient of interest is β_3 – the DID estimator representing the effect of the typhoon on remittances. $\boldsymbol{X_{it}}$ is a vector of time-varying controls that include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads. $\boldsymbol{\delta_j}$ represents region-specific time trends, and u_{ijt} is the idiosyncratic error. Standard errors are clustered at a region level since the treatment varies at the region level.

Equation (2.1) will be estimated in three ways to show robustness: 1.) Ordinary Least Squares (OLS), 2.) Probit for participation and Tobit for levels, and 3.) Iacus, King, and Porro's (2011) Coarsened Exact Matching (CEM)-weighted OLS based on typical migrant household characteristics. The use of CEM is also meant to partially address the issue with the dataset wherein migrants cannot be directly linked to remittance-receiving households. A key assumption in the use of DID is the parallel trend assumption which requires that treatment and control groups exhibit a parallel trend in the absence of a policy change (in this case, the typhoon). This is verified through a placebo test estimating equation (1) using the 2011-2013 APIS dataset, a period before Typhoon Haiyan. In addition, time series graphs of remittance incidence and levels are provided using the 2008, 2010, 2011, 2013, and 2014 APIS rounds.

2.4.4. Threats to identification

A direct threat to the identification strategy, and what prevents claiming what would otherwise be a true, causal effect of the typhoon, is a magnitude 7.2 earthquake that hit Region 7 on 15 October 2013 (Mas, Bricker, Kure, Adriano, Yi, Suppasri, and Koshimura, 2015; NDRRMC, 2014b). Even though the earthquake is localized to Region 7, the confounding effect cannot be ignored since according to the NDRRMC (2014b), the earthquake not only had impacts for Region 7, but for Region 6 as well. Its impacts were comparable to the typhoon as it caused landslides, casualties, and household and sectoral damages. Unfortunately, because the APIS dataset is unable to disaggregate observations lower than the regional level, the identification strategy cannot be implemented at a more precise level. This may be expected to cause an overestimation of the impact of the typhoon on remittances since both natural disasters warrant an increase in remittances as a form of insurance or aid. Alternatively, it is reasonable to assume that estimates would reflect the impact of large, debilitating disasters in general. In this light, I check for robustness by excluding regions hit by the earthquake and note the changes in the estimated coefficients.

Second, the APIS excludes migrants nor does it have a migrant indicator. Excluding information on migrants may overestimate the impact due to groups having incomparable probability to receive remittances. Furthermore, if it turns out that affected regions are also major migrant-sending regions, the likelihood to receive remittances will naturally be higher as well. To address this, I collect region-level registered emigrant data from the CFO to see if this is indeed the case. Additionally, to improve precision and to provide a check for robustness, I include estimates using CEM to weight observations based on migrant-household characteristics[3]. The CEM implementation is discussed further in Appendix 2.A.4.

Third, there is an apparent attrition in 2014 possibly due to people from affected regions seeking asylum in unaffected regions (Chiu, 23 November 2013). Eastern Visayas (Region 8) had experienced the largest attrition (from 590 households in 2013 to 300 in 2014). Unfortunately, the cross-sectional nature of each round of the APIS Survey does not allow any longitudinal tracking to accurately filter the sample. In this regard, I perform t-tests comparing the means of selected characteristics the samples of households in affected regions before and after the typhoon. Table 2.A.1.4 in the Appendix presents the comparison of total income, expenditure, ownership of house and lot, receipt of domestic remittances, household head age and highest grade completed. It appears that only a few characteristics are statistically different, and in general, characteristics of households in affected regions remain comparable before and after the typhoon. Only in region 6 are income, expenditure, and the incidence of domestic remittances higher in 2014. Region 7 shows a lower proportion of high school graduate heads, and a higher proportion of those with post-secondary education. In region 7 and 8, it is notable that there are more households that own their dwelling in 2014, and more of them receiving remittances. This may indicate that households left behind may be richer and may have a higher probability of receiving remittances. This would cause the coefficient to be overestimated. To this regard, I control for house and lot ownership and household head highest grade completed in the estimating equation as these are indicators that may not be directly impacted by the typhoon (except indirectly through outmigration). Furthermore, this may absorb systematic differences in the outcomes of households left behind after the typhoon and improve the precision of the DID estimate.

In light of collateral events, competing explanations, and survey attrition, and given the direction these issues would drive coefficients, the corresponding responses mentioned above were implemented to reinforce the validity of the identification strategy and show the reliability and robustness of results. Nevertheless, I exercise caution in interpreting the results and treat the estimates as upper-bound.

[3] CEM assigns weights on observations based on "bins" they belong to in accordance with selected variables. Bins are determined by family size, household head educational attainment and age, and owning house and lot.

2.5. Results

In the exposition of the remittance response to the typhoon, I start by presenting statistics on the registered emigration from each region, followed by a simple comparison of descriptive statistics of outcomes and covariates. I then present the trend of outcomes for affected and unaffected areas, and the main results of the model. This is followed by the placebo test, an investigation into channels, alternative outcomes, and heterogeneities stratified by various characteristics.

2.5.1 Descriptive Statistics

Table 2.2 reports the number of registered permanent Filipino emigrants and OFWs from 2010 to 2015 disaggregated by region of origin. It may be noted that while there is a general trend of the number of emigrants increasing across the board, the number decreased in 2013 (the year when the typhoon hit). This is true for permanent migrants across all regions and not just affected regions. The finding for OFWs are slightly different in that some regions post increases in OFWs from 2013 onwards, but this is observed in both unaffected and affected regions. This should help rule out any potential systemic disparity caused by the typhoon differentially impacting affected and unaffected regions' ability to send migrants. In addition, it may be noted that only 11.55% of total permanent emigrants come from affected regions and that the largest migrant senders (regions 13, 3, 4a, and 1) come from unaffected regions. The same may be observed for temporary migrants. This should rule out an alternative explanation that remittances are higher in affected regions, not because of the typhoon, but because these regions send more migrants and thus have a higher propensity to receive remittances.

Table 2.3 provides a simple comparison of the variables used in the model between affected and unaffected regions before and after the typhoon. The average remittance incidence for unaffected regions is higher than affected regions in 2013 but this is reversed in 2014 when the remittance incidence in affected regions jumps by 3.7 percentage points, although the difference between the two groups is not that large. On the other hand, remittance levels were higher for unaffected regions in both years. This may suggest that in response to the typhoon, more migrants were sending remittances, but not necessarily higher amounts. Looking at other characteristics that may be an indication of wealth, households in unaffected areas tend to have higher income, expenditure, and more households who own the house and lot they live in. Furthermore, affected regions tend to have more households with lighter housing materials (Table 2.A.1.5 in the Appendix). Conversely, there are more households in unaffected regions that receive domestic remittances in both years and there is no visible indication of a jump after the typhoon. In terms of demographic information about the household head, those in affected areas tend to be 2 years older. They also have lower educational attainment with most of their heads not finishing elementary school, and a higher proportion of household heads in unaffected areas finishing high school and college. Regional disaggregation of the variables presented here are available in Tables 2.A.1.5, 2.A.1.6 and 2.A.1.7 of the Appendix with additional notes in Appendix 2.A.5.

Table 2.2. Registered permanent Filipino emigrants and OFWs by region of origin, thousands

		2010	2011	2012	2013	2014	2015	Total (1988-2018)*	% of Nat'l Total*
4B	MIMAROPA	641 [63]	682 [71]	702 [47]	645 [50]	603 [49]	723 [44]	12,531	0.60%
6	W. Visayas	3,012 [170]	3,013 [183]	3,344 [202]	2,891 [216]	3,551 [200]	4,119 [213]	72,979	3.48%
7	C. Visayas	5,134 [135]	5,250 [149]	5,711 [122]	5,281 [149]	5,383 [151]	6,149 [154]	126,283	6.02%
8	E. Visayas	1,355 [41]	1,301 [43]	1,462 [51]	1,399 [37]	1,435 [26]	1,621 [64]	30,330	1.45%
ALL AFFECTED		10,142 [409]	10,246 [447]	11,219 [422]	10,216 [452]	10,972 [425]	12,612 [475]	242,123	11.55%
1	Ilocos	10,899 [194]	9,569 [199]	8,906 [193]	8,322 [188]	8,738 [190]	10,554 [232]	233,828	11.15%
2	Cagayan	2,100 [125]	2,115 [136]	2,111 [135]	1,876 [151]	2,043 [155]	3,363 [147]	45,361	2.16%
3	C. Luzon	14,168 [294]	13,280 [309]	13,427 [313]	12,624 [319]	13,196 [360]	15,199 [369]	343,832	16.40%
4A	CALABARZON	16,657 [327]	16,672 [356]	15,670 [402]	15,562 [422]	15,645 [415]	16,620 [438]	335,390	15.99%
5	Bicol	1,236 [63]	1,489 [71]	1,476 [78]	1,441 [76]	1,507 [79]	1,792 [76]	34,147	1.63%
9	W. Mindanao	677 [47]	875 [41]	956 [40]	817 [39]	822 [60]	988 [56]	17,777	0.85%
10	N. Mindanao	1,735 [61]	1,817 [76]	2,062 [71]	1,885 [62]	1,865 [79]	2,170 [69]	40,126	1.91%

11	S. Mindanao	2,461 [57]	2,684 [50]	3,197 [60]	2,689 [60]	2,823 [63]	3,449 [76]	55,538	2.65%
12	C. Mindanao	870 [86]	833 [95]	884 [95]	927 [94]	958 [107]	1,221 [108]	18,133	0.86%
13	NCR	22,370 [282]	20,968 [270]	20,931 [280]	19277 [294]	19463 [244]	21,236 [269]	669,759	31.94%
14	CAR	2,021 [37]	2,133 [41]	2,007 [47]	1829 [50]	1918 [51]	2,906 [56]	45,732	2.18%
15	ARMM	26 [63]	18 [65]	33 [56]	16 [53]	22 [42]	41 [37]	583	0.03%
16	CARAGA	698 [29]	702 [35]	759 [27]	739 [34]	717 [46]	846 [42]	14,491	0.69%
	ALL UNAFFECTED	75,918 [1665]	73,155 [1742]	72,419 [1796]	68,004 [1843]	69,717 [1891]	80,385 [1975]	1,854,697	88.45%

Note: Values in [ ] represent temporary migrants. * only available for permanent migrants.

Source: CFO, (2020); Survey of Overseas Filipinos.

Table 2.3. Descriptive statistics of selected characteristics of affected and unaffected regions before and after Typhoon Haiyan

	Unaffected		**Affected**	
	2013	2014	2013	2014
Remittance Incidence	0.2009	0.1994	0.1678	0.2048
	(0.4007)	(0.3996)	(0.3738)	(0.4036)
Remittance Level	12,784.10	14,482.61	10,299.13	11,225.10
	(47,936.32)	(54,864.51)	(40,216.62)	(39,830.31)
Total Income	115,608.13	124,778.08	96,282.29	96,080.34
	(158,922.74)	(150,632.17)	(172,838.07)	(106,229.26)
Total Expenditure	95,789.33	104,348.50	77,554.13	83,651.19
	(94,682.78)	(107,654.61)	(96,673.54)	(92,797.65)
Own House and Lot	0.6592	0.6610	0.5406	0.5819
	(0.4740)	(0.4734)	(0.4985)	(0.4934)
Received Domestic Remittances	0.4548	0.4600	0.5632	0.5773
	(0.4980)	(0.4984)	(0.4961)	(0.4941)
Household Head Age	49.76	50.32	51.87	52.09
	(14.29)	(14.30)	(14.96)	(14.65)
Highest Grade Completed (Head)				

No Grade Completed	0.0273	0.0231	0.0320	0.0279
	(0.1631)	(0.1501)	(0.1761)	(0.1647)
Elementary Undergrad.	0.1805	0.1800	0.3027	0.2899
	(0.3846)	(0.3842)	(0.4595)	(0.4538)
Elementary Grad.	0.1818	0.1798	0.1874	0.1926
	(0.3857)	(0.3841)	(0.3904)	(0.3944)
High School Undergrad.	0.1212	0.1521	0.1178	0.1298
	(0.3264)	(0.3591)	(0.3225)	(0.3361)
High School Grad.	0.2443	0.2193	0.1695	0.1632
	(0.4297)	(0.4138)	(0.3753)	(0.3696)
Post-Secondary	0.0337	0.0398	0.0303	0.0451
	(0.1804)	(0.1955)	(0.1715)	(0.2076)
College Undergrad.	0.0941	0.0865	0.0606	0.0588
	(0.2920)	(0.2811)	(0.2387)	(0.2353)
College Grad. Or Higher	0.1119	0.1129	0.0956	0.0882
	(0.3153)	(0.3165)	(0.2942)	(0.2836)
Post-Baccalaureate	0.0046	0.0062	0.0038	0.0046
	(0.0675)	(0.0787)	(0.0619)	(0.0674)

Source: Authors' computation, APIS 2013-2014.

Standard deviations in parentheses

2.5.2. Main Results

Figure 2.3(a) illustrates the proportion of households in unaffected and affected areas that received international remittances in the period 2008-2014 while Figure 2.3(b) shows the trend for remittance levels. These are based on available APIS rounds (2008, 2010, 2011, 20113, and 2014). While unaffected regions generally have higher incidence prior to the typhoon, both groups follow the same growth path and visibly exhibit a parallel trend. Subsequently, after the typhoon, a slight decline may be seen for unaffected regions whereas affected regions experienced a sharp jump. These comparable growth trends in the absence of the typhoon lends reinforcement to the parallel trend requirement, supporting the validity of the underlying assumption of the DID approach. This is verified in a placebo test in the following subsection.

On the other hand, a parallel trend is less apparent for remittance levels. Unaffected regions have higher remittance levels than affected regions, but their growth patterns are generally different from each other. Moreover, after the typhoon, there is no indication of a drastic jump for affected regions which was visible in their remittance incidence, nor is there any sign of the gap closing between the two groups. In contrast to the finding for remittance incidence, this casts doubt on the validity of the DID approach for remittance levels. Furthermore, while it may be seen that remittance levels increase for all regions following the typhoon, there is no visible structural difference between affected and unaffected regions in terms of rate of growth. This may be suggestive that remittances are channeled almost evenly after the typhoon. I proceed with this analysis as this may still contribute to our knowledge about the remittance response during disasters from a policy perspective although this may set up an expectation that no effect may be visible when I test for the response of remittance levels to the typhoon. In Figure 2.A.1.1 in the Appendix, I add the 2003, 2006, 2009 and 2012 rounds of the FIES to the APIS data and I find similar conclusions for both outcomes. The parallel trend is evident for remittance incidence, and while there is some semblance of a parallel trend for remittance levels, the growth pattern in the absence of the shock between the two groups may still be arguably different.

Table 2.4 reports the impact of typhoon Haiyan on the probability of receiving remittances based on equation (2.1). Columns 1-3 report the OLS results, columns 4-6 report the marginal effects from the probit estimation, and columns 7-9 report the CEM-weight-adjusted OLS results. The DID coefficients report a positive impact on the likelihood of receiving remittances. This is consistent with Su and Mangada (2018) and Brown et al (2014) where debilitating natural disasters trigger "knee-jerk" responses from migrants, leading to remittances sent as a form of aid and insurance. The coefficient is stable around 3.8% across increasing controls and estimation procedures with the increasing R-squared reinforcing the inclusion of chosen controls. This translates to a 14 percent increase (2.8 percentage points) in the likelihood for households in affected regions to receive remittances. This increase translates to about 75 more families receiving remittances in affected regions in the year following a major disaster. In the context of a crisis, this marginal increase may prove critical to the survival of a community especially when formal aid is slow to mobilize (Su and Mangada, 2018).

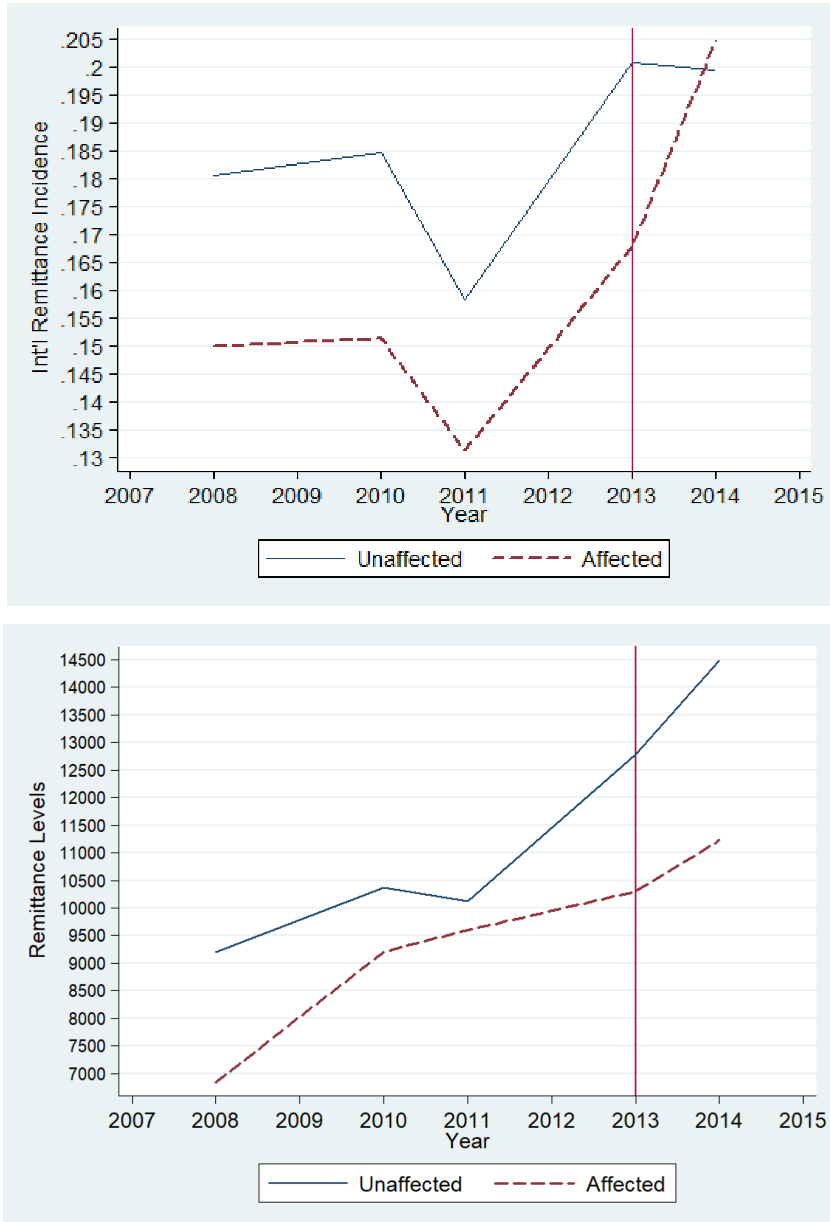

Figure 2.3. Average remittance (a) incidence and (b) levels between unaffected and affected areas over time, APIS only.

Source: Author's computation, APIS 2008, 2010, 2011, 2013, and 2014.

On average, there is indication that households in affected regions have a lower probability to receive remittances since affected regions tend to be poorer, have lower human capital accumulation, and may have weaker infrastructure and institutions, although this result is not robust across model specifications. Lastly, there appears to be no statistically significant time trends in any specification or estimation procedure.

In a similar fashion, Table 2.5 reports the impact on remittance levels. It may be noted that the findings are conflicting based on the approach used. On one hand, OLS and CEM results reveal that DID coefficients are statistically insignificant. This is consistent with the findings of Bragg et al (2018) and Brown et al (2014) that remittances may spike a quarter after a disaster but this may be offset by reductions in subsequent remittances so the total may not necessarily be higher by the end of the year. On the other hand, the Tobit estimates indicate that remittance levels *do* increase significantly following a disaster. This indicates that purely for remittance-receivers, remittances increase and potentially double as a response to the crisis. This agrees with most macroeconomic studies and may reveal that among those long-time receivers of remittances, even higher levels are sent as aid after disasters. However, with the lack of evidence for a clear parallel trend for remittance levels, I cannot rule out confounding factors in the determination of the outcome, and so I take caution in interpreting these results and consider them only suggestive at best.

The DID coefficient retains its algebraic sign and increases in magnitude when excluding region 6 (increases to 5.31%) and both region 6 and 7 (increases to 6.8%) to potentially remove the impact of the Bohol earthquake (Table 2.6). However, when excluding only region 7, the magnitude of the DID coefficient increases but becomes insignificant. This may indicate that I cannot fully disentangle the driving effect of the earthquake. This is expected since Tacloban city, which was hit heaviest, is in region 8. The region was also reported to have the largest jump in terms of remittance incidence among all regions (about a 10-percentage point increase), followed by region 7 (4-percentage point increase). For remittance levels, it may be seen that the lack of significance only carries over when excluding region 6. When excluding region 7 and both region 6 and 7, not only does the DID coefficient become negative, but it is also significant, which is in direct conflict with the findings presented earlier. I take this inconsistency as a sign that several factors may be confounding the process of clear inference. Therefore, in the succeeding extended analyses section, I comment only on remittance incidence (the process with which I have a clearly valid identification strategy) and exclude remittance levels to avoid giving out any misleading recommendations.

Table 2.4. Estimates of remittance incidence using OLS, Probit, and CEM weight-adjusted OLS, 2013-2014 APIS

	OLS			Probit^			CEM^^		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DID	**0.0385****	**0.0380****	**0.0389****	**0.144****	**0.0380****	**0.0389****	**0.0352****	**0.0391*****	**0.0406*****
	(0.0160)	**(0.0164)**	**(0.0172)**	**(0.0607)**	**(0.0164)**	**(0.0172)**	**(0.0142)**	**(0.0141)**	**(0.0141)**
Affected	-0.0331	-0.00844	-0.108***	-0.124	-0.00844	-0.108***	-0.0100	-0.0110	-0.109***
	(0.0261)	(0.0230)	(0.00892)	(0.0979)	(0.0230)	(0.00892)	(0.00977)	(0.00976)	(0.0195)
Year	-0.00150	-0.00345	-0.00380	-0.00537	-0.00345	-0.00380	-0.000970	-0.00335	-0.00393
	(0.00652)	(0.00661)	(0.00659)	(0.0234)	(0.00661)	(0.00659)	(0.00612)	(0.00609)	(0.00604)
Controls^^^	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Region-specific time trends	No	No	Yes	No	No	Yes	No	No	Yes
Mean outcome		0.2009			0.2009			0.2009	
R-squared	0.001	0.063	0.079	0.0007	0.063	0.079	0.000	0.015	0.031
Observations	21,333	21,333	21,333	21,333	21,333	21,333	20,957	20,957	20,957

Source: Author's calculation, APIS 2013-2014

Notes Standard errors clustered by region in parentheses. *, **, *** indicates significance at 10%, 5% and 1% levels, respectively.

^Marginal effects are reported

^^Matching based on family size, household head educational attainment and age, and owning house and lot. Before matching Multivariate L1 distance = 0.4811; after matching Multivariate L1 distance: 0.4068; Number of strata = 428; Number of matched strata = 324. Unmatched in control = 354, unmatched in treatment = 22. Adjusted R-squared is reported.

^^^ Control variables include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads.

Table 2.5. Estimates of remittance levels using OLS, truncated regression, and CEM weight-adjusted OLS, 2013-2014 APIS

	OLS			Tobit ^			CEM^^		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DID	**-772.5**	**-559.8**	**-791.6**	**12,950***	**13,300****	**13,197****	**-1,121**	**-484.4**	**-725.1**
	(1,422)	**(1,145)**	**(1,183)**	**(6,668)**	**(6,779)**	**(6,590)**	**(1,771)**	**(1,744)**	**(1,749)**
Affected	-2,485	1,354*	-7,303***	-17,308	-4,747	-61,664***	-1,009	-274.2	-7,491***
	(2,102)	(641.2)	(752.0)	(12,873)	(11,209)	(4,644)	(1,216)	(1,203)	(2,416)
Year	1,699**	-1.095	1,313*	2,720	1,493	1,089	1,730**	1,345*	1,294*
	(662.2)	(1,497)	(644.9)	(3,112)	(3,123)	(3,231)	(760.7)	(750.6)	(748.0)
Controls^^^	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Region-specific time trends	No	No	Yes	No	No	Yes	No	No	Yes
Mean outcome		12,784			12,784			12,784	
R-squared	0.001	0.072	0.079	0.0001	0.0134	0.0164	0.000	0.032	0.039
Observations	21,333	21,333	21,333	4203	4203	4203	20,957	20,957	20,957

Source: Author's calculation, APIS 2013-2014

Notes: Standard errors clustered by region in parentheses, *, **, *** indicates significance at 10%, 5% and 1% levels, respectively.

^Observations are left-censored at remittance level = 0; Pseudo R-squared is reported.

^^Matching based on family size, household head educational attainment and age, and owning house and lot. Before matching Multivariate L1 distance = 0.4811; after matching Multivariate L1 distance: 0.4068; Number of strata = 428; Number of matched strata = 324. Unmatched in control = 354, unmatched in treatment = 22. Adjusted R-squared is reported.

^^^ Control variables include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads.

Table 2.6. Estimates of remittance participation excluding Region 6 and 7

Dependent Variables	Remittance Participation				Remittance Level			
	All regions	w/o Region 6	w/o Region 7	w/o Region 6 & 7	All regions	w/o Region 6	w/o Region 7	w/o Region 6 & 7
DID	**0.0389****	**0.0531****	**0.0403**	**0.0678****	**-791.6**	**-637.5**	**-1,838***	**-2,643****
	(0.0172)	**(0.0202)**	**(0.0237)**	**(0.0299)**	**(1,183)**	**(1,623)**	**(1,007)**	**(1,219)**
Affected	-0.108***	-0.115***	-0.108***	-0.122***	-7,303***	-7,229***	-6,869***	-6,318***
	(0.0089)	(0.0104)	(0.0119)	(0.0150)	(752.0)	(910.8)	(789.2)	(788.9)
Year	-0.0038	-0.0036	-0.0037	-0.0034	1,313*	1,314*	1,322*	1,324*
	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(644.9)	(644.9)	(647.4)	(647.7)
R-squared	0.079	0.081	0.081	0.082	0.079	0.080	0.079	0.080
Observations	21,333	19,836	20,072	18,575	21,333	19,836	20,072	18,575

Source: Author's calculation, APIS 2013-2014

Notes: Standard errors clustered by region in parentheses, **, *** indicates significance at 5% and 1%.

Control variables include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads. Also includes region-specific time trends.

To synthesize, it may be said that *remittances increase in the aftermath of disasters to serve as aid; however, this occurs through more people receiving remittances, although it is inconclusive whether the amounts they receive increase from their usual levels as well*. The increase in remittance incidence (around 75 more households in affected areas) during the typhoon may have resulted in an increase in overall remittances by PHP 959,000 across all affected regions, which is a sizeable amount especially in the context of survival during crisis.

2.5.3. Placebo Test

To complement the visual representation of the parallel trend in Figure 3 earlier, I provide a formal test of the parallel trend by running a placebo test. I estimate the same specification as in the main results but using the 2011-2013 APIS which are periods before the typhoon and without any natural disaster shock. This is reported in Table 2.7. It may be seen that the DID coefficient is statistically insignificant, which indicates that the knee-jerk response I found earlier does not exist in the absence of any disaster. There remains the average difference between affected and unaffected regions and a positive time trend. This implies that the remittances response presented earlier is not driven by regional or time characteristics but by the typhoon.

Table 2.7. Placebo test: Remittance participation

Dependent Variable	Remittance Participation		Remittance Level	
	(1)	(2)	(3)	(4)
DID	**-0.00606**	**0.0154**	**-1,955**	**1,003**
	(0.0136)	**(0.0213)**	**(1,399)**	**(2,105)**
Affected	-0.0270	-0.0965***	-530.3	-6,531***
	(0.0214)	(0.0202)	(2,256)	(2,036)
Year	0.0425***	0.0476*	2,655**	-462.0
	(0.00986)	(0.0231)	(935.2)	(543.5)
Controls^	No	Yes	No	Yes
Region-specific time trend	No	Yes	No	Yes
R-squared	0.003	0.086	0.001	0.077
Observations	52,927	12,220	52,927	12,220

Source: Author's calculation, APIS 2011-2013

Note: Robust standard errors in parenthesis, *, **, *** indicates significance at 10%, 5% and 1%.

^Control variables include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads

2.5.4 Channels and Alternative Outcomes

I now look at other indicators that may have been directly affected by the typhoon and that may have prodded the remittance response. I run the same specification as equation (2.1) but for total income, total expenditure, whether the household received domestic remittances from internal migration, whether the household received disaster relief, education spending, and health spending. Table 2.8 presents these results. It may be seen that the typhoon has greatly decreased the total income (column 1) of households by about PHP 9,500 (approximately USD 200) for the year it hit. This figure is about 10% of the average annual income for affected households. This may be expected with the significant damage the typhoon caused to livelihoods and residences.

Furthermore, it appears that the typhoon decreased total spending (column 2) although the coefficient is statistically no different from those unaffected by the typhoon. When I look at a few essential components of spending, food spending (column 3) decreased slightly although this effect is statistically insignificant. On the other hand, education spending (column 4) decreased by about PHP 820 (USD 17) which is about 25% of the average education spending for affected households. This may suggest that education takes the back seat (or the severe damage to educational infrastructure) following a crisis whereas something more essential that warrants resilience, such as food, remains irresponsive. Health spending (column 5) is slightly higher although this is statistically insignificant as well. Presumably, the statistically insignificant response of total spending, and particularly food and health spending, may indicate the role that remittances served to insure households and smoothen spending. This may also partly be thanks to the expected typhoon response which is evident from the immensely greater incidence of disaster relief (column 6). Su and Mangada (2018) suggest that remittances and relief may be substitutes during this crisis, so I test for whether this is true in the extended analysis. Lastly, domestic remittance incidence (column 7) is found to be statistically irresponsive which is slightly surprising given that incidence is innately higher for affected regions. This suggests that domestic remittances may not fulfill the same role that international remittances have, serving as insurance during crises. This may be because international remittances have a much higher local currency value than domestic remittances, reflecting the vast difference in wages across countries.

Table 2.8. The effect of the typhoon on select alternative outcomes

Variable	Total Income	Total Expenditure	Food Spending	Education Spending	Health Spending	Received Disaster Relief	Domestic Remittance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DID	**-9,523***	**-3,238**	**-371.3**	**-814.4***	**169.2**	**0.189**	**0.0131**
	(5,066)	**(4,839)**	**(1,811)**	**(267.8)**	**(1,346)**	**(0.0728)**	**(0.0371)**
Affected	-19,845***	-34,331***	-12,108***	-1,905***	-1,911***	-0.0954**	0.234***
	(3,413)	(2,820)	(1,003)	(201.1)	(621.7)	(0.0366)	(0.0179)
Year	7,346***	7,569**	3,847***	521.3**	184.6	0.0036	0.00739
	(2,423)	(2,643)	(1,182)	(222.0)	(390.2)	(0.0074)	(0.0177)
R-squared	0.308	0.406	0.445	0.134	0.033	0.149	0.113
Observations	21,333	21,333	21,333	21,333	21,333	21,333	21,333
Placebo DID^	5,529	5,302	1,166	388.9	150.3	-0.0276	0.0450
	(6,620)	(6,037)	(2,671)	(397.8)	(1,184)	(0.0389)	(0.0517)
Observations	12,220	12,220	12,220	12,220	12,220	12,220	12,220

Source: Author's calculation, APIS 2013-2014

Notes Standard errors clustered by region in parentheses. *, **, *** indicates significance at 10%, 5% and 1% levels, respectively.

Control variables include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads. Also includes region-specific time trends.

^Placebo tests are conducted using APIS2011-2013 and the same specification for all alternative outcomes.

2.5.5. Heterogeneity Analysis

Su and Mangada (2018) claimed that during Typhoon Haiyan, only the middle-class was able to receive remittances during the crisis since remittance mobility is hindered by class-based inequality. Low-income households were unable to mobilize remittances. Despite the potential endogeneity of income and the typhoon, I investigate the presence of heterogenous impacts by stratifying equation (2.1) by income decile. Income deciles and their distribution in the sample are presented in Table 2.A.1.8 in the Appendix. In addition, I look at the remittance response as well stratifying by the household head's educational attainment, housing tenure, receipt of domestic remittances, and receipt of disaster relief as a precursor to the extended analysis. Table 2.9 reports the DID coefficients stratified by the proposed characteristics.

Panel A of Table 2.9 reports heterogeneity by per capita income decile. Only a few deciles show statistically significant It may be seen for third decile households (average monthly per capita income of PHP 1,907 / USD 37) that both the remittance incidence and levels increase due to the typhoon, and these are robust to including control variables. The increases in incidence and level are much higher than the general results presented earlier. The results for fourth decile households (monthly per capita income of PHP 2,387 / USD46) are similar with the third decile except the remittance incidence coefficient is not robust to the inclusion of controls. It may be noted that the third and fourth deciles are low-income non-poor households. A few other non-robust results appear: fifth decile households report lower remittance levels but only when controls are added, and tenth decile households have higher incidence but only without controls. While I acknowledge these additional findings, I refrain from including them in any discussion for policy.

The consistent findings for the third and fourth deciles challenge Su and Mangada's (2018) observation for Tacloban that low-income households cannot mobilize remittances during crises and only middle-income households can[4]. Higher income deciles typically have no incentive to tap into remittances potentially due to alternative forms of credit or aid, the option to migrate, or having more resilient housing. If it is possible for lower-income households to tap into remittances during crisis (although perhaps not immediately), the extent that class-based inequality hampers remittances as insurance may not be as much as what we might expect. Even if remittances may not be immediately mobilized after the disaster, the results suggest that remittances may still come in for lower-income households to help in their recovery.

[4] Middle-income households are divided into lower-, middle-, and upper-middle income. Lower-middle income households typically start at the sixth decile.

Looking at heterogeneities by household head's educational attainment (Panel B of Table 2.9), it appears that those with lower attainment have a higher probability of receiving remittances. Households with heads with no grade completed show the largest increase in remittance incidence (around 14% higher), along with those with only high school undergraduate attainment (around 7.5% higher). Those with college undergraduate attainment report higher incidence as well but this is not robust. It appears that for heads with post-secondary, college graduate, and post-baccalaureate level attainment, the likelihood of receiving remittances or the level of remittances are lower, indicating that these households tend not to rely on remittances as an insurance mechanism.

Table 2.9. Heterogenous impacts by income decile, household head educational attainment, housing tenure, domestic remittance receipt, and disaster relief.

Panel A. *Per Capita Income Decile*

Dependent Variable:	**Remittance Participation**		**Remittance Level**	
	Basic	Full Controls^	Basic	Full Controls^
First Decile	0.0203	0.0238	-120.0	-96.50
(n= 2,365)	(0.0197)	(0.0199)	(203.4)	(222.6)
Second Decile	0.0361	0.0439	-48.18	-61.17
(n= 2.351)	(0.0369)	(0.0420)	(406.8)	(391.6)
Third Decile	0.0889**	0.0860**	2,288**	1,889**
(n= 2,276)	(0.0360)	(0.0372)	(948.7)	(801.6)
Fourth Decile	0.0768*	0.0682	1,954**	1,780**
(n= 2,208)	(0.0439)	(0.0446)	(855.5)	(819.7)
Fifth Decile	0.0263	0.0175	-776.3	-1,161*
(n= 2,126)	(0.0180)	(0.0149)	(571.6)	(561.6)
Sixth Decile	0.0368	0.0487	-2,568	-2,001
(n= 2,075)	(0.0435)	(0.0563)	(1,994)	(2,404)
Seventh Decile	0.0202	0.0255	176.6	1,791
(n= 2,004)	(0.0277)	(0.0353)	(2,260)	(2,351)
Eighth Decile	0.0345	0.0414	1,765	1,404
(n= 1,997)	(0.0410)	(0.0395)	(6,283)	(5,676)
Ninth Decile	-0.0202	-0.0250	-7,525	-6,977
(n= 1,976)	(0.0430)	(0.0433)	(5,803)	(5,486)
Tenth Decile	0.0817*	0.0861	6,952	2,615
(n= 1,955)	(0.0437)	(0.0495)	(10,860)	(10,616)

Panel B. *Household Head Highest Grade Completed*

Dependent Variable:	**Remittance Participation**		**Remittance Level**	
	Basic	Full Controls^	Basic	Full Controls^
No Grade Completed	0.131***	0.146**	1,182	1,166

(n= 559)	(0.0426)	(0.0567)	(1,163)	(1,222)
Elementary Undergrad.	0.0336	0.0328	-333.7	-566.6
(n= 4,348)	(0.0212)	(0.0216)	(606.8)	(597.5)
Elementary Grad.	0.0285	0.0323	710.7	969.4
(n= 3,896)	(0.0254)	(0.0273)	(1,124)	(1,386)
High School Undergrad.	0.0851**	0.0745*	4,774	3,288
(n= 2,857)	(0.0366)	(0.0377)	(3,098)	(2,685)
High School Grad.	0.0416	0.0493	-942.7	-279.9
(n= 4,664)	(0.0414)	(0.0395)	(2,427)	(1,919)
Post-Secondary	-0.00963	0.00504	-10,469	-11,727**
(n= 785)	(0.0557)	(0.0616)	(6,683)	(4,546)
College Undergrad.	0.0760	0.0983*	3,504	5,405
(n= 1,795)	(0.0558)	(0.0483)	(6,960)	(6,943)
College Grad. Or Higher	-0.0239	-0.0210	-7,966*	-8,688*
(n= 2,311)	(0.0442)	(0.0431)	(4,541)	(4,861)
Post-Baccalaureate	-0.399*	-0.610***	-87,030**	-108,063
(n= 110)	(0.200)	(0.196)	(31,065)	(67,541)

Panel C. *Housing Tenure*

Dependent Variable:	**Remittance Participation**		**Remittance Level**	
	Basic	Full Controls^	Basic	Full Controls^
Own House & Lot	0.0258	0.0336	-3,352*	-2,611**
(n= 13,648)	(0.0188)	(0.0221)	(1,780)	(1,195)
Renting House & Lot	0.144***	0.113**	19,224***	12,038**
(n= 1,592)	(0.0474)	(0.0452)	(5,504)	(5,556)

Panel D. *Received Domestic Remittances*

Dependent Variable:	**Remittance Participation**		**Remittance Level**	
	Basic	Full Controls^	Basic	Full Controls^
Did Not Receive	0.0295	0.0361	-2,042	-1,908
(n= 11,091)	(0.0275)	(0.0283)	(2,398)	(2,004)
Received	0.0513**	0.0495**	877.6	780.0
(n= 10,242)	(0.0198)	(0.0219)	(1,410)	(1,204)

Panel E. *Received Disaster Relief*

Dependent Variable:	**Remittance Participation**		**Remittance Level**	
	Basic	Full Controls^	Basic	Full Controls^
Did Not Receive	0.0219	0.0195	-107.6	-398.6
(n= 20,693)	(0.0141)	(0.0149)	(1,769)	(1,316)
Received	0.121	0.0157	971.3	3,501
(n= 640)	(0.162)	(0.191)	(4,791)	(8,869)

Source: Author's calculation, APIS 2013-2014

Standard errors clustered by region in parentheses, *, **, *** indicates significance at 10%, 5% and 1%.

^Control variables include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads. Also includes region-specific time trends.

In Panel C of Table 2.9, households that own the house and lot they dwell in report no statistically significant response in remittance participation and lower remittance levels received. This may reinforce what I found earlier that richer households (hence those more likely to own their dwellings) are less likely to rely on remittances to cope with disasters. On the other hand, I find very large, positive responses in both participation and levels among households that are renting their house and lot. Renting may be viewed as riskier when it comes to housing, and hence these households may be considered more vulnerable. In this case, remittances may act as a safety net for these households to secure something crucial for their survival.

When stratifying in terms of variables which may serve as alternative forms of coping mechanisms during disasters, it appears that remittance incidence increases during disasters only for those who receive domestic remittances as well (Panel D of Table 2.9). This may not be informative because of endogeneity with the typhoon, but at most, this may be suggestive of either wealth effects (only households with the ability to send migrants can receive remittances) or a complementarity between domestic and international remittances although this explanation is slightly in contrast with the earlier finding that domestic remittances did not increase as a response to the typhoon. Stratifying by receipt of relief (Panel E of Table 2.9) reveals no heterogeneity at all since I find statistically insignificant coefficients for both receivers and on-receivers of aid. This is uninformative likely because the typhoon determines both remittances and relief simultaneously. However, to probe into the interaction of remittances and relief during crises, I explore alternative specifications of the remittance equation in the next section.

2.6. Extended Analysis

In this section, I extend the investigation looking at how remittances may be influenced by the receipt of disaster relief and the quality of a region’s infrastructure and institutions. Deshingkar and Aheeyar (2006) and Wu (2006) highlight the crucial role that remittances played during the 2004 Indian Ocean Tsunami as it responded faster than formal aid. However, access was barred due to bank closures, restricted geographical access, loss of documents, and physical displacement. Le De, Gaillard, and Friesen (2013) emphasize that a disaster may not be born from the natural environment, but rather from inadequacies in disaster preparedness due to low socioeconomic status, deficient infrastructure, or weak institutions. I first investigate whether remittances and relief are substitutes in the context of the period surrounding Typhoon Haiyan. I also look at whether a region's infrastructure and institutions affect the receipt of remittances during crises. I only focus on using remittance participation/incidence as it is the only outcome which exhibited the parallel trend. However, this extended analysis is deemed exploratory, considering any conclusion derived from the results as merely suggestive at best. Nevertheless, even a correlational analysis can contribute much to our knowledge about the relationship among remittances, relief, and regional institutions, given the lack of attention directed towards this topic particularly in the context of disasters.

2.6.1. Disaster Relief

The Philippine government's response to Typhoon Haiyan was hampered by breakdowns in communication, poor infrastructure, and the lack of coordination (Saban, 2015). Foreign humanitarian aid responded immediately to fill these gaps, but studies identified a disjoint between aid targeting and the local culture, causing resentment especially among non-beneficiaries within the same community (Dalgas, 2018; Field, 2017; Ong, Flores, and Combinido, 2015). Field (2017) characterizes this as a "disconnect between the disaster priorities of many affected Filipinos and the programming of an externally driven response applying the disaster management formula" (p.338). When international aid agencies evaluate a household's vulnerability, receiving remittances (regardless of size) potentially lowers a household's priority in receiving aid (Su and Mangada, 2018). What relationship do remittances and relief have during crisis? Is relief crowded out by remittances? Or do remittances substitute for the lack of relief?

To empirically establish the interplay of remittances and relief, I look at two additional specifications of equation (2.1). First, I straightforwardly add a binary indicator of the receipt of relief ($Relief_{it}$[5] takes the value of 1 when the household received relief and 0 otherwise) as a control variable and observe its correlation with remittance incidence. Second, I augment the main regression equation into a triple-difference (DDD) equation:

$$\begin{aligned} Remit_{it} = \beta_0 + \beta_1 Affected_i + \beta_2 Year_t + \beta_3 (Affected_i * Year_t) + \beta_4 Relief_{it} \\ + \beta_5 (Affected_i * Relief_{it}) + \beta_6 (Year_t * Relief_{it}) + \beta_7 (Affected_i \\ * Relief_{it} * Year_t) + \boldsymbol{\pi X} + \boldsymbol{\delta_j} * Year_t + u_{it} \end{aligned} \tag{2.2}$$

[5] The APIS inquires whether any family member received support for disaster relief but does not provide a disaggregation by source or nature.

Equation (2.2) looks at the impact of receiving relief vis-à-vis the typhoon on the likelihood of receiving remittances. Similar to the main model, β_1, β_2, and β_3 represent average region characteristics, the time trend, and the remittance response to the typhoon, respectively. β_4 represents the average impact of a household that received relief, β_5 represents the average effect of a household in an affected region that received relief, β_6 represents the impact of receiving relief in the typhoon year, and β_7 is the DDD estimator indicating how the likelihood of receiving remittances is influenced by receiving relief during the onslaught of the typhoon. $\boldsymbol{X}$ is the same vector of household characteristics as in equation (2.1), and $\boldsymbol{\delta_j}$ are region-specific time trends.

Table 2.10 summarizes the analyses on the relationship between remittances and relief. Columns (1) and (2) present the simple correlation while columns (3) and (4) present the DDD estimates. In terms of correlation, it shows relief has no definitive impact on remittances on average. A negative coefficient is reported but this becomes positive when controls are included. Looking at the DDD estimates, while it may be seen that the receipt of relief decreases the likelihood of receiving remittances on average, this is not robust to the inclusion of chosen controls. Even when looking at the DDD coefficient which suggests a positive relationship during the typhoon, the standard errors are visibly large which renders it statistically insignificant. The issue that Su and Mangada (2018) raised may be more verifiable with a closer look to the time the typhoon hit. The length of time covered by the survey covers the possible receipt of remittances months after the typhoon, so the very large variation may be clouding the relationship of the two factors. The typhoon simultaneously determines both relief and remittances, so any causal inference is not possible. Suggestively, the coefficients tell us that remittances and relief are substitutes on average but may complement each other during and in the period directly following a disaster. Alternatively, the estimates show that remittances are sent during disasters without having any variation with respect to the receipt of relief. This may imply that OFWs send remittances during disasters regardless of whether relief is delivered, painting remittances as a resilient, reliable safety net during crises. Appendix 2.A.6 discusses the issues surrounding the formula that international humanitarian agencies use for targeting and how it led to adverse emotional impacts on the affected community.

2.6.2. Remittance Facilitators

A region's vulnerability (or resilience) to disasters may be influenced significantly by its institutions (Le De et al, 2013), and though remittances may serve as insurance, access to remittances may be disrupted when institutions are not resilient enough to facilitate remittance mobility (Su and Mangada, 2018). Communication and transportation infrastructure, local governance, and banking play vital roles during disasters, both in making regions more resilient and facilitating the flow of remittances. As mentioned in Section 2.3, I collect various indicators to serve as proxies for the quality of communication and transportation infrastructure and governance and banking institutions[6]. While by no means perfect or holistic, these indicators offer a glimpse of the level of development and quality of infrastructure and institutions in each region.

Table 2.10. How remittances interact with relief.

	Correlates		Triple Difference	
	(1)	(2)	(3)	(4)
	Basic	Full Controls^	Basic	Full Controls^
Affected	-0.0332	-0.106***	-0.0346	-0.101***
	(0.0259)	(0.00609)	(0.0264)	(0.00706)
Year	-0.00147	-0.00388	-0.000607	-0.00321
	(0.00650)	(0.00658)	(0.00666)	(0.00663)
Affected*Year	0.0406***	0.0349***	0.0219	0.0237*
	(0.0120)	(0.0100)	(0.0141)	(0.0124)
Relief	-0.0115	0.0212	-0.111**	-0.0291
	(0.0755)	(0.0691)	(0.0413)	(0.0284)
Affected*Relief			0.125	0.0422
			(0.151)	(0.194)
Year*Relief			-0.0323	-0.0305
			(0.0395)	(0.0345)
DDD^^			0.0995	0.0919
			(0.173)	(0.199)
R-squared	0.001	0.079	0.003	0.080
Observations	21,333	21,333	21,333	21,333

Source: Author's calculations, APIS 2013-2014

Standard errors clustered by region in parentheses. *, **, *** indicates significance at 10%, 5% and 1%.

^Control variables include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads. Also includes region-specific time trends

^^The triple difference coefficient is based on the interaction between relief and the typhoon DID term, affected and year 2014.

Table 2.11 presents summary statistics of the infrastructural and institutional indicators for affected and unaffected regions. Compared to unaffected regions, affected regions have fewer telephone and radio

[6]Indicators used for communication are telephone density, number of radio stations, number of broadcast TV stations, number of cable TV networks; for transport: aircraft movement, air passenger movement, airports; for governance: calamity funds, internal revenue allotment, and revenue collection; and for banking: number of ATMs and electronic banking facilities and number of branch offices.

infrastructure, lower aircraft movement despite having more airports, but have more television infrastructure. Affected regions also have lower calamity funds and revenue collections, fewer ATMs and banking offices. However, it may be noted that the standard deviations for unaffected regions are generally larger than their means, which indicates very large variability. This may imply that even though the mean values for unaffected regions are higher, it is likely that some affected regions may be performing better than some of the unaffected regions.

Table 2.11. Indicators of regional infrastructural and institutional capacity by affected and unaffected regions and measurements

	Variable	Measure	Affected	Unaffected
Communication	Telephone Density	Phone lines / 100 pop'n	2.06 (1.19)	7.01 (9.9)
	Radio Stations	# of radio stations in 2013	20797.84 (12731.66)	38100.54 (54682.51)
	Broadcast TV stations	# of broadcast stations	312.155 (134.93)	247.04 (163.41)
	Cable TV Networks	# of Cable TV Networks	116.25 (62.10)	89.79 (78.10)
Transport	Aircraft movement	# of flights	34001.45 (18938.82)	76079.55 (138236)
	Air passenger movement	# of people	3286012 (2283320)	6446057 (1.21e+07)
	Airports	# of airports	5.6 (2.06)	4.15 (2.26)
Governance	Calamity Funds	PHP	2.08e+08 1.44e+08	1.26e+09 (3.60e+09)
	Internal revenue allotment	Million PHP	4993.62 (740.94)	6535.53 (3905.07)
	Revenue collection	Million PHP	7881.51 (4206.48)	172773.50 (385774.70)
Banking	ATM and Electronic Banking	# of ATMs and Electronic Banking Facilities	637.41 (375.89)	1532.11 (2093.97)
	Banking Offices	# of branches/offices	471.29 (205.41)	936.35 (1040.53)

Source: Author's calculation, PSY 2015; BSP, 2018.
Standard deviations in parentheses.

To estimate the impact these remittance facilitators have on the likelihood of receiving remittances, I merge the region-specific infrastructure and institutions data with the 2013-2014 APIS. I generate a collective measure of remittance facilitators to make the different measures of remittance facilitators comparable. I use a weighted normalized index used in Acosta (2010) to combine the several remittance facilitator indicators (Appendix 2.A.7 discusses this in greater detail). This index represents the quality of institutions a region has relative to the other regions, with the index being positive if the region's institutions are higher than the national average, and negative if otherwise. I then generate a binary indicator equal to 1 if a region's index is nonnegative implying it has strong facilitators relative to the other regions.

The intention of this is to be able to run a DDD approach like that for relief, however, because of the very large spread in the indicators of unaffected regions, there is no variation for the affected group. That is, all affected regions were recorded to have relatively better institutions than many unaffected regions. Because of this, I re-specify the approach of my analysis to highlight the effect of differences in the quality of facilitators among affected regions only. The index identifies the performance of a region compared to other regions, so by limiting the sample to only affected regions, I can internally rank the quality of their facilitators and generate the variation needed to test the effect of facilitators on remittances. I then run a simple DID approach only for affected regions using OLS to see how the various institutions are correlated with remittances.

$$Remit_{it} = \beta_0 + \beta_1 GoodI_{jt} + \beta_2 Year_t + \beta_3 (GoodI_{jt} * Year_t) + \boldsymbol{\pi X} + \boldsymbol{\delta_j} * Year_t + u_{it} \qquad (3)$$

Where $Remit_{it}$ is the same binary variable, $GoodI_{jt}$ = 1 if region *j*'s index is non-negative, and = 0 if it is negative. β_1 may be interpreted as the average effect, β_2 is the time trend, and the DID coefficient β_3 may be interpreted as the impact of having good institution during the typhoon year. Note that since I am after impacts from a regional level, the vector of controls excludes region fixed effects but still includes wealth, household head education and family size. $\boldsymbol{X}$ is the same vector of household characteristics as in equation (2.1), and $\boldsymbol{\delta_j}$ are region-specific time trends.

Table 2.12 reports the response of remittances to having good facilitators during the typhoon. Looking at the average effects of facilitators, it appears that remittance incidence is generally higher for regions with relatively good facilitators (except communication). Among those the increase remittances, good governance and banking appear to contribute the most, confirming the suggestions of Effiong and Asuquo (2017) and Endo and Afram (2011). Communication infrastructure appears to be negatively associated with remittance incidence which may indicate that the role communication plays in building local capacity crowds out remittances. Good communication infrastructure does not translate to better connectedness between a migrant and his family. The DID coefficients for all types of facilitators are negative, although only transport infrastructure and banking are the only statistically significant ones. This negative coefficient is seemingly counterintuitive, however, recalling Effiong and Asuquo (2017), how governance institutions affect the flow of remittances may not be straightforward. What the results may imply is that during crises, remittances act independently of the level of infrastructure and institutions in the region and may even serve as a substitute for deficient infrastructure and institutions. This reinforces remittances as insurance against poor institutions and infrastructure in addition to the adverse effects of natural disasters.

Table 2.12. DID estimates of having good facilitators during the typhoon year on remittances, affected regions only

	Dependent Variable: Remittance Participation			
	Communication	Transportation	Governance	Banking
	(1)	(2)	(3)	(4)
Good Facilitators	-0.0557***	0.0425*	0.119***	0.0765***
	(0.0192)	(0.0236)	(0.0199)	(0.0193)
Year	0.0409**	0.0820***	0.0469***	0.0636***
	(0.0165)	(0.0227)	(0.0141)	(0.0187)
DID^	-0.0160	-0.0826**	-0.0375	-0.0459*
	(0.0231)	(0.0338)	(0.0249)	(0.0238)
R-squared	0.089	0.091	0.090	0.090
Observations	4,315	4,315	4,315	4,315

Source: Author's calculations, APIS 2013-2014 and compiled dataset of institutional characteristics

Notes: Standard errors clustered by region in parentheses. *, **, *** indicates significance at 10%, 5% and 1%. Control variables include house and lot ownership, housing unit floor area, family size, and a vector of the highest grade completed dummies of household heads. Also includes region-specific time trends

^DID coefficients are based on the interaction between having relatively good facilitator and the post-typhoon year. Each column represents a different equation based on the kind of facilitator.

2.7. Conclusion

The rapid increase of migration across the world has led to an expansion of the roles that remittances serve for developing countries. This study looks at the role of remittances as informal aid and insurance in times of disaster. While my results are not entirely novel, the primary contribution of the study is the utilization of a natural experiment that exploits the randomness of the path of a single, yet large, destructive typhoon to identify the remittance response in a DID approach. This strategy highlights the use of single-event identification strategies to determine the localized effects of disasters. I find that more households are receiving remittances in affected regions (higher incidence), but the amount they receive (levels) is not necessarily larger. The size of the response, though small, may play a substantive role for communities during disasters. During the typhoon, households suffered significant losses in income. However, expenditures, particularly on food, were not statistically lower, perhaps thanks in part to remittances. I also find heterogeneity of the remittance response at the third- and fourth-income deciles which are comprised of low-income households. This provides evidence that class-based inequality may not hamper remittance mobility during disasters. Furthermore, the remittance response also appears greater for poorer, less-educated households that rely on domestic remittances.

In the correlations I establish in the extended analysis, I find only statistically insignificant evidence that remittances and relief substitute each other in general, although they may be complements during crises. It may be more certain to say that remittances are sent independently from relief. Moreover, having good facilitators (communication and transport infrastructure, and governance and banking institutions) may aid the flow of remittances in general, although it is yet unclear whether they enhance mobility during crises. My results do point, however, at the possibility that remittances also serve to insure households from a region's deficient infrastructure and institutions.

Altogether, my findings characterize international remittances as a formidable and resilient, risk-coping mechanism insuring households against shocks as well as their own (and their region's) vulnerability. These results suggest that migrant diasporas may have a larger role during crises and this study serves as a call to support migrants and their households and to reduce the barriers to sending remittances. International humanitarian agencies are urged to work with local institutions to improve their targeting and the administration of aid. However, despite having remittances and relief as safety nets, the devastation of disasters will only be magnified if a region is vulnerable. This vulnerability may be reduced by correcting socioeconomic imbalances, structural weaknesses in infrastructure and institutions, and enhancing a regions' general preparedness with clear information systems, evacuation protocols, relief distribution, urban planning, and reconstruction plans. The lessons here may be extended to other countries that rely on migration for resilience as well (Sri Lanka, Haiti, Somalia, Pakistan, Indonesia, and Sudan).

Among the limitations I can enumerate is the lack of intricacy of the APIS. Being able to disaggregate deeper than the regional level is paramount in my identification strategy and should allow for a stronger geographic-based approach. Being able to control for migrant characteristics, remittance flow channels (especially since the Philippines is a major migrant-sending country), and sources of relief should help improve the precision of estimates. Having data on disaster-preparedness and resilience indicators of regions will certainly be more informative than infrastructural and institutional capacity to assess a region's vulnerability and thus ability to mobilize remittances during a disaster. Of course, investing in the expansion of communication, transportation, governance, and banking can increase local service delivery during disasters, but only when these institutions are made resilient can I prevent the "real disaster" from occurring.

Chapter 3

Host country institutional heterogeneities and Filipinos' labor market assimilation[7]

Abstract

Understanding the labor market assimilation of immigrants has been of utmost importance in the international migration literature especially with the unprecedented increase in global migrants. However, little work has been done in comparing the assimilation experience of migrants around the world given the significant differences in social institutions across destinations. This study explores the role of heterogeneities in cultural institutions, migration networks and immigration policies in the labor market assimilation of Filipinos in Canada, Greece, Malaysia, Spain, and the US. I use the census data of the five countries taken from the IPUMS-I, wage data taken from ILOSTAT, and institutional and cultural data taken from various sources. The study develops a profile of Filipinos in each country and looks at the assimilation of Filipinos in each country given their respective institutions. I find that cultural similarity, migrant networks, and selective immigration policies aid assimilation, whereas cultural diversity may hamper it. In investigating the channels through which assimilation occurs, I find that the heterogeneities in institutional factors change Filipinos' returns to education and migrants go through occupational and industrial upgrading across time.

[7] Paper title: "Pliant like the bamboo: Institutional heterogeneities of host countries and the labor market assimilation of Filipinos around the world". *Pliant like the bamboo* refers to the story based on Philippine folklore written by Ismael Villanueva Mallari, a Filipino writer in English. The story is summarized (poorly) as follows: *A mango tree and a bamboo tree were arguing as to who was stronger and called the wind to help them come to a decision. The wind blew its hardest. The mango tree stood fast and unyielding as it knew it was strong and sturdy. It was too proud and sure of itself that it would not sway. In the end, it was uprooted and felled. The bamboo tree, with its wisdom, knew it was not as sturdy as the mango tree. When the wind blew, the bamboo swayed, bending its head gracefully and letting the wind have its way. Eventually, the wind got tired of blowing and there stood the bamboo tree in all its beauty and grace.*

3.1 Introduction

In recent years, international migration has grown at an unprecedented pace. The global migrant stock was estimated at 266 million in 2017 from 172 million in 2000 (Ratha et al, 2018). These figures are a mixture of economic migrants, family migrants, and asylum-seekers. With this comes the issue of immigrant assimilation in host countries, defined loosely as migrants adjusting to life in the host country. Towards the end of the nineteenth century, the large waves of international migration across the world sparked debates in host countries' governments regarding the management of immigrants, particularly their level of education, skills, and overall adaptability to the local community. In recent years, the tradition and growth of international migration has urged host countries to continue developing immigration policies which may control the volume, origin, direction, or internal composition of immigrants (Czaika and De Haas, 2013) in an effort to regulate their stock of migrants or ensure that they receive "higher quality" migrants. The lack of a proper strategy to help immigrants assimilate may lead to social and economic exclusion, which in turn may affect their success and hence their contribution to the host society (Algan, Dustmann, Glitz, and Manning, 2010). This has led to the careful study of assimilation most prominently in countries that have experienced the largest immigrant flows such as the US, Germany, UK, Canada, and Australia. However, little is known regarding the factors varying across countries that may influence migrants' assimilation.

This paper investigates how cultural institutions, migration networks, and immigration policies are associated with immigrants' wage and employment assimilation. I use a comparative approach on five countries and an alternative model specification that utilizes only immigrants from one origin to emphasize the role of institutional differences among host countries. To my knowledge, this study is the first to use a broader spectrum of countries and includes countries that have not yet been studied in comparative works making it the largest comparative study to date. It is also the first to use the specification with one immigrant group across multiple countries. I look at the assimilation experience of Filipino migrants in Canada, Greece, Malaysia, Spain, and the US.

Algan et al (2010) described assimilation as not being limited to immigrants abandoning their origin identities and conforming with the host society, but includes equal opportunity, living in harmony with cultural diversity, and mutual acceptance and tolerance. For this study, *assimilation* is narrowed down to that in the labor market and *will be defined as immigrant wages and employment rates converging with that of natives as they spend more time in the host country*.

The pioneering work of Chiswick (1978) in the US was instrumental in guiding succeeding works as it established the conventional wisdom surrounding the assimilation process. He provided a comparison of the earnings and returns to schooling and labor market experience of immigrants and natives and found that immigrants incur a penalty to their earnings upon arrival. This gap then closes as immigrants spend time in the host country and eventually overtakes the earnings of natives. The initial gap is due to the lack of host-specific human capital and the imperfect transferability of human capital accumulated externally and the crossover is explained by favorable selection of migrants[8]. This has served as the conventional wisdom regarding immigrant assimilation and later studies have confirmed this for Australia (Chiswick and Miller, 1995), Canada (Baker and Benjamin, 1994), Germany (Basilio, Bauer, and Kramer, 2017), Israel (Friedberg, 2000), and Spain (Izquierdo, Lacuesta, and Vegas, 2009).

Studies have expanded further and have looked at the heterogeneities that influence assimilation. Among these things are the similarity (or difference) of home and host country in terms of labor markets, industrial structure, institutions and educational quality, the immigrants' proficiency in the host-country language, the size and maturity of migrant networks, and the nature of immigration policies. Having similar educational systems or comparable educational quality may aid in sending a signal to employers thus improving the transferability of human capital acquired from home countries (Basilio et al, 2017; El-Araby and Ragan, 2010). Proficiency in the host country's language not only gives a direct signal but also improves the rate at which host-specific human capital is accumulated (Chiswick and Miller, 1995). A larger, long-established migrant network may aid in the adjustment of newly arrived migrants (Hatton and Leigh, 2011) but may also encourage segregation which discourages integrating into the host culture (Mane and Waldorf, 2013). Lastly, selective immigration policies such as a points-system based on a set of observables such as education, skill, and language proficiency may ward off lower-skilled migrants thus leading to a smaller gap between immigrants and natives (Cobb-Clark, 2003; Miller and Neo, 2003)

Although the number of comparative (cross-country) works on immigrant assimilation have been increasing, the discussion on the role of social institutions, migration networks, and migration policies has been limited and are often treated as channels. Studies that directly test for the impact of these factors are even fewer. This study seeks to fill this gap.

[8] Chiswick (1978) explained that the imperfect transferability of human capital is due to the differences between host and home country labor markets, employers having less information on the value of schooling or work experience from the home country, or the lack of formal recognition of qualifications. Favorable selection posits that migrants (having to leave their home country) are positively selected in such that for the same level of schooling, experience and other demographic characteristics, immigrants have higher innate ability, ambition and motivation.

In meeting my primary objective, I use the case of migrants from the Philippines as it is one of the largest migrant-sending countries in recent history. Filipino migrants are mostly economic and family migrants: they migrate to maximize earnings by exploiting wage differentials and to reunite with existing family migrants. There are barely any Filipino refugees (if any at all). Migrants from the Philippines may be classified into permanent and temporary migrants. Permanent migrants are typically a mixture of family and economic migrants that seek to reside and eventually acquire permanent residency or citizenship in their host country. Temporary migrants, usually OFWs, are mostly economic migrants that are engaged in contract work and have a higher likelihood of return migration. In addition, temporary migrants are classified into land-based migrants, who are the traditional types of migrants, and sea-based migrants who are seamen and those engaged in maritime logistics. In 2018, new permanent migrants numbered 73,719 increasing the total permanent migrant stock to 2.4 million with the most popular destinations (largest migrant stocks) including the US (approximately 60.5%), Canada (20.1%), Japan (6.2%), Australia (5.9%) and Italy (1.7%) (CFO, 2020). OFWs on the other hand, was estimated at 2.3 million in 2018 alone with the top destinations including Saudi Araba (24.3%), United Arab Emirates (15.7%), Hong Kong (6.3%), Kuwait (5.7%), Taiwan (5.5%), and Qatar (5.2%) (Perez, 2019). In this study, I look at the assimilation of only land-based Filipino migrants but consider both permanent and temporary migrants. While the dataset does not allow me to distinguish permanent and temporary migrants, I internalize this by grouping countries in the sample according to majority permanent migrants ("permanent" destinations), and majority temporary migrants ("temporary" destinations), and estimating the assimilation profile for Filipinos in both. Countries in my sample include two top destinations: Canada and the US, and less popular destinations but with a relatively sizeable Filipino community: Greece, Malaysia, and Spain.

This study provides three key contributions. *First*, it generates a profile of Filipinos in the sample of five countries, focusing on their educational attainment, and occupational and industrial distribution as these may reveal potential channels of economic assimilation. *Second*, to my knowledge, it may be the first to directly establish how cultural similarities and diversity, migration networks, and immigration policies are associated with the wage and employment assimilation using a comparative approach with one sending country and multiple receiving countries. This method filters out concerns about immigrant heterogeneity and highlights differences in host country institutions more intensely. Given the difficulty in disentangling competing explanations and endogeneity concerns, this study rests far from claiming causality. However, the scarcity of studies on the institutional factors affecting assimilation and those using the unique framework of this study prods that even establishing correlations would contribute new knowledge to the assimilation and transferability literature. Nevertheless, learning from seminal literature, I do my best to account for competing explanations and confounding effects when specifying the model. *Lastly*, this study develops brief assimilation case studies for each country in the sample, examining carefully how the combinations of institutions in each country may have led to the assimilation (or lack thereof) of Filipinos.

The remainder of this chapter is organized as follows: Section 3.2 briefly reviews the seminal works and methodological improvements to assimilation studies, the international transferability of skills which is the conceptual framework adopted in this study, the role of the each factor that may influence assimilation, and cross-country comparative studies on assimilation; Section 3.3 discusses the different sources of data used in the analyses as well as key variable calculations; Section 3.4 presents the empirical strategy; Section 3.5 presents the profiles of Filipinos in the sample, the general model on the factors of assimilation, the channels through which assimilation occurs, and the country case studies; lastly, Section 3.6 concludes, provides policy implications, and a brief discussion on limitations.

3.2 Review of Literature

The earliest work on assimilation was put forth by Chiswick (1978) who used the 1970 Census of Population, a cross-sectional (CS) dataset, and found that the earnings of foreign-born men were lower but increased as they spent more time in the US. They also have lower returns to education and experience. By fixing the human capital and demographics of immigrants and natives, Chiswick further simulates their earnings profiles and concludes that immigrants start with lower earnings, but as it increases over time in the US, they eventually equal, and later (after 10-15 years) exceed the earnings of natives. This served as the conventional wisdom for later studies.

However, Chiswick's (1978) analysis was limited by its CS nature. Many studies came forth to point out the pitfalls on the use of CS (and even repeated CS) and have recommended improvements (Borjas, 1985, 1995; Friedberg, 2000; Lubotsky, 2007; Abramitzky et al, 2014). Among the methodological issues that may confound CS estimates are: 1.) selective return migration, 2.) changes in cohort quality, 3.) normalization of comparison groups, 4.) unobserved heterogeneity on the selection of immigrants and the endogeneity of post-migration schooling and experience decisions, and 5.) measurement error stemming from homogenizing human capital acquired in origin and host countries. Appendix 3.A.1 provides a more detailed review of literature on methodological issues of estimating immigrant assimilation.

Implicitly, assimilation occurs in two perceived stages (Cobb-Clark, Hanel and McVicar, 2012): *first* is the gap in outcomes upon arrival, and *second* is the convergence over time spent in the host country.

The initial gap in earnings may be attributed to the imperfect transferability of human capital acquired externally, which may be explained by differences in home and host country labor markets and imperfect information of employers (Chiwick, 1978). Chapman and Iredale (1993) associate this gap with the lack of formal recognition (certification/licensing) of skills acquired from immigrants' origin countries, and national qualifications frameworks tend to influence this immensely. Chiswick and Miller (2010) link this to why many immigrants are overeducated: because very high investment in education prior to migration may not be readily transferable[9] and so these migrants often accept an occupational downgrade. This same reason may be linked to why origin-country human capital is valued much lower than human capital acquired in the host-country (Friedberg, 2000). It may be noted that transferability tends to be better and wages mirror that of natives more when the home and host country are highly similar (Basilio et al, 2017). Oreopoulos (2011) highlighted Canadian employers valuing foreign education less than Canadian education being partially responsible for struggling skilled immigrants in Canada.

Convergence is the process through which immigrant outcomes gravitate toward same levels of natives. Convergence occurs when immigrants invest in acquiring host-specific human capital explicitly (e.g. formal schooling) and implicitly (e.g. learning by living) as they spend more time in the host country (Chiswick and Miller, 2011). Explicit investments in schooling and training allows for faster convergence since host-acquired human capital is valued higher than that of external source (Friedberg, 2000; Chapman and Iredale, 1993). Once convergence has been achieved, immigrant earnings' may then overtake that of natives with more years spent in the host country. This is attributed to favorable selection, that is, for the same education, training and demographics, immigrants that stay tend to have higher motivation, ability, and ambition compared to natives (Chiswick and Miller, 2010).

Chiswick, Lee and Miller (2005) find that the initial gap and eventual convergence may occur through occupational mobility. In their study, they posit a "U-shape" pattern for occupational mobility from the last job in the origin to the first job in the destination, and to subsequent job changes as the migrant stays in the host country. The initial "downgrade" in occupational status upon migration is due to the imperfect transferability of human capital[10]. After a few years and as the immigrant acquires host-specific human capital (be it language, recognition, or accreditation), the migrant would experience a movement upward the occupation ladder. They find that mobility improves with education, host language proficiency,

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[9] An example in Chapman and Iredale (1993) are lawyers. Practicing law not only requires skill but also very high knowledge of local laws. A lawyer that has learned much of the legal environment of his home country may not immediately work as a lawyer in the host country because it may have a completely different legal environment.

[10]A lawyer may have imperfect transferability due to differences in legal systems, so they may start only as a clerk in a courthouse rather than a professional. Doctors may need an additional license so they may start as an associate.

and pre-existing migrant networks. They also find that occupational mobility is heterogenous to the type of migrant (refugees, economic migrants), wherein the less transferable the skill, the deeper the initial downgrade. Simon, Ramos and Sanroma (2014) found that for a country with a segmented labor market such as Spain, the initial downgrade tends to be steeper and occupational mobility is hampered if not altogether blocked due the sheer size of the secondary segment[11]. Alternatively, assimilation may also occur through industrial mobility (transitioning to higher-paying industries) and regional mobility (moving to other regions, potentially with higher income or larger migrant networks) (Izquierdo et al, 2009). A handful of studies have also documented the heterogeneity of assimilation with the origin of the immigrant (Chiswick, 1978; Borjas, 1985; El-Araby and Ragan, 2010; Chiswick and Miller, 2010; Abramitzky et al, 2014; Basilio et al, 2017). The consensus tends to be that assimilation in a host country tends to be better for migrants whose origin is verifiably "similar" to the host country.

Assimilation may vary largely with similarities and differences between the home and host countries' institutions. Thus, I now look at the role of institutions namely culture (and specifically language), migration network, and immigration policy on assimilation. I also look at comparative studies to see how differences in host country institutions may impact assimilation.

Culture is comprised of language, beliefs, values, symbols and artifacts that are telling of the social norms in a society. Among these elements, language is the easiest to quantify and is therefore, to my knowledge, the only aspect of culture that is given attention in assimilation studies. Language skills are effectively a form of human capital as it is intrinsic and productive in the labor market (Chiswick and Miller, 2010). Language is often represented as fluency or proficiency, coming from an English-speaking background, or an origin that speaks the host-country language. The consensus appears to be that proficiency in the host country language increases earnings, the acquisition of host human capital and the return to education and experience (Friedberg, 2000; Chiswick and Miller, 1995). It has been documented that coming from an English-speaking (or dominantly English-fluent) background increases earnings in the US (Abramitzky et al, 2014), Australia (Tam and Page, 2016), Canada (Oreopoulos, 2011), and Israel (Chiswick and Miller, 1995). However, for the case of Australia, Chiswick and Miller (2010) identify that although coming from a Non-English-Speaking Background may imply less transferability of skills, it does

[11] Segmented labor markets are typically divided into the primary and secondary segment (Simon et al, 2014). The primary segment is composed of high-wage occupations (typically ISCO88 classifications 1-4) with better work conditions, prestige and promotion. The secondary segment is made up of lower paying occupations (ISCO88 classifications 5-9) that are unstable, unskilled, and with little prospect for upward mobility. Segmented labor markets are prevalent in industries with loose labor regulations, protectionist regulations (permanent employment is given to citizens, whereas new entrants get less-protected jobs), and the use of informal and irregular employment arrangements (Fellini and Guetto, 2019).

not necessarily mean the initial penalty is larger. They attribute this to a more intense selection in migration which allows only migrants with the highest ambition or ability knowing they will move to a destination that speaks a different language. Tam and Page (2016) also find that proficiency in language can potentially improve a variety of economic, social, and health outcomes such as the likelihood of finishing a tertiary degree and gaining employment, the likelihood of marrying a native and gaining citizenship, self-assessed health, and the likelihood of purchasing private health insurance and insurance duration. However, neither language, cultural similarity, nor diversity has been a focal point of any comparative study.

To my knowledge, how the other elements of culture may affect immigrant assimilation has remained unstudied. Beliefs, values, symbols, and artifacts reflecting society are difficult to quantify and any form of quantitative representation may be subject to large measurement error. In theory, the ease (or difficulty) of a migrant's assimilation will depend on how fast he may adjust to how a society communicates (apart from language), their belief system (ranging from work ethic to religion and perception about religion), and how they dispense judgment on desirable and undesirable matters. The similarity (or lack thereof) of an immigrant's origin with the host country may play a large role in his assimilation. Diversity, on the other hand, may have ambiguous effects. Societies with high ethnical fractionalization may have a different attitude towards immigrants as compared to ethnically unanimous ones. Diverse societies may perhaps be more accepting as they are used to different races sharing the same space. Alternatively, diverse societies may have less-welcoming environments when different races are subject to discrimination. Given how Filipinos come from a highly religious (Catholicism is the dominant religion) and a relatively ethnically unanimous society, I test how a culturally similar and culturally diverse host society may impact their assimilation. I also specifically test for the impact of religious similarity and diversity, and ethnic fractionalization.

Migration networks pertain to the culture of migration a sending country has with respect to a destination country. This is typically represented by historical migration and stock of previous migrants in a country. Migrants may also be dichotomized into permanent (those who migrate to get citizenship) and temporary (eventual return migrants). The literature on the effect of migration networks on labor market outcomes and assimilation are met with conflicting results. The earliest works done by Chiswick and Miller (2005) and Cortes (2008) found that ethnic concentration in an area may lead to poorer labor market outcomes due to lower wages. In a comparative study of Canada and the US, Kaushal and Lu (2015) echo this result and add that network effects decrease selectivity such that both the likelihood of attaining a tertiary degree and that of host language proficiency decrease. However, a recent work by Hatton and Leigh (2011) found that although a crowding effect exists (relative wage decreases with a larger present migrant stock), a culture of migration from the past strongly increases relative wages. This may be due to older migrants helping newer migrants find jobs, but newer migrants will need to compete with each other. In their comparative work of Albanian and Italian immigrants in the US, Mane and Waldorf (2013) found that a larger network with a history of immigration increases the transferability and hence the return on human capital acquired from the home country. However, they also found that a larger migrant history would decrease incentives to assimilate as new migrants of that network may stay in their own enclave. A peculiar case is that of Filipino nurses in the US. Filipino nurses in the US enjoy a wage premium despite toughter, adverse working conditions due to very strong positive selection (Cortes and Pan, 2015). Dustmann (1993) highlighted that it is important to distinguish between permanent and temporary migrants since the intended length of stay will affect a migrant's human capital investment. He suggested that the optimal level of human capital is lower for temporary migrants due to the shorter duration of their stay, hence a flatter earnings profile.

Migration policies typically influence the volume, origin, direction, and composition of immigration toward a host country (Czaika and De Haas, 2013). Policies that regulate the volume typically include quotas or immigrant caps. Policies on origin tend to select migrants based on their origins, particularly if any bilateral agreements on the movement of people or trade of skills are in place. Policies controlling the direction of migration selectively chooses the destination of migrants within the host country if, for example, certain regions need development and therefore requires stocks of specific skills. Policies that restructure the composition of immigration may seek to balance the proportion of immigrants according to race, skill level, migrant types (economic, family, or refugees) or purpose (business, citizenship or education). Migration policies may be classified as either liberal or selective, although in practice, immigration policies are more nuanced than this. For example, the US may be considered relatively liberal in such that its visa is more receptive as it is based on kinship ties and hence more welcoming of family migrants (Miller and Neo, 2003). The US also has an extensive history of immigration dating back to its open-door policy in the late 1800s, and later they received several refugees from the war. On the other hand, Australia may be considered more selective since it issues visas according to a points system which places heavier weights on qualifications and experience and grants additional points for people with skills that can fill occupational shortages or those directly nominated by Australian employers (Chapman and Iredale, 1993). After 1999, the change toward an even stricter immigration policy[12] was found to increase the human capital of immigrants and hence improved participation and decreased unemployment (Cobb-Clark, 2003).

[12] According to Cobb-Clark (2003), in 1999, Australia increased the number of its skill-based visas granted and decreased family-related visas. The points test also became more stringent in imposing requirements on minimum age, skill, and English skills of the migrant and her spouse. Furthermore, a change in their welfare policy excluded

Several comparative studies (but only on the US, Australia, and Canada) look at differences in immigration policies and how these may impact the labor market outcomes and assimilation of immigrants. Miller and Neo (2003) concluded that in flexible labor markets (i.e. US), immigrant wages tend to start lower but increase over time and employment tends to be higher. Selective labor markets (e.g. Australia, Canada) tend to increase the educational attainment and language proficiency of immigrants (Kaushal and Lu, 2015) and give higher initial wages with no change over time, but higher unemployment due to the more stringent workplace requirements. Kaushal, Lu, Denier, Wang, and Trejo (2016) had similar findings on Canada and the US where immigrant wages grew in the US but not in Canada (which is relatively more selective). In a comparative study of the US, Canada, and Australia, Antecol, Kuhn, and Trejo (2006), however find a conflicting result that Australia's inflexible wage and generous unemployment insurance (prior to the policy change in 1999) lead to assimilation in employment rather than wage. They find that among the three, Australia appears to be the most selective, the US the most liberal, and Canada in the middle. Kaushal and Lu's (2015) finding appears to confirm Antecol et al's (2006) where unemployment insurance increases the negative selectivity of migrants when they are also eligible for the welfare benefit.

This paper aims to contribute to the literature in three ways. *First*, this study contributes to the literature on institutions and assimilation by *directly* testing the effect of culture, language, migration networks, and immigration policies on immigrants' assimilation through wages and employment. *Second*, Kaushal and Lu (2015) comment that estimates in comparative works may be biased if native profiles have structural differences across countries, and that it may be more appropriate to compare recent migrants from the same country sending to different countries. Therefore, with the framework based on Filipinos migrating to five different countries, this study would be the first to apply this methodology and would do so with the largest comparative sample including countries that have been studied before (US, Canada, Spain), and countries that have not yet been studied (Malaysia, Greece). *Lastly*, this study would be the first to test for the effects of cultural similarities and differences (aside from language) on assimilation, particularly religious similarity, diversity, and ethnic fractionalization.

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immigrants from receiving income support. Coupled with an improvement in the labor market, these changes increased the selectivity of migrants in a way that low-skill candidates are weeded out and discouraged.

3.4 Data Sources

To meet the objectives of the study, I combine data from three sources: the IPUMS-I, wage data from ILOSTAT, and institution data from various sources. The main dataset I use comes from the IPUMS-I which is a collection of census data (typically the Census of Population and Housing) of several participating countries[13] (Minnesota Population Center, 2019). The census data in the IPUMS-I are available in a free, online platform where variables are harmonized across countries to facilitate comparative studies. Despite this, the variables available in each country's census still depend on the information collected by the statistical agencies so not all variables are necessarily available in each dataset. Therefore, the countries in this study were conveniently selected based on the availability of variables required for testing assimilation using the proposed framework. I look for two criteria in selecting which countries to include: Filipinos must be identifiable from the country of birth variable, and the year of arrival must also be available. Based on these two criteria, I pool one to two rounds of five countries' census data in the sample: Canada 2001 and 2011 (1,726,619 individuals), Greece 2001 and 2011 (2,085,492 individuals), Malaysia 2000 (435,300 individuals), Spain 2001 (2,039,274 individuals), and the US 2000 and 2010 (17,143,158 individuals), for a total of 23,429,843 observations[14]. The census data from IPUMS-I reflects individual-level data. Aside from birthplace and year of arrival, IPUMS-I census data also have variables on employment, age, educational attainment, and subnational indicators.

A limitation of using the IPUMS-I data is that not all country censuses directly report wages. Therefore, I introduce a wage index that reflects the "occupational score" an individual may have depending on his occupation and industry. This is similar to the strategy employed by Abramitzky et al (2014). The occupational score may be thought of as a ranking of industry-occupation combinations and would improve comparability across countries as differences in purchasing power is no longer an issue.

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[13] I acknowledge the following statistical agencies that originally produced the data collected in IPUMS-I: Statistics Canada (Canada), National Statistics Office (Greece), Department of Statistics (Malaysia), National Institute of Statistics (Spain), and Bureau of the Census (US). The IPUMS-I is a collaboration of the University of Minnesota, various National Statistical Offices, international data archives, and other international organizations, and is funded by the US National Science Foundation and the Demographic and Behavioral Sciences Branch of the National Institute of Child Health and Human Development.

[14] An apparent limitation in the selection of countries into the sample is the exclusion of the Middle East, which is a major destination. This is not particularly worrisome as the indices used in classifying institutions are based on relative values, so including/excluding countries may change each country's classifications but should have similar results which are primarily based on institutional heterogeneities. The characteristics of the Middle East is somewhat represented by cultural similarity (or the lack of it), the lack of diversity, a large migration network, and a fairly selective immigration policy. In addition, while the Middle East is a popular destination for Filipino migrants, there is still large value in analyzing assimilation in "less popular" destinations as this would highlight the effect of having (or not having) an extensive migration network in the destination.

I collected industry and occupation monthly wage data from ILOSTAT (International Labour Organization, 2019). Industry wages are categorized according to the International Standard Industrial Classification (ISIC68) and occupational wages are categorized according to the International Standard Classification of Occupations (ISCO88).

Let there be m industries and n occupations. Let $\boldsymbol{w_i}$and $\boldsymbol{w_j}$ be the $m \times 1$ and $n \times 1$ vectors of wages for the m industries and n occupations, respectively. Say, that $\boldsymbol{w_i}$and $\boldsymbol{w_j}$ are available over years t. I construct the wage score for each country and gender as follows:

1. Take the average wage for each industry in $\boldsymbol{w_i}$ and each occupation in $\boldsymbol{w_j}$ over time. Then take the grand average (across averages) for industries $\overline{\overline{w_i}}$ and occupations $\overline{\overline{w_j}}$.
2. Set the grand average for industries and occupations as the respective references to establish the ranking of industries and occupations. This is done by dividing each element of $\boldsymbol{w_i}$ by $\overline{\overline{w_i}}$ and dividing each element of $\boldsymbol{w_j}$ by $\overline{\overline{w_j}}$. The resulting vectors are $\widetilde{\boldsymbol{w_i}}$and $\widetilde{\boldsymbol{w_j}}$. Note that each element of $\widetilde{\boldsymbol{w_i}}$and $\widetilde{\boldsymbol{w_j}}$. indicate the ranking of the ith industry and the jth occupation relative to $\overline{\overline{w_i}}$ and $\overline{\overline{w_j}}$. The vectors therefore reveal the "hierarchy" among industries and occupations.
3. Generate the wage score matrix by multiplying the two vectors $\widetilde{\boldsymbol{w_i}}$and $\widetilde{\boldsymbol{w_j}}$ as $\widetilde{\boldsymbol{w_i}}\widetilde{\boldsymbol{w_j}}^{\boldsymbol{T}}$. The result is an $m \times n$ matrix with elements $\widetilde{w_{ij}}$ as the wage score of an occupation i in an industry j.
4. Individuals then get linked to their corresponding $\widetilde{w_{ij}}$ based on their industry and occupation.

The advantages of this strategy are that variation will not be limited by industry and occupation separately, but also purchasing power may be comparable across countries. This strategy assumes, however, that the "rankings" of occupations across the "rankings" of industries (e.g. professionals will always have higher scores than technicians, and professionals in services will always have higher scores than professionals in agriculture). It also assumes that the wage, occupational and industrial structure is unchanged across the time period, that is, there are no major policy changes and definitions and groupings of occupations and industries do not change over the period. Appendix 3.A.2 presents the accompanying tables to the wage computation. The average "ranking" of occupations and industries is reported in Table 3.A.2.1. The average matrix of industry-occupation wage scores for all countries is shown in Table 3.A.2.2 while Tables 3.A.2.3 to 3.A.2.12 report the industry-occupation wage score matrices by country and sex. However, this strategy is notably far from perfect, particularly in that it fails to account for within-industry, within-occupation, or within-industry-occupation variation of wages.

Data on cultural institutions, migrant networks and immigration policies are difficult to pinpoint from one source and, to my knowledge, is a lot harder to come by. I gather this information from a hodgepodge of different sources. I proxy for cultural similarity using country level indicators: the proportion of the population that speak English (which was taken from respective census data and the Eurobarometer 2012) and percentage of Christianity which is taken from the Pew Research Center (2014). Cultural diversity is made up by linguistic diversity indices (LDI) collected from the SIL International 2017 publication *Ethnologue: Languages of the World, Twentieth Edition* and the UNESCO 2008 World Report *Investing in Cultural Diversity and Intercultural Dialogue*. In addition, a religious diversity index (RDI) is taken from the Pew Research Center (2014) and a measure of ethnic fractionalization listed in Wikipedia based on Fearon (2003). Migration network data include the number of Filipino permanent and temporary migrants in 1999 (CFO, 2019). From this database I compute the permanent-temporary migrant ratio in 1999, and the percentage of permanent, temporary, and total migrants that go into the sample countries. As for immigration policies, as there is a lack of databases that may quantify immigration policies, I compute ad hoc measures from the IPUMS-I data that may be indicative of liberal or selective immigration policies. I use the percentage of immigrants with citizenship (however, this excludes the US since the citizenship indicator is not available), the skilled-unskilled immigrant ratio, the percentage of skilled and unskilled migrants relative to the immigrant population.

3.4 Methodology and Empirical Strategy

In estimating the assimilation profile of immigrants, Chiswick (1978) augmented the Mincerian log-wage equation[15] to include a foreign birth indicator to reveal the initial gap, linear and quadratic terms for years since migration (YSM) to test for assimilation and later on calculate the crossover time with natives, and an indicator whether a foreign person was naturalized to see any citizenship effects. To correct for return migration and changing cohort quality, Borjas (1985) used a repeated cross-section and decomposed within-cohort and across-cohort effects. To do this, rather than using linear and quadratic terms for YSM, Borjas (1985) included a vector of dummies pertaining to YSM cohorts grouped into intervals (just arrived, 1-5 years, 6-10 years, and so on, until 31+ years). YSM estimates can be improved further by including aging effects to weed out the effect of experience, arrival cohort effects to account for changes in cohort quality, and time fixed effects to take out aggregate demand effects such as changes in wage structure or inflation

[15] The Mincerian equation typically regresses the logarithm of wage on human capital characteristics such as years of schooling, years of experience, and experience-squared.

(Borjas, 1995). In their analysis using longitudinal data, Abramitzky et al (2014) used occupational score rather than log-wages and adopted Borjas' (1995; 1985) empirical strategy.

Given the progression of empirical works, the "basic" assimilation equation for an individual *i* from origin *j* of arrival cohort *m* in a certain country at time *t* would be:

$$y_{ijmt} = \alpha_0 + \boldsymbol{\beta}_{t-m}\boldsymbol{YSM}_{t-m,it} + \boldsymbol{\gamma}_m\boldsymbol{M}_{imt} + \boldsymbol{\pi X} + \sigma_j + \tau_t + u_{ijmt} \tag{3.1}$$

y_{ijmt} is the outcome (wage or occupational/wage score, employment), $\boldsymbol{YSM}_{t-m,it}$ is a vector of dummy variables indicating groups of intervals of how long a person has stayed in the country, $\boldsymbol{M}_{imt}$ is a vector of arrival cohort dummies representing cohort fixed effects to account for changes in cohort quality, $\boldsymbol{X}$ is a vector of time-variant individual-level control variables (i.e. age, educational attainmen[16]t) and time-invariant subnational fixed effects, σ_j represents country of origin fixed effects, τ_t represents time fixed effects, and u_{ijmt} represents the idiosyncratic error term. The vector $\boldsymbol{\beta}_{t-m}$ comprise the coefficients of interest and how β_{t-m}'s change across YSM_{t-m} indicates assimilation. If the β_{t-m} associated with earlier YSM are negative, this indicates the initial gap that immigrants experience relative to natives. Assimilation is said to occur if β_{t-m} start negative then approach zero, or become statistically insignificant across YSM, indicating that outcomes of immigrants are statistically the same as that of natives.

To establish the links between cultural institutions, migration networks, immigration policies, and assimilation, I build on the conventional empirical models of assimilation and generate a differential assimilation profile using classifications based on countries' aforementioned factors. The difficulty in using the mixed data on institutions, however, is that when each indicator is included in the same equation, very high correlation among these variables may confound estimates. To provide a more parsimonious measure for each factor, I calculate indices for cultural similarity, cultural diversity, migrant network, and immigration policy using a weighted normalized index (Acosta, 2010) by grouping various indicators under each factor. These indices reveal a country's "ranking" in that certain area relative to the mean among countries in the sample. This is done for all four factors and Table 3.1 summarizes the components of each index. Appendix 3.A.3 presents the formula used for the index. It follows that if the value for a country's

[16] Educational attainment is measured at the time of the census because education upon migration is unavailable in all countries' census data. Nevertheless, educational attainment is included to disentangle the returns to education from wage and employment assimilation. While not perfect, an added measure to address heterogeneity in the quality of incoming cohorts is the inclusion of the vector of cohort fixed effects.

index is positive, this means it ranks higher or reports indicators higher than the mean in the sample. The opposite is true if the index reports a negative value.

Table 3.1. Components of factor indices.

Cultural Similarity	**Cultural Diversity**
• Percentage of English Speakers • Percentage of Christians	• Linguistic Diversity Index (SIL International and UNESCO) • Religious Diversity Index • Ethnic Fractionalization Index
Migration Network[17]	**Immigration Policy**
• Ratio of permanent to temporary migrants in 1999 • Percentage of p*ermanent* Filipino migrants to a country in 1999 • Percentage of *temporary* Filipino migrants to a country in 1999 • Percentage of total Filipino migrants to a country in 1999	• Ratio of skilled to unskilled immigrants • Percentage of skilled immigrants • Percentage of unskilled immigrants • Percentage of immigrants with host-country citizenship (excluding US)

The components of cultural similarity are selected based on observable aspects of Filipino society. Although English is only their second language, majority of Filipinos speak English and are relatively fluent[18]. At the same time, majority of Filipinos are practicing Christians [about 92.6% according to the Pew Research Center (2014)], particularly Roman Catholics. These aspects of Philippine culture are among the easiest, if not the only ones currently available to quantify. The components of cultural diversity combine the Linguistic Diversity Indices of SIL International and UNESCO and includes indices for religious diversity and ethnic fractionalization to reflect the composition of peoples in different countries. The Philippines is relatively unanimous in terms of religion and ethnic composition. These indices and their effects are largely driven by language since language is both a form of human capital and a facilitator necessary to acquire host-country human capital (Chiswick and Miller, 1995). The migration network is

[17] Percentage of Filipino migrants to a country is relative to total Filipino migrants of that year for each type.

[18] The education system is tailored to be taught dominantly in English; Math, Science, and all other subjects are taught in English except for the subject "Filipino". English is also used as a significant mode of verbal and written communication along with Filipino, *Tagalog* and other major languages. For example, people from the Visayas island groups are more likely to be fluent in English and their local language (commonly known as *Bisaya*) than the local language in Luzon, which is *Tagalog*.

mostly made up of information on the past migration flows from the Philippines. It is necessary to distinguish between permanent and temporary migrants, and hence "permanent" and "temporary destinations" as pointed out by Dustmann (1993) as these will not only have an impact on the level of human capital they bring with them, but also their intended stay in the host country. Out of these factors, the hardest to classify is the immigration policy of host countries. I proxy for a country's immigration policy primarily using the ratio of skilled to unskilled immigrants, as the immigration policy of a country will most likely be reflected on the skill composition of immigrants. Selective countries will tend to have higher proportions of skilled immigrants and liberal countries will tend to have more unskilled immigrants. I also look at the percentage of immigrants with host-country citizenship to proxy for the ease or likelihood of attaining naturalization (although Chiswick (1978) claims no impact for citizenship). However, I acknowledge the caveat that the actual elements of classifying countries' immigration policies are a lot more nuanced than how I try to capture it (Kaushal and Lu, 2015; Antecol et al, 2006; Cobb-Clark, 2003; Miller and Neo, 2003). Nonetheless, I proceed with caution using the current data sources and will update accordingly based on the available of new, more reliable, or more detailed data.

I then generate binary variables, H_c, for each country *c*, equal to 1 if a country's index is positive, indicating high levels of a factor relative to other countries in the sample, and 0 otherwise. Immigration policy is defined differently where a positive index reflects a more selective migration policy, and a negative index reflects a more liberal migration policy. This binary indicator is favored over the direct use of the indices as this will allow me to clearly classify the assimilation profiles according to the dichotomies established by the indices. I then modify equation (3.1) to include interaction terms between YSM and H_c for individuals *i* in country *c* as follows:

$$y_{icmt} = \alpha_0 + \widetilde{\boldsymbol{\beta}}_{t-m} H_c \times \boldsymbol{YSM}_{t-m,it} + \boldsymbol{\gamma}_m \boldsymbol{M}_{imct} + \boldsymbol{\pi X} + \varphi_c + \tau_t + u_{it} \tag{3.2}$$

Where y_{ict} is the occupational wage score and employment status of individual *i* in country *c*, with arrival cohort *m* at time *t*. H_c is the binary indicator whether country *c* has *high levels* of a certain determinant. For migration policy, H_c and I add host country fixed effects φ_c and drop origin fixed effects because all immigrants come from the Philippines. The new coefficients of interest are $\widetilde{\boldsymbol{\beta}}_{t-m}$ which may be interpreted as differential slopes added to $\boldsymbol{\beta}_{t-m}$, (when H_c = 0), allowing us to distinguish between assimilation in high- and low-index countries. $\boldsymbol{X}$ contains the same covariates in equation (3.1) but includes occupation and industry fixed effects only for the employment equation and not the occupational wage score equation since this variable is computed based on occupation-industry structure outlined previously.

While the specification of the estimating equation tries to address issues in changes in cohort quality and the normalization of comparison groups, an apparent limitation is that it cannot directly address issues on migrant self-selection (which is typically driven by origin country characteristics of income distribution and mobility costs as per the Roy model [Borjas, 1987]), and selective return migration. The migrant self-selection issue may be partially addressed since all immigrants come from the same sending country, thus ruling out any variation affecting differences in income distribution and mobility costs. However, there are structural differences in the occupations and educational attainment of Filipinos in different countries. In this regard, the inclusion of host country fixed effects may be able to account for this as it is a way to account for skill composition of Filipino migrants to each destination country, albeit being an imperfect measure. This is also internalized later on when presenting an estimation comparing the assimilation profiles of Filipinos going to relatively "permanent" and "temporary" destinations. Unfortunately, selective return migration cannot be fully accounted for given that any pooled dataset is a poor substitute for longitudinal data. I acknowledge this limitation, however proceed with the analyses since the main purpose of this study is to lay the groundwork for utilizing the unique set up of one sending country and multiple destination countries to highlight the role institutional differences may have in influencing labor market assimilation. While I make no assertion for causality, I contend that even correlational evidence from a new angle contributes new knowledge to the literature on assimilation.

I estimate equation (3.2) using OLS and include only people of working age (18-64). Occupations and industries relating to public administration and national defense are omitted because immigrants typically do not occupy these jobs. I also exclude natives who report positive levels of YSM or a year of arrival. Natives are defined as those born in the host country and had no history of migrating into the host country. Immigrants are defined as those of foreign birth. I also test for the effects of each component of the indices to see how these facets affect assimilation and check for robustness to disaggregated measures where subnational variation is available. I acknowledge the disproportionate distribution of observations toward the US and so to see whether results are being driven by the US sample, I check for robustness by excluding the US entirely. In addition, I check for differences in assimilation with respect to the sectoral intensity of countries. Specifically, I look at how assimilation may differ with respect to the contribution to employment and GDP of the agricultural, industrial, and services sectors. Lastly, I inspect the cohort quality effects of each regression. Appendix 3.A.5 reports the tables and figures when excluding USA, Appendix 3.A.6 for disaggregated components, Appendix 3.A.7 for subnational variation, and Appendix 3.A.9 for sectoral intensity.

3.5 Results

3.5.1 Profile of Filipinos in the Sample

In my analysis of assimilation, I begin by presenting descriptive statistics on human capital characteristics of Filipino migrants to establish their profile. Table 3.2 presents distribution of Filipinos in the sample relative to natives and other immigrants. In the sample of 23,429,843 individuals, 88.35% are natives (20,699,671 individuals) and 11.65% are immigrants (2,729,949 individuals). Filipinos number 113,767 which comprises 0.49% of the entire sample. The Filipino migrant network appears to be largest in Canada where they make up 1.25% of the sample and 5.93% of the immigrant population. Relative to the immigrant population, the network is largest for Malaysia (8.28%), followed by Canada (5.93%), then the US (4.4%)

Table 3.2. Distribution of Filipinos, natives, and immigrants across countries in the sample.

Country	*# of Filipinos*	*% Filipinos*	*% of Natives*	*Census count*	*Filipinos % of immigrants*	*# of immigrants*
CA	21,582	1.25	78.89	1,726,619	5.93	364,434
GR	1,459	0.07	89.09	2,085,492	0.63	227,454
MY	2,481	0.57	93.09	435,300	8.28	30,083
SP	815	0.04	94.73	2,039,274	0.77	107,394
US	87,430	0.51	88.33	17,143,158	4.40	2,000,584
Total	113,767	0.49	88.35	23,429,843	4.17	2,729,949

Source: IPUMS-I, authors' calculation.

There is a noticeable pattern across host countries in terms of the educational attainment of Filipinos and immigrants (Table 3.3). Countries with observably "selective" immigration policies such as Canada and the US[19] tend to have more highly educated migrants. More than half of Filipinos in Canada have a university degree (52.5%), which is higher than the proportion for Canadians (23.8%) and other immigrants (37.5%). The same may be said in the US where 44.6% of Filipinos are university degree holders whereas there is only 23.5% that are university degree holders among Americans and 22.6% among other immigrants. There is also a significant proportion of Filipino secondary degree holders in Greece (60.1%,

[19] Note the contradiction that while several studies consider the US to have a "liberal" immigration policy, this is relative to countries in their sample. As may be seen in the latter sections of this study, compared to Spain, Greece, and Malaysia, the US may be considered "selective" given the criteria that I use.

and larger than natives and other immigrants), Canada (42%, but less than natives and other immigrants), the US (48.7%), and Spain (34.3%). This is somewhat consistent with the findings of Cobb-Clark (2003) which found that selective countries Malaysia is a peculiar case since Filipinos tend to have lower educational attainment compared to natives and other immigrants. Filipinos that have less than Primary Education make up the lion's share (76.2%), which is strikingly higher than Malaysians (31.4%) and other immigrants (44.2%). The proportion of formal degree holders are much lower as well.

Table 3.3. Educational attainment of Filipinos, natives and immigrants across countries.

	Less than Primary			Primary			Secondary			University		
Host Country	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*
CA	3.13	7.18	8.10	2.40	10.36	8.48	**42.01**	58.62	45.92	**52.46**	23.84	37.50
GR	2.86	3.34	4.72	19.99	34.61	33.10	**60.17**	44.90	46.72	16.99	17.15	15.46
MY	**76.23**	31.39	44.19	18.87	53.11	21.59	1.52	4.42	2.64	3.38	11.07	4.77
SP	11.31	8.28	10.15	**46.34**	49.90	43.29	**34.34**	33.50	35.97	8.00	8.32	9.99
US	1.33	0.71	7.78	5.36	9.82	22.60	**48.74**	65.93	47.04	**44.57**	23.54	22.57

Source: IPUMS-I, authors' calculation. Figures may not add up to 100% because of undisclosed or missing responses.

A similar pattern may be found in the occupational distribution of Filipinos across countries (Table 3.4). Large shares of Filipinos in Canada work as Technicians (21.6%) and Professionals (13.3%). These occupations tend to have tighter skill requirements hence the probable need for university degrees. The US has the highest proportion of Filipinos that work as Professionals (18.4%) and have a lot of Filipino Technicians (11.2%) and Clerks (20%) as well. There are also a lot of Filipino Service Workers in Canada (20.5%), Spain (20.7%), and the US (16.6%). Malaysia appears to be a peculiar case. Given that most Filipinos in Malaysia have less than Primary Education, 15.68% of Filipinos are agricultural workers and only 14.8% are working in Elementary Occupations. However, about 44.1% are either unemployed or work in unclassified occupations. On the other hand, Greece (where 60.2% of Filipinos have secondary degrees) and Spain (where 46.3% have primary degrees and 34% have secondary degrees) have the largest proportion of Filipinos working in Elementary Occupations (65.7% and 30.2%, respectively).

As for the industrial distribution of Filipinos (Table 3.5), large concentrations appear for the Health and Social Works sector (22.1% in the US and 17.4% in Canada) where skill requirements tend to be higher. There are also relatively more Filipinos in Canada and the US that work in Manufacturing (13.6% and 11.9%, respectively) and Wholesale and Retail Trade (12.2% and 11.6%). On the opposite end of the skill spectrum, there are insurmountably large concentrations of Filipinos in Private Household Services in Greece (59.7%) and Spain (24.8%) as these are countries that Filipinos typically go to work as maids, valets, or babysitters. In addition, about 17.8% of Filipinos in Spain work in hotels and restaurants. Malaysia appears to be a unique case relative to the other countries as there is a large proportion of Filipinos in unclassified industries (or potentially unemployed), and concentrations in Agriculture (17.6%), Construction (10.6%) and Manufacturing (10%)

It may be said that Filipinos in the sample have a broad range of educational attainment and this may be heavily linked to the countries they go to, and occupations and industries they work in. These large differences also reveal the need to control for these factors in the assimilation equations where possible (these factors may all be included in the employment equation, but only the educational attainment may be included in the wage score equation since the wage score is computed based on occupation and industry).

3.5.2 Main results

Before I report the estimates for equation (3.2), I briefly present the classification of each country in the sample (Table 3.6) according to the indices computed using the criteria in Table 3.1. H_c =1 for an index if a country has relatively high levels (compared to other countries) of cultural similarity, cultural diversity, or migration network, or if their migration policy is comparatively selective.

Canada has comparatively high cultural similarity and diversity, a low Filipino migration network (despite it being a popular destination for permanent migrants, historically, it has a low network compared to the massive network in the US), and comparatively the most selective migration policy. Greece has high cultural similarity, comparatively the lowest cultural diversity and Filipino migration network, and a liberal migration policy. Malaysia is comparatively the least culturally similar and the most culturally diverse, has a low Filipino migration network and the most liberal migration policy. Spain, given its history in colonizing the Philippines, surprisingly has low cultural similarity and diversity (this has a lot to do with a very low proportion of the population that speaks English despite being a dominantly Christian country), low Filipino migration network, and a liberal migration policy. The US has the highest cultural similarity among the five countries and comparatively the largest Filipino migration network, low cultural diversity, and a selective migration policy compared to other countries in the sample (as opposed to the analysis done in the comparative studies of Kaushal and Lu [2015],. Antecol et al [2006], and Miller and Neo [2003] where the US is depicted to be the relatively liberal country compared to Canada and Australia).

Table 3.4. Occupational distribution of Filipinos, natives and immigrants across countries.

		Canada			Greece			Malaysia			Spain			United States		
ISCO	*Occupation*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*
1	Managers	5.06	9.28	8.97	0.64	4.66	2.57	0.57	4.46	3.59	3.83	5.67	4.76	6.3	9.73	7.68
2	Professionals	**13.27**	16.51	17.93	0.71	9.49	5.35	0.43	3.92	1.57	4.51	7.54	5.98	**18.43**	12.93	9.79
3	Technicians	**21.55**	12.11	10.93	1.78	5.52	2.93	1.38	8.03	3.04	4.24	6.73	5.20	**11.17**	8.81	7.35
4	Clerks	8.51	8.85	1.02	2.00	5.9	3.29	0.71	6.58	1.80	3.15	6.03	4.25	20	17.14	11.70
5	Service Workers	**20.46**	16.93	15.21	9.71	11.05	11.61	5.61	8.00	8.46	**20.66**	11.42	12.37	**16.64**	15.38	16.27
6	Agricultural	0.55	2.89	1.21	2.71	6.76	4.02	**15.68**	7.94	16.81	0.55	2.22	1.56	0.45	1.43	1.68
7	Crafts	5.59	8.31	6.40	1.64	8.02	15.55	8.03	5.69	6.22	3.83	9.61	9.27	5.17	9.64	9.38
8	Plant and Machine Workers	7.77	6.15	6.93	3.85	4.31	3.90	8.12	9.15	15.61	1.23	3.96	2.92	8.03	9.28	11.87
9	Elementary	6.59	3.79	4.00	**65.67**	3.92	18.43	**14.77**	6.38	23.92	**30.23**	6.7	16.5	4.09	4.13	7.97
	Not in universe	10.64	15.19	21.39	10.49	38.66	31.26	**44.09**	37.74	17.93	27.77	39.7	36.97	9.21	11.2	16.13

Source: IPUMS-I, authors' calculation
Note: Not in universe typically includes unemployed people and those in occupations not classified in the ISCO.

Table 3.5. Distribution of Filipinos, natives, and immigrants across industries

		Canada			Greece			Malaysia			Spain			United States		
ISIC	*Industry*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*	*PH*	*Host*	*Immi.*
10	Agriculture	0.45	2.21	1.09	1.14	7.12	8.11	**17.58**	8.62	20.23	0.55	3.64	5.56	0.97	2.07	3.5
20	Mining	0.55	1.75	0.6	0.00	0.16	0.14	0.29	0.17	0.17	0.00	0.14	0.11	0.07	0.45	0.18
30	Manufacturing	**13.63**	9.22	11.35	1.43	6.65	8.55	**10.02**	13.01	19.94	2.74	10.74	7.68	**11.92**	12.59	13.97
40	Utilities (EGW)	0.29	0.43	0.28	0.21	0.77	0.40	0.05	0.52	0.19	0.14	0.41	0.22	0.42	0.87	0.33
50	Construction	2.16	5.74	4.13	0.79	4.04	12.51	**10.59**	4.13	7.95	3.83	6.9	9.63	1.8	6.25	6.75
60	Wholesale and Retail	**12.24**	13.83	12.05	3.21	10.39	8.74	5.94	7.74	8.03	6.02	9.42	7.94	**11.63**	14.3	13.01
70	Accommodation	8.39	5.03	5.71	6.07	4.05	7.44	3.56	3.6	5.65	**17.78**	3.51	7.15	7.03	5.2	8.03
80	Transport and Logistics	3.64	5.01	4.48	6.00	4.46	2.98	2.00	3.95	2.88	2.05	4.08	3.23	4.9	4.56	3.84
90	Financial Services	5.14	3.98	4.77	0.36	1.74	0.66	0.05	2.20	0.69	0.82	1.67	0.94	5.33	4.16	3.01
100	Public Administration	2.60	6.25	3.40	0.79	4.58	1.57	0.81	6.56	2.43	1.09	4.89	2.18	5.14	5.24	2.37
111	Real Estate	9.31	8.62	11.17	5.64	4.56	4.51	0.33	2.21	1.75	5.06	4.62	4.76	6.64	6.98	7.35
112	Education	3.02	6.63	5.49	0.79	4.44	2.38	0.48	4.42	1.24	3.01	3.71	2.73	4.42	9.3	5.94
113	Health	**17.43**	9.27	7.64	1.21	3.36	2.53	0.19	1.51	0.65	2.19	3.67	2.94	**22.13**	8.56	6.93
114	Other Services^	10.51	6.85	6.44	1.28	3.2	2.16	0.33	1.11	1.19	2.19	1.86	1.94	7.48	7.94	7.55
120	*Private Household Services^^*				**59.67**	0.17	4.64	3.37	0.49	8.3	**24.76**	1.03	6.02	0.92	0.32	1.12
	Not in universe	10.64	15.19	21.39	10.49	38.66	31.26	**43.61**	37.5	17.57	27.77	39.7	36.97	9.21	11.2	16.13

Source: IPUMS-I, authors' calculation

Note: Not in universe typically includes unemployed people.

^ 114 Other Services includes services of membership organizations (trade unions, political and religious organizations), repair of computers, personal and household items, washing and dry-cleaning, hairdressing, and funeral activities.

^^ 120 Private Household Services typically includes services such as maids, cooks, valets, butlers, carers, and babysitters, which are employed by private households.

Table 3.6. Classification of countries according to indices.

	Cultural Similarity	*Cultural Diversity*	*Migration Network*	*Migration Policy*
CA	**High** (0.777)	**High** (1.372)	Low (-0.603)	**Selective** (2.633)
GR	**High** (0.322)	Low (-3.069)	Low (-1.318)	Liberal (-0.418)
MY	Low (-1.671)	**High** (2.613)	Low (-0.103)	Liberal (-2.716)
SP	Low (-0.683)	Low (-0.441)	Low (-1.137)	Liberal (-0.081)
US	**High** (1.255)	Low (-0.475)	**High** (3.161)	**Selective** (0.581)

Source: Various institution data, authors' calculation.

With these classifications, I proceed to present the assimilation profiles of Filipinos, first as a pooled regression with no country fixed effects [as in equation (3.1)], and then with country-level institutions classifications [as in equation (3.2)]. I present my findings by plotting the coefficients $\boldsymbol{\beta}_{t-m}$ when H_c = 0 and $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ when H_c =1 across YSM.

Figures 3.1(a) and 3.1(b) present the Filipino wage and employment assimilation profiles, respectively (Table 3.A.4.1 in the Appendix). Noticeably, Filipinos have an initial wage disadvantage of (-31) which steadily decreases to around (-17) after 31+ years. This indicates that the wages of Filipinos experience convergence somewhat to that of natives, although never fully assimilate (not statistically different from natives' wage scores). The change of the gap in terms of wage scores may occur through a movement upward in terms of industry or occupation. For example, with an absolute gap of 31 an immigrant may transition from being a Clerk in a relatively low value-adding sector like Agriculture to a relatively higher value-adding sector such as Manufacturing. Another example is that with an absolute gap of 17, an immigrant in the Wholesale and Retail Trade sector may transition from the lowest paid Elementary Occupation to a more decent-paying job as a Clerk (see Table 3.A.2.1 and 3.A.2.2 in the Appendix for a comprehensive view of occupational and industrial transition based on the calculated wage score).

As for employment assimilation, it may be seen that Filipinos initially suffer a 6% disadvantage in employment rate but this converges with natives up to 10 YSM. At 11 years, they gain an advantage ranging from 3% 11-15 YSM to 5.3% higher employment rates after 31+ YSM.

When I exclude the US (refer to Figure 3.A.5.1 and Table 3.A.5.1 in the Appendix), I find a similar pattern but with a slightly lower gap in wage [(-20) initially, increasing to (-32) in 1-5 YSM, but decreasing to (-14) at 31+ YSM]. There appears to be convergence, but never full assimilation. As for employment, Filipinos appear to have statistically similar employment rates as natives in the first 5 years, but they gain a 4-10% advantage from 6-10 to 31+ YSM. This implies that the inclusion of the US gives a robust direction of penalties/advantages but tends to push the wage and employment coefficients downward (larger wage advantage, smaller employment advantage).

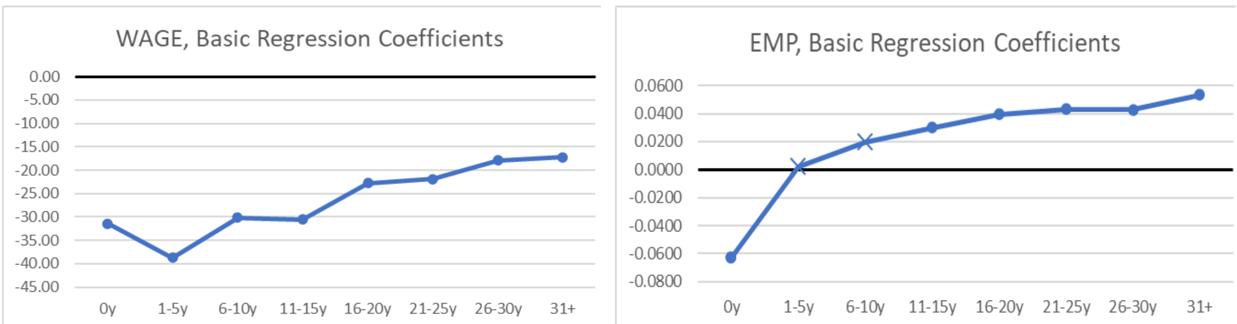


Figure 3.1. (a) Wage and (b) Employment assimilation profile, basic pooled regression.

Note: Points represent differential wages over YSM, these are relative to natives of each host country. These points are statistically significant at any of either 10%, 5%, or 1% levels. Points with "x" symbolize statistically insignificant coefficients.

Cultural Similarity

Figures 3.2(a) and 3.2(b) (based on Table 3.A.4.2 in the Appendix) depict the assimilation profile of Filipinos in countries with high and low cultural similarity with the Philippines. It may be seen that although there is no complete assimilation with natives, there is convergence as the statistical difference becomes closer to the wages of natives. Furthermore, the wage profiles of Filipinos in higher-similarity countries (CA, GR, US) are closer to that of natives' (smaller penalty) than those in lower-similarity countries and suggest that convergence begins in 6-10YSM. This reinforces the claim of Chiswick and Miller (1995) that language serves as both human capital and a facility to acquire additional human capital over time, making it easier for Filipinos to access higher-paying occupations. Being in a country with low cultural similarity however, gives a larger penalty and does not show any sign of convergence until around 31+ YSM. In this case, the difficulty in adjustment to a very different culture or a different dominant religion may restrict the transferability of human capital.

Looking at the employment assimilation profile, it may be seen that the employment rate for Filipinos is higher than natives and the advantage widens over YSM. It appears that Filipinos in high-similarity countries start with a disadvantage upon arrival (7.2% lower than natives at 0 YSM), but this is closed in 1-5 YSM, and they receive an advantage from 6-10 YSM onwards. However, the advantage is lower compared to Filipinos in low-similarity countries. Despite better transferability in high-similarity countries, the comparatively lower employment rate may potentially be due to competition or crowding effects since Filipinos carry similar skills to that of natives in high-similarity countries, whereas those in low-similarity countries end up taking lower-paying jobs unwanted by natives.

Excluding the US paints a slightly different picture (Figure 3.A.5.2 and Table 3.A.5.2 in the Appendix). Filipinos' wage penalty and employment advantage are smaller and the difference between Filipinos in high- and low-similarity countries tend to be less pronounced and at times overlap. Furthermore, I find similar results when I disaggregate the index into its components (percentage of English speakers [Figure 3.A.6.1 and Table 3.A.6.1] and percentage of Christians [Figure 3.A.6.2 and Table 3.A.6.2]).

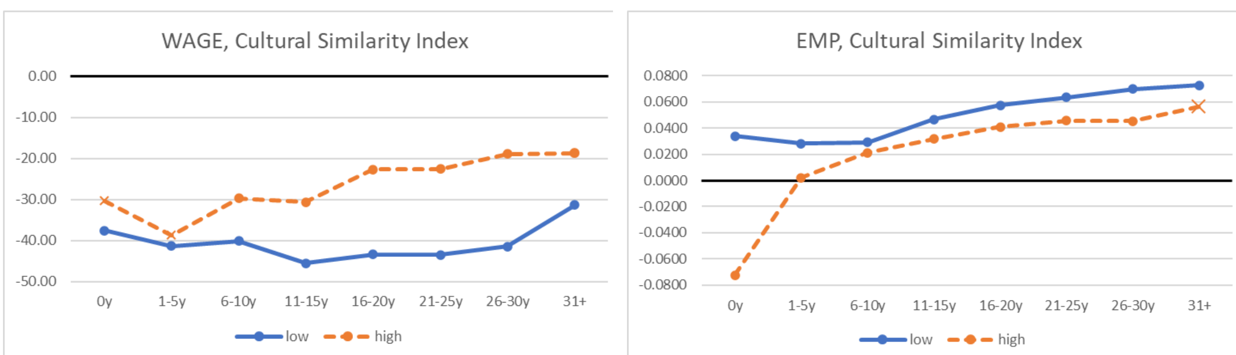


Figure 3.2. (a) Wage and (b) Employment assimilation profile by cultural similarity.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Cultural Diversity

When looking at the effect of cultural diversity (Figure 3.3(a) and 3.3(b); Table 3.A.4.3 in the Appendix), it appears that being in high-diversity countries puts Filipinos in a significantly lower assimilation profile across longer YSM compared to those in low-diversity countries although the opposite is true upon arrival. From 1-5 YSM onwards, the wage score penalty for those in high-diversity countries is around 20 points larger compared to those in low-diversity countries. And where Filipinos in low-diversity countries statistically assimilate around 26-30 YSM, those in high-diversity countries still have a large disadvantage. In terms of employment, Filipinos in high-diversity countries start with an advantage whereas those in low-diversity countries start with a disadvantage. Starting around 1-5 YSM however, both groups appear to have an advantage over natives. Visually, it appears that those in high-diversity countries have lower employment rates than those in low-diversity countries, but this difference is not consistently statistically significant. It may then be said that from 1-5 YSM onward, Filipinos have the same employment assimilation profile regardless of diversity.

When excluding the low-diversity US (Figure 3.A.5.3 and Table 3.A.5.3 in the Appendix), the wage penalty becomes smaller and the difference between high and low diversity countries is the same however smaller as well. The employment advantage becomes larger, as well as the gap between those in high and low diversity countries. Furthermore, the employment advantage decreases from 16-20 YSM onwards.

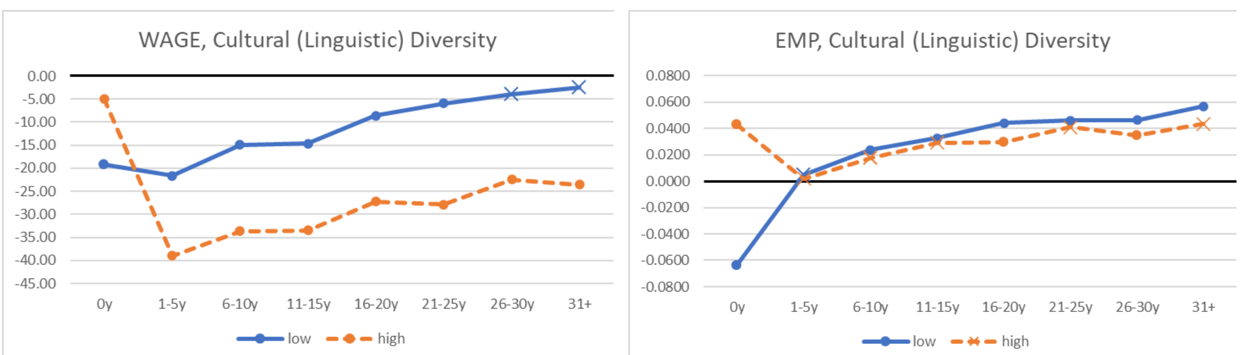


Figure 3.3. (a) Wage and (b) Employment assimilation profile by cultural and linguistic diversity.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

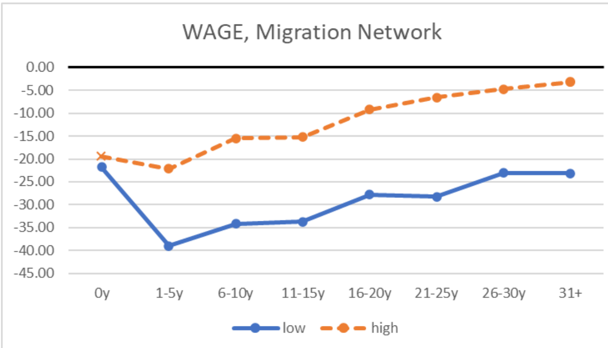
To my knowledge, no study has investigated how diversity may influence immigrant wage assimilation. An explanation I can offer about why diversity may hinder convergence and assimilation is that countries with a history of great diversity may have a more complex human capital pool, decreasing the transferability of skills and the returns to education and labor market experience, thus making it harder for immigrants from less diverse origins to adapt. The Philippines has low diversity, so moving to a high-diversity country may require a more difficult adjustment process when dealing with other cultures.

When I attempt to test the effects of the disaggregated components of the diversity index (Figure 3.A.6.3 and Table 3.A.6.3 in the Appendix), I find that cultural diversity cannot be disentangled from both religious and linguistic diversity since these factors are perfectly collinear in the sample. The results mirror what is presented above. Comparing countries with low- and high-fractionalization gives a slightly different picture (Figure 3.A.6.4 and Table 3.A.6.4 in the Appendix). Filipinos in countries with high ethnic fractionalization tend to have lower wage scores than those low fractionalization countries upon arrival and up to 1-5 YSM. From 6-10 YSM onward, the wage penalty for those in high fractionalization countries becomes smaller than those in low fractionalization countries, but the difference is statistically insignificant. They only appear to statistically assimilate with natives around 31+ YSM. As for employment, it appears that the employment advantage is consistently lower for those in high fractionalization countries.

A potential explanation I could offer is that a more fractionalized society has a more complex human capital pool, making it harder for employers to read signals about immigrants' human capital. This may potentially obscure wage assimilation and employability as in Malaysia where Filipinos are generally restricted to lower-skill work.

Migration Network

Figures 3.4(a) and 3.4(b) (Table 3.A.4.4 in the Appendix) illustrate the effect of the migration network on wage and employment assimilation profiles, respectively. It appears that having an extensive migration network puts Filipinos on a higher assimilation path in terms of wage score although there is no statistical difference upon arrival. This confirms Hatton and Leigh's (2011) and Mane and Waldorf's (2013) findings of a potential crowding effect with newly arrived migrants, but improved transferability with a more extensive network of historical immigration. I believe this is evident in terms of employment as well seeing that Filipinos in a high-network country have a disadvantage upon arrival, but this is immediately eliminated and roughly has statistically the same employment rate from 1-5 YSM onwards as those in low-network countries. With a higher historical migration network, not only would the host society and employers be more accepting and perceptive of the skills brought by immigrants, but earlier migrants of the same network may help new migrants find work.



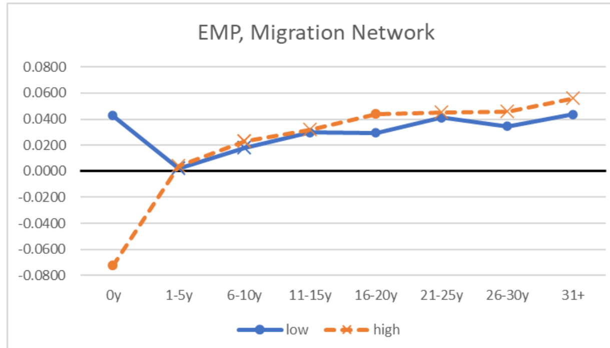


Figure 3.4. (a) Wage and (b) Employment assimilation profile by migration network.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Excluding the US (which is a large, historic destination of Filipino migrants), however, paints a different picture (Figure 3.A.5.4 and Table 3.A.5.4 in the Appendix). The wage score of Filipinos in high network countries decreases and gets overtaken by those in low network countries from 11-15 YSM onwards. The results for the employment profile indicate an employment advantage which is higher than those in low-network countries, but the gap statistically closes around 6-10 YSM onwards. This may indicate poorer labor market outcomes due to saturation as per the earlier works of Chiswick and Miller (2005) and Cortes (2008). A crowding effect may also cause existing immigrants to downgrade occupation if newer immigrants are higher-skilled.

In looking at the impacts of the disaggregated components of the migration network index, I focus on the percentage of the Philippines' historical migrants that go into a country and the ratio of permanent to temporary migrants to a country (Figures 3.A.6.5 and 3.A.6.6, and Tables 3.A.6.5 and 3.A.6.6, respectively the Appendix). The importance of looking at the distribution of historical migration is straightforward and, as mentioned previously, may influence the culture of acceptance of the host society and facilitate the entry and adjustment of new migrants (Hatton and Leigh, 2011). In addition, the permanent-temporary migrant ratio is interesting to look at since it reveals the nature of migrants' stay in a country which may affect the type (or level) of skills that migrants bring into a country (Dustmann, 1993). A country with a culture of permanent migrants will have more Filipinos that have higher skills and greater incentives to assimilate and may likely be more accepting of immigrants, thereby facilitating of assimilation. Conversely, a country with a history of being a temporary destination may be less accepting of migrants especially when they do not spend long enough times in the country to learn about the culture and assimilate.

I find that Filipinos in historically popular destinations have no clear, consistent difference in wages when compared to Filipinos in non-historical countries. In addition, much like the finding above, historical destinations penalize Filipinos' employment rates upon arrival (lower than natives) potentially due to crowding, and have a clearer, much lower employment rate compared to Filipinos in non-historical countries. Meanwhile, a higher wage score profile is apparent for Filipinos in "permanent" destinations[20] compared to those in "temporary" destinations which may indicate that permanent migrants have a stronger will to assimilate. However, as expected, Filipinos in "temporary" destinations have a consistently higher employment rate possibly thanks to their motivation of migrating solely for an economic purpose. Temporary migrants may not stay long enough to increase their wage, but they would ensure that they are able to secure employment.

Immigration Policy

Figures 3.5(a) and 3.5(b) (Table 3.A.4.5 in the Appendix) present the difference in the assimilation profiles of Filipinos in countries with comparatively liberal and selective migration policies. It may be seen that Filipinos in selective countries are put on a higher wage assimilation profile than those in liberal countries, with the gap widening from 6-10 YSM and only closing a little at 31+ YSM. However, the employment rate of those in selective countries start out lower than natives upon arrival, and although they gain an advantage over natives from 1-5 YSM onwards, it remains lower than that for Filipinos in liberal countries. This supports the findings of Miller and Neo (2003) stating that it is easier to find employment in liberal countries, but wage gaps start out larger. In selective countries, although it is harder to gain employment, those that can secure employment tend to get paid higher wages. These results may be picking up the stronger recognition of (and stricter qualifications for) professional skills and educational attainment that

[20] The countries that have more permanent migrants relative to temporary migrants are Canada, the US and surprisingly, Spain. While Canada and the US are known destinations for would-be permanent Filipino migrants, permanent migrants from the Philippines to Spain has a relatively larger share of total permanent migrants from the Philippines (around 1.3% in 1999) as compared to Greece and Malaysia (0.0033% and 0.0120%, respectively). Excluding Spain from being classified as a permanent destination based purely on comparing the sheer number of permanent migrants would yield the results in the section for immigration policy (where the US and Canada are considered the countries with a relatively selective immigration policy). The use of the permanent-temporary ratio reveals whether the country is attracting more permanent migrants compared to temporary migrants.

the US and Canada have compared to Greece, Malaysia, and Spain. Noticeably, countries with more liberal immigration policies are also the countries with more unskilled immigrants, which may imply that though it is easier for immigrants to find employment, they are also given the jobs that natives may not want (which are typically unskilled, low-paying work). Of particular note is Spain whose labor market is highly segmented, preventing immigrants from moving up to higher-paying work (Fellini and Guetto, 2019; Simon et al, 2014).

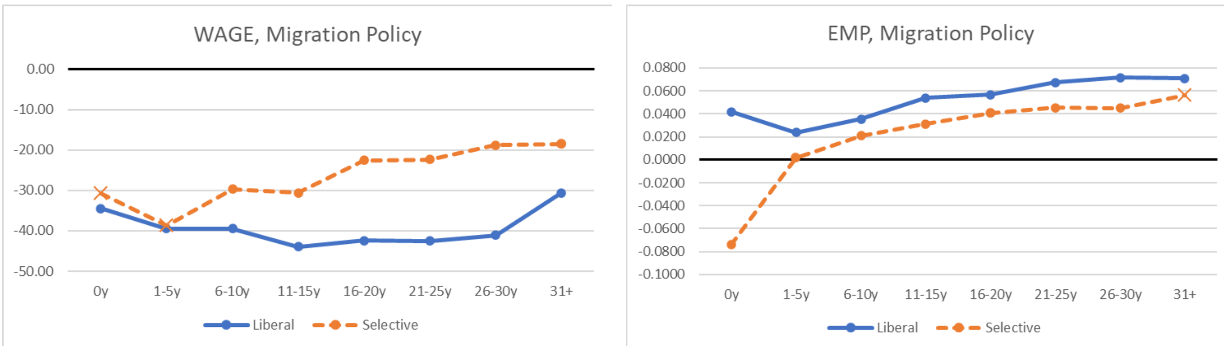


Figure 3.5. (a) Wage and (b) Employment assimilation profile by migration policy.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "Selective" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Liberal" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

When excluding the US (Figure 3.A.5.5 and Table 3.A.5.5 in the Appendix), I find a different picture where the wage gap starts out larger in selective countries but crosses over those in liberal countries after 11-15 YSM and becomes statistically similar from 21-25 YSM onwards. The employment profile is roughly similar as the finding above except it becomes statistically similar to those in liberal countries starting 11-15 YSM.

When I investigate the disaggregated components of the migration policy index, I focus more on components that have subnational variation such as the skilled-unskilled immigrant (all) ratio and the proportion of all immigrants with host nationality (refer to Figures 3.A.7.1 and 3.A.7.2, and Tables 3.A.7.1 and 3.A.7.2 respectively in the Appendix. Analysis using country-level variation is also available in Tables 3.A.6.7 and 3.A.6.8, and Figures 3.A.6.7 and 3.A.6.8, respectively). It is important to note that countries with selective migration policies[21] tend to have a larger proportion of skilled migrants (ISCO 1-4) relative to unskilled migration (ISCO 5-9) and more naturalized immigrants. Filipinos in regions with a skilled-unskilled ratio greater than 1 suffers a larger wage gap with natives than Filipinos in regions where the ratio is less than 1. The employment rate advantage is statistically similar between the two groups although both appear to have a disadvantage upon arrival. This may indicate more intense competition in occupations with other immigrant groups. In terms of the proportion of immigrants with a host nationality, there appears to be no clear difference in the wage score assimilation between Filipinos in regions with high and low proportions of immigrants with host nationality. This agrees with Chiswick's (1978) findings that the ease of receiving citizenship may not affect assimilation. The result for employment mirrors the results presented above with the employment rate advantage of Filipinos in regions with a high proportion of immigrants with host nationality being lower than Filipinos in low-proportion regions. This lends support to the claim that countries where more immigrants aspire to become citizens would make it harder for immigrants to secure higher-paying occupations. It may be misleading to infer that this association is due to the ease in gaining citizenship because a "immigrant-citizen network" effect may be captured as well. Canada is the country with the largest proportion of naturalized immigrants, and although this does not strongly suggest that acquiring citizenship is easier, it may have been made easier for migrants due to positive selection (those that are given visas are also more skilled and may meet host human capital requirements more effectively). Unfortunately, I take caution in giving this interpretation given the difficulty in disentangling these two effects given the current data.

Cohort quality effects

I briefly comment on the cohort quality effects in each model (Appendix 3.A.8). Overall, looking at wage estimates, I find positive, albeit decreasing cohort quality over time. Such is the case when I look at the basic regression, and the heterogeneities by cultural similarity and migration policy. However, when I test for the heterogeneities by cultural diversity and migration network, I find that there is no discernible pattern or significance for cohort quality. Conversely, cohort quality in terms of employment rate, unanimously (across all heterogeneities) appears to start with a distinct disadvantage but improves over time such that the most recent cohorts have statistically similar employment rates with natives. However, when I look at cohort quality effects per country (Figure 3.A.10.2 in the Appendix), it appears that there is no discernible pattern in wage for all countries except Spain which exhibits positive effects in earlier cohorts, but this

[21] In the case of the US, although it has been classified as relatively more selective than Greece, Malaysia, and Spain, skilled migrants are fewer than unskilled migrants. It occurs that the difference between skilled and unskilled migrants is lower compared to the three other countries.

dissipates completely in contemporary cohorts. As for employment, I find no significant cohort effects for Canada, but negative, albeit disappearing cohort effects for Greece and the US.

Findings on effects of different sectoral intensity

I also briefly comment on the wage and employment assimilation profiles of Filipinos based another potential source of heterogeneity – sectoral intensity (defined as proportion of total employment in agriculture, industry, and services, respectively). I focus on the results of employment intensity on a subnational level (Table 3.A.9.2 and Figure 3.A.9.2 in the Appendix) to allow for greater variation but analysis using country-level variation is also available in the same section of the supplementary material (Table 3.A.9.1 and Figure 3.A.9.1), however less preferred. It appears that Filipinos residing in regions that are either agriculture- or service-intensive gives the wage profile that is closest to natives. However, Filipinos in agriculture-intensive regions statistically assimilate at 21-25 YSM whereas those in service-intensive regions have a lasting disadvantage. Meanwhile, Filipinos in industry-intensive regions show the largest wage gap. In terms of employment, Filipinos all start with a disadvantage upon arrival (with the disadvantage for those in Service-intensive regions lasting until 1-5 YSM) but become advantaged with longer YSM. The advantage grows over time for all intensities with Filipinos in agriculture-intensive regions having the largest advantage at 31+ YSM, and those in service-intensive regions having the lowest.

3.5.3 Country case studies

I now develop short case studies of Filipinos in each country in the sample. In doing so I briefly look at the migration profile of Filipinos into the country and then attempt to link the heterogeneities I propose to the labor market assimilation profile of Filipinos. In doing the latter, I modify equation (3.2) as the following fixed-effects regression:

$$y_{icmt} = \alpha_0 + \ddot{\boldsymbol{\beta}}_{\boldsymbol{c,t-m}} \boldsymbol{C} \times \boldsymbol{YSM}_{t-m,it} + \boldsymbol{\gamma}_m \boldsymbol{M}_{imct} + \boldsymbol{\pi X} + \varphi_c + \tau_t + u_{it} \tag{3.3}$$

The major change in equation (3.3) involves replacing H_c with C, which is the pure country fixed effect, and interacting it with $\boldsymbol{YSM}_{t-m,it}$ to get $\ddot{\boldsymbol{\beta}}_{\boldsymbol{c,t-m}}$. The rationale in this specification is to let all factors be captured in C to find how Filipino assimilation captured by $\ddot{\boldsymbol{\beta}}_{\boldsymbol{c,t-m}}$ for country c compares to that in other countries. Figure 3.6 (Table 3.A.4.6 in the Appendix) presents the (a) wage and (b) employment coefficients of the country fixed-effects and YSM interaction of equation (3.3) using OLS. I complement this with individual country regressions presented in Table 3.A.10.1 and Figure 3.A.10.1 in the Appendix.

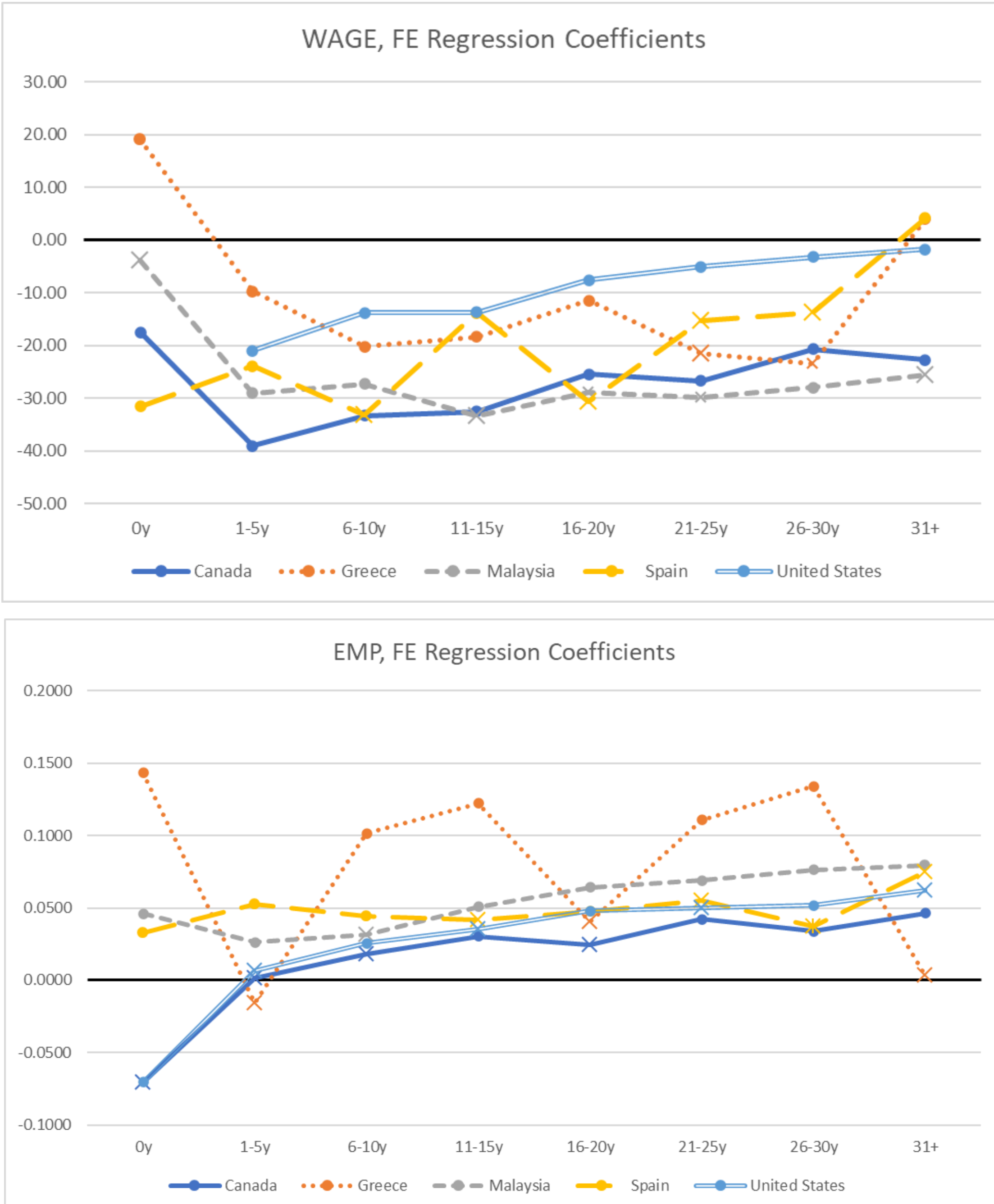


Figure 3.6. (a) wage and (b) employment assimilation profiles using a country fixed effects regression.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients. Note: Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. Canada is the base category. Other countries represents the $\boldsymbol{\beta}_{t-m} + \ddot{\boldsymbol{\beta}}_{c,t-m}$, which is the Canada assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the respective per-country differential slope $\ddot{\boldsymbol{\beta}}_{c,t-m}$.

Canada

Canada is one of the major destinations of Filipino migrants with 489,869 migrants in total (20% of total registered emigrants) as of 2018 (CFO, 2020). The migration culture of Filipinos to Canada started in the 1960s but growth accelerated in the early 1970s with the influx of economic migrants (typically live-in caregivers). Despite this, the migration network has grown relatively late compared to the US. In the sample, large proportions of Filipino immigrants were documented to have stayed in Canada for around 1 to 20 years (26, 19, 13, and 11% for 1-5, 6-10, 11-15 and 16-20 YSM, respectively). Looking at the wage and employment assimilation profiles of Filipinos in Canada, it appears that Filipinos here have the largest wage gap and the lowest employment advantage. This may be expected since natives occupy the highest paying jobs and industries, and overeducation among Filipinos is evident (although many Filipinos are in the Health industry). Despite having comparatively high cultural similarity and a selective immigration policy, this may be contradicted by a relatively low migration network and high diversity. The individual country regression provides similar results for wage but shows that employment rates are statistically no different as that for natives.

Greece

In contrast to Canada, Greece is a significantly unpopular destination for Filipino migrants (registered emigrants do not even comprise 1% of total emigrants from the Philippines) (CFO, 2020). Greece itself has seen emigration as a way to aid its economy after World War II but this decreased drastically in the 1970s and was replaced by the immigration of Asians, Africans and Poles who worked in construction, agriculture and domestic services in the 1980s. The surge in Filipino migration to Greece only started in the 1990s so the network is still very young. In the sample, about 26% of Filipinos stayed in Greece for 6-10 years, whereas 22% stayed for 1-5 years, and 20% for 11-15 years. These are relatively long periods of time considering that most Filipinos migrants to Greece are temporary. However, Greece has the lowest proportion of Filipinos staying for more than 25 years. Surprisingly, Filipinos in Greece have the second smallest wage gap and the highest employment rate advantage in the sample. This is somewhat expected because despite the low migration network (with Filipino migrants being mostly temporary) and most of the Filipinos occupying low-paying elementary occupations in private household services, the country has high cultural similarity low diversity, and a liberal migration policy. The individual country regressions mirrors these results although the wage gap is presented to be larger.

Malaysia

Much like Greece, Malaysia is also a less-popular destination for Filipino migrants with the number of emigrants also not reaching 1% in 2018 (CFO, 2020). Despite a rich history of immigration by Chinese, Arabic and Indian traders, Malaysia only saw the flow of Filipinos in the late ‘50s, which grew sporadically from the 1970s to the 1990s. About 21% of Filipinos in Malaysia were recorded to stay for 16-20 years, and about 17% stayed for 6-10 years. Malaysia also has one of the lowest proportion of Filipinos staying for more than 20 years among the countries in the sample. Filipinos in Malaysia have one of the largest wage gaps (comparable to Canada) but has the second-highest employment advantage for longer YSM. This appears in the individual country regression as well. This may be expected since Malaysia has the lowest cultural similarity, the highest diversity, and has the most liberal migration policy among countries in the sample. Moreover, the Philippine migration culture to Malaysia had always been dominated by temporary migrants in low-skill occupations and industries (mostly in agriculture and unclassified occupations/industries). The natives are significantly more highly educated and occupy the highest-paying jobs and industries.

Spain

Spain and the Philippines had more than 300 years of history between them, with Spain colonizing and reforming the Philippines since the 1500s. However, the culture of contemporary migration of Filipinos to Spain remained bleak over the years. Even though Spain is identified as a major destination for Filipino migrants, migration to Spain never soared to levels of that in other countries (also less than 1% of total emigrants in 2018) (CFO, 2020). The largest proportion of Filipinos in Spain (about 26%) are currently only residing for 1-5 years. However, although few, compared to other countries, Spain has the largest proportion of Filipinos that have stayed for more than 30 years (around 16%). Despite having low diversity, Spain has low cultural similarity (having the lowest proportion of English speakers), migration network (despite having more permanent migrants than temporary), and a liberal immigration policy. It evidently also has a highly segmented labor market with a very large secondary segment (Fellini and Guetto, 2019; Simon et al, 2014). Neither the wage nor employment profile of Filipinos are statistically different from Filipinos in Canada so they have a large, persistent wage gap but a modest advantage in employment rate. Because of the highly-segmented labor market, natives occupy the highest paying jobs and industries, while immigrants may be denied from occupational upgrading and are kept at low-paying jobs (such as service workers and elementary occupations) that natives do not want to occupy.

United States of America

When it comes to Filipino migration flows, there is no close comparison to the US. In 2018, emigration to the US accounted for around 60% of total emigration from the Philippines (CFO, 2020). The Philippines and the US have a long-running relationship politically, and the flows of migration to the US started in the 1940s with the number of Filipino migrants growing to hundreds in the 1950s and surging to thousands since the late ‘60s well onto the ‘90s. Contemporary migration flows have also remained very large. In the sample, the distribution of Filipinos across YSM is fairly even. The largest proportion are those that have stayed for 6-10 years (17.3%), followed by 11-15 years (16.7%) and 16-20 years (16.1%). The US also has a high proportion of Filipinos staying for more than 30 years. In addition to the largest Filipino migrant network, the US has the highest cultural similarity with the Philippines, a relatively low diversity, and although being documented by the index as having a comparatively selective immigration policy, is actually quite liberal in practice. There are also a lot more Filipinos with University degrees, and those occupying higher paying jobs (i.e. Professionals, Technicians) and industries (i.e. Health) relative to natives and other immigrants. As may be expected, the wage profile of Filipinos in the US is the highest among all countries (lowest gap) and they have a modest and persistent advantage in employment.

Despite the analyses I present, I take caution in interpreting the assimilation profile of Filipinos for each country. Although I argue that assimilation may depend on cultural similarity, diversity, migrant networks, and immigration policies, endogeneities may exist in the form of correlation, reverse causality, and unobserved country, regional, and individual characteristics. Testing for these factors require more detailed information and potentially longitudinal data, and unfortunately, is beyond the scope of this study.

3.5.4 Transferability, and Occupational and Industrial Mobility

In this section, I inspect two channels through which assimilation may occur. *First*, since I find that the heterogeneities in culture, migrant networks, and immigration policies can affect Filipinos’ advantages and disadvantages in wage and employment, I investigate how these heterogeneities can influence the transferability of human capital that Chiswick (1978) and Friedberg (2000) point out to be responsible for causing initial gaps. I investigate whether heterogenous impacts on the returns to education exist with variations in the institutional factors. *Second*, I investigate how convergence may occur across time. Given that the main dependent variable depends on occupation and industry, I check whether Filipinos can “upgrade” wages by moving toward higher-paying occupations or industries over time spent in the host country (Abramitzky, et al, 2014; Chiswick, Lee, and Miller 2005).

Transferability and returns to education

In testing the impact of the institutional factors on the returns to human capital, I once again modify equation (3.2) to explicitly show the differences in the returns to education as follows:

$$y_{icmt} = \alpha_0 + \boldsymbol{\delta_{it}}\boldsymbol{Educ_{it}} + \widetilde{\boldsymbol{\delta}}_{\boldsymbol{it}} H_c \times \boldsymbol{Educ_{it}} + \widetilde{\boldsymbol{\beta}}_{t-m} H_c \times \boldsymbol{YSM}_{t-m,it} + \boldsymbol{\gamma}_m \boldsymbol{M}_{imct} + \boldsymbol{\pi X} + \varphi_c + \tau_t + u_{it} \tag{3.4}$$

$\boldsymbol{Educ_{it}}$ is exactly how educational attainment is controlled for in equation (3.2): as a vector of dummies indicating the highest educational attainment of the observation *i* at time *t*. It is comprised of four categories: Less than Primary (which is the base category), Primary, Secondary, and University Degree. By introducing the interaction term $H_c \times \boldsymbol{Educ_{it}}$, I am able to test the difference in returns to education due to the heterogeneity in the institutional factor by estimating the vector of parameters $\widetilde{\boldsymbol{\delta}}_{\boldsymbol{it}}$. I estimate using OLS and only for Filipinos in the entire sample.

Table 3.7 reports estimates for equation (3.4). Across all models, it may be seen that higher levels of educational attainment are associated with higher levels of wage scores and employment. It may be seen that countries with high cultural similarity place a slight disadvantage for immigrants with primary and secondary schooling whereas there is a small positive, however statistically insignificant advantage for university degree holders. Conversely, those with secondary and university degrees enjoy higher employment rates, with those with tertiary enjoying a net positive employment rate. This may indicate a higher difficulty in bringing lower levels of human capital especially when the native populace shares the same set of skills. Cultural diversity slightly increases the return on primary education but slightly decreases the return on secondary education and significantly decreases the return on tertiary education in both wage and employment. The finding on tertiary education reinforces the imperfect transferability of human capital especially when the destination country is entirely different in various aspects (such as Chapman and Iredale's [1993] example about lawyers). Primary education suffers from a slight wage disadvantage with a high migration network possibly implying harder competition (crowding), whereas secondary and tertiary education receive larger advantages in both wages and employment. The latter may indicate easier transferability of higher education when a pre-existing network has integrated into the host society. Lastly, selective countries tend to disadvantage primary and secondary degree holders in terms of wage, but expectedly increases the wage and employment of university degree holders. This is no surprise since selective countries impose several human capital requirements on migrants, creating incentives for highly educated migrants to enter.

Table 3.7. Institutional factors and how the transferability of education may be affected.

	Cultural Similarity	*Cultural Diversity*	*Migration Network*	*Migration Policy^*
Panel A. Wage score equations				
Primary	4.59**	-1.09	3.80***	5.13***
Secondary	23.14***	19.89***	14.89***	22.11***
Uni	58.37***	73.77***	34.01***	51.08***
H_c x Primary	**-12.05*** **	**5.31***	**-4.98***	**-12.68*** **
H_c x Secondary	**-10.34***	**-5.47** **	**5.12***	**-9.25** **
H_c x Uni	**1.46**	**-40.21*** **	**39.95*** **	**8.83*** **
Observations	75,302	75,302	75,302	75,302
R^2	0.2581	0.2701	0.2701	0.2582
Panel B. Employment equations				
Primary	-0.0008	0.0232	-0.0026	-0.0004
Secondary	-0.0035	0.0385*	-0.0003	-0.0001
Uni	-0.0049*	0.0687***	0.0068	-0.0180*
H_c x Primary	**-0.0054**	**-0.0264**	**0.0271**	**-0.0060**
H_c x Secondary	**0.0243***	**-0.0375***	**0.0402***	**0.0210**
H_c x Uni	**0.0511*** **	**-0.0610*** **	**0.0640*** **	**0.0645*** **
Observations	65,230	65,230	65,230	65,230
R^2	0.0174	0.0180	0.0181	0.0174

Source: IPUMS-I, author's calculations.

Note: ^ H_c for Migration Policy indicates a relatively selective immigration policy.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Robust standard errors used. Uses person weights.

Occupational and industrial transition

In looking at the occupational and industrial mobility of Filipinos, I first group together occupations into primary and secondary labor market occupations as in Simon et al (2014). Past studies that have looked at occupational mobility have used longitudinal data to trace how immigrants changed occupations across survey rounds (Abramitzky et al, 2014; Chiswick, Lee and Miller, 2005). Unfortunately, as I do not have the luxury of using panel data, I look at the change in occupation of Filipino migrants over YSM. Table 3.8 reports the occupational transition of Filipinos over time and I find evidence of Filipinos' occupational upgrading over YSM (the occupational transition disaggregated into ISCO88 occupations may be found in Table 3.A.11.1 in the Appendix). It may be seen that over time spent in the host country, an increasing number of Filipinos work in the better-paid, higher-security primary occupations and an increasingly lower proportion are working in the more unstable secondary occupations. However, I take caution in interpreting these results. The drawback to this approach is that cohort quality effects and return migration are not considered and therefore, growth rates across YSM may be inflated.

To provide a slight improvement, I take inspiration from Borjas' (1985) cohort decomposition. I restrict the following analysis to Canada, Greece, and the US – countries in the sample with at least two census rounds. I track YSM cohorts in the earlier survey round (2000 or 2001) and add 10 years to it to see what cohort it would be in the next survey round (2010 or 2011). By following how a cohort's occupational composition changes across survey rounds, I may be able to improve the precision on the occupational transition of Filipinos. However, this approach may address the issue of changing cohort quality, but it does not fully take return migration or any additional migration into account.

Table 3.8. Occupational transition of Filipnos between primary and secondary occupations across YSM.

YSM	*0*	*1-5*	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31+*
Primary Occupations	32.12	42.25	47.5	51.87	54.63	57.67	61.76	57.99
Secondary Occupations	34.23	43.65	41.48	38.75	35.89	34.1	29.41	28.63
# of Filipinos	523	14,182	16,216	14,424	13,928	10,653	9,000	9,986

Note: Does not add up to 100% because of missing proportion unemployed or not in labor force. As in Simon et al (2014), primary occupations are comprised of ISCO88 codes 1-4, and secondary occupations are comprised of ISCO88 codes 5-9.

Table 3.9 reports the results (the disaggregated occupational transition is in Table 3.A.11.2). I find evidence of occupational upgrading as earlier cohorts occupy more primary occupations and less secondary occupations across 10 years. However, I find that this phenomenon halts at the 16-20 "before" cohort. From the 21-25 YSM cohort to the 46-50 YSM cohort, it may be inferred that unemployment and attrition have decreased both the proportion of Filipinos in primary and secondary occupations. A few exceptions include the 36-40 "before" cohort where primary occupations have increased, and the 41-45 and 46-50 "before" cohorts where those in secondary occupations increased. I posit that the latter phenomenon occurs since secondary occupations have less requirements and may be easier to take up even during older age.

I apply the same two methods in investigating the industrial transition of Filipinos. Table 3.10 reports the industrial mobility of Filipinos across YSM without controlling for cohort quality effects. Similar to the findings for occupational mobility, it is apparent that over time, more and more Filipinos are being employed in higher paying industries (industries with a wage score greater than 1 – implying higher than average nominal wages), and those in lower-paid industries decrease..

Table 3.9. Tracking within-cohort occupational transition of Filipinos between primary and secondary occupations

YSM, t	*0*	*1-5*	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31-35*	*36-40*	*41-45*	*46-50*
Primary Occupations	38.51	43.68	48.06	53.46	58.11	59.7	63.97	61.4	53.01	53.25	61.33
Secondary Occupations	34.03	42.7	42.08	38.36	34.4	33.32	28.3	28.31	32.61	31.95	26.67
# of Filipinos	335	8,159	11,759	10,996	9,358	7,173	6,650	3,723	1,196	554	225

YSM, t+10	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31-35*	*36-40*	*41-45*	*46-50*	*51-55*	*56-60*
Primary Occupations	51.16	51.24	53.25	56.98	60.51	58.11	59.38	57.53	58.65	45.45	55
Secondary Occupations	37.88	38.87	36.67	34.56	31.21	29.74	24.32	24.32	28.85	37.88	32.5
# of Filipinos	139	5,572	3,962	3,095	4,041	3,238	2,140	1,671	1,509	518	104

Note: Does not add up to 100% because of missing proportion unemployed or not in labor force. As in Simon et al (2014), primary occupations are comprised of ISCO88 codes 1-4, and secondary occupations are comprised of ISCO88 codes 5-9.

Table 3.11 presents the results of the Borjas-style (1985) within-cohort tracking of industrial transition (the disaggregated version is in Table 3.A.11.3 in the Appendix). For simplicity, I group industries by their wage score (greater than one and less than one) and sum the proportion of Filipinos in each industry. Again, I find similar results to that of what I found above. I find that cohorts experience a transition from lower-paying to higher-paying industries across survey rounds. The upgrading in industries appears to last for longer than the occupations, with only the 36-40 and 46-50 "before" cohorts experiencing decreases in the proportion of Filipinos in higher paying industries and increases in those in lower-paying industries. With this, I confirm that occupational and industrial upgrading occurs over time and may partially be responsible for the labor market convergence and assimilation of Filipino migrants.

Table 3.10. Industrial transition of Filipinos across YSM.

Score	*ISIC*	*YSM*	*0*	*1-5*	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31+*
1.42	90	Financial Services	3.44	3.18	4.08	5.6	5.89	6.61	6.52	5.18
1.41	20	Mining	0.00	0.24	0.11	0.11	0.19	0.13	0.12	0.17
1.39	40	Utilities (EGW)	0.19	0.22	0.17	0.3	0.37	0.53	0.62	0.72
1.21	100	Public Administration	1.72	2.62	3.02	4.2	5.1	5.32	5.83	7.37
1.18	112	Education	3.63	3.62	3.45	3.94	4.16	3.91	4.3	5.34
1.14	113	Health	10.13	16.44	22.55	20.54	20.53	21.14	22.5	19.63
1.04	111	Real Estate	5.74	8.21	6.1	6.72	6.91	6.9	7.6	7.16
		Cumulative of (>1) score	24.85	34.53	39.48	41.41	43.15	44.54	47.49	45.57
0.99	80	Transport and Logistics	2.87	3.04	3.59	4.38	4.82	5.87	5.46	6.71
0.94	30	Manufacturing	8.22	11.96	12.12	12.71	12.03	12.77	12.23	10.77
0.89	50	Construction	1.15	1.68	1.84	1.93	2.04	2.22	2.43	2.50
0.73	60	Wholesale and Retail	8.6	12.83	12.31	12.36	12.21	10.59	9.86	8.73
0.71	114	Other Services	4.97	8.39	7.42	7.52	6.96	7.44	7.02	6.64
0.57	10	Agriculture	1.34	1.23	1.40	1.04	1.36	1.15	1.28	1.07
0.55	70	Accommodation	8.99	9.48	8.56	7.60	7.00	5.95	5.03	4.37
	120	Private Household Services^	5.54	3.07	2.65	2.08	1.54	1.71	0.71	0.55
		Cumulative of (<1) score	41.68	51.68	49.89	49.62	47.96	47.7	44.02	41.34
		# of Filipinos	523	14,182	16,216	14,424	13,928	10,653	9,000	9,986

Note: Does not add up to 100% because of missing proportion unemployed or not in labor force.
^ private household services are typically a low paying industry comprised of domestic helpers and carers. Nominal wage data is not available in ILOSTAT.

Table 3.11. Tracking within-cohort industrial transition of Filipinos across YSM

YSM, t	*0*	*1-5*	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31-35*	*36-40*	*41-45*	*46-50*
Cumulative of (>1) score	29.55	34.03	38.76	41.4	43.81	43.45	47.36	46.5	45.31	39.71	37.78
Cumulative of (<1) score	43	52.77	51.75	50.82	49.23	49.96	45.23	43.36	40.64	45.67	50.22
# of Filipinos	335	8,159	11,759	10,996	9,358	7,173	6,650	3,723	1,196	554	225

YSM, t+10	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31-35*	*36-40*	*41-45*	*46-50*	*51-55*	*56-60*
Cumulative of (>1) score	45.91	45.57	47	49.81	52.01	47.64	47.9	48.27	43.26	46.98	32.5
Cumulative of (<1) score	43.54	44.95	43.77	42.35	40.25	40.63	36.2	34.55	44.22	36.37	55
# of Filipinos	3,962	3,095	4,041	3,238	2,140	1,671	1,509	518	104	66	40

Note: Does not add up to 100% because of missing proportion unemployed or not in labor force. Industries with wage score > 1 include financial services, mining, utilities, public administration, education, health, and real estate. Industries with wage score < 1 include transport and logistics, manufacturing, construction, wholesale and retail trade, other services, agriculture, accommodation, and implicitly, private household services.

3.6 Conclusion

Understanding the labor market assimilation of immigrants has been of utmost importance in the international migration literature especially with the unprecedented increase in international migrants around the world. A lot of work has been done looking at the experience of several immigrant groups in one or a few countries. A lot of the seminal works point toward the imperfect transferability of origin country human capital to explain the initial gap in earnings and attribute the convergence of wages with natives to the acquisition of destination-specific human capital. However, little work has been done in comparing the assimilation experience of migrants around the world where there are significant differences in social institutions. This study is the first to explore the role that heterogeneities in cultural institutions, migration networks and immigration policies may have in the labor market assimilation of immigrants. Furthermore, this study is also the first to focus solely on the experience of migrants from one origin as they go out to different countries. The uniqueness of this framework contributes much to the literature on assimilation and transferability despite endogeneity not being fully addressed. Nevertheless, the estimating equation accounts for potential confounders and alternative explanations to better identify the effect of institutional heterogeneities on assimilation. I look at migrants from one of the largest migrant-sending countries in the world – the Philippines – to weed out sending country effects. I collect census data from five countries namely Canada, Greece, Malaysia, Spain, and the US compiled in the IPUMS-I database. I use nominal monthly occupational and industrial wage data from ILOSTAT to construct a wage score based on the relative ranking of industries and occupations across countries. Lastly, I collect institutional data from a variety of sources and construct normalized indices of each factor to categorize countries into relatively high or low levels of an institution.

In sum, I find that **cultural similarity** amplifies human capital transferability to *lessen the wage gap* and helps facilitate convergence, but *slightly crowds out employment rates*. Conversely, **cultural diversity** tends to *widen the wage gap* and *decreases the employment rate advantage*. **Migration networks** may be the strongest facilitator of convergence and assimilation in both wage and employment as it significantly closes the wage gap with natives and the saturation of the migrant culture may only cause crowding upon arrival while still maintaining an employment rate advantage with longer YSM. Lastly, **selective immigration policies** tend to give higher wages and facilitate assimilation potentially through more positive migrant selection but seeking employment may be harder. In looking at the channels through which assimilation may occur, I find that the proposed institutional factors create differential effects in the returns to education – which explain differences in the gaps in wages and employment. Furthermore, I find evidence of occupational and industrial upgrading. Filipinos are moving from lower-paying to higher-paying jobs and industries across time, and this may be facilitating the convergence of wages to that of natives.

Although the findings in this study may not directly contribute toward the crafting of policies pertaining to the flows of migration by either sending or host countries, it contributes greatly in understanding the factors that influence the experience of migrants in countries where several institutional differences may exist. From the perspective of major migrant-sending country, understanding the factors influencing the adjustment process is crucial in determining an appropriate skill base for would-be migrants to acquire, because ultimately this will impact not only their contribution to the sending country, but their contribution to the host country as well when they send remittances. Eventually, understanding the factors influencing assimilation, and readjusting the skill base of migrants may improve their overall welfare.

Through the course of writing this paper, I acknowledge a handful of limitations and avenues for future research. First, estimates may need adjustment using appropriate weighting. Private household services are known to be a major industry where Filipinos are concentrated in other countries. However, this industry was not directly testable because nominal monthly wage data was not available at ILOSTAT. Given its long, rich history of migration, there may be a need to check period/era effects stemming from the "waves of migration" from the Philippines as each wave may have structural differences. Additional robustness checks may be performed as well. Alternative definitions for migrant networks such as the current percentage of Filipinos by subnational division or traditional migration (earliest record of migration) may provide a unique identification strategy and may be interesting. Lastly, to complement the initial set of channels I tested for in the study, it may be interesting to see how the heterogeneities in institutional factors may affect the occupational and industrial transition of immigrants. Identifying additional sources of institutional heterogeneities would continue to prove important in explaining differences in the assimilation experiences across host countries.

Chapter 4

The spatial spillovers of migration on education

Abstract

Understanding the spillover effects of migration is a subject that warrants more attention especially with the growing number of migrants around the world. The sheer prospect of migration may be enough to generate a brain gain alongside the phenomenon of brain drain. With the CBMS 2015 dataset and Hotspot Analysis using spatial statistics techniques, I use the geographic information of households to establish migrant peer networks for non-migrant households based on their proximity to a migrant and the clustering of migrant households around them. The key identifying assumption I use for isolating proximity and neighborhood effects is that the geographical distribution of households within a smaller neighborhood may be considered random after controlling for sorting into broader neighborhoods. I find that there are no discernible effects on primary and secondary enrolment, but migrant proximity and clustering is associated with higher tertiary enrolment. Furthermore, I find no evidence for entrepreneurial activity as a channel and only suggestive evidence for the receipt of community remittances.

4.1 Introduction

International migration has grown at an extraordinary rate in the last few decades – with the global migrant stock approximating 266 million in 2017 (Ratha, De, Kim, Plaza, Schuettler, Seshan, and Yameogo, 2018). Much of these flows come from developing countries where migration is perceived by people as an avenue to improve their household's welfare. However, studies have debated on the impacts of migration and the largest concern is that of the brain drain, where, due to the wage differentials across countries, the migration to higher-wage countries (usually more developed) decreases the stock of skills and professionals in lower-wage countries (usually developing). In addition, international migration has been claimed to disrupt the studies of left-behind children (in the case of parental migration) (Wang, 2012), to directly impinge on migrants' wellbeing due to separation, exploitative practices, and abusive working conditions (Asis, 2006), and to hinder the advancement of a society because of the aspiration to leave (David, 2013). Migration is often linked to remittances which has often been criticized to fuel spending on leisure items and vices as well as erroneously believed to cultivate attitudes of mendicancy because it is seen to reduce labor force participation.

In contrast to these pessimistic views, studies have come forth presenting evidence of positive impacts of international migration. Recent studies such as Mergo (2016) and Martey and Armah (2020) found that migration enhances the welfare of left-behind families, suggesting that migration increases household expenditures although it is quite conflicted whether this is being driven by productive investments or consumer goods. Martey and Armah (2020) further posit that migration reduces weekly working hours as well as household poverty. Stark, Helmenstein and Prskawetz (1997, 1998) present theoretical evidence that migration alters the incentive structure faced by individuals. And so, while the flight of workers causes a "brain drain", the new incentive structure caused by the prospect of migration induces the further acquisition of skills and human capital, potentially leaving the home country with a lot more human capital than they would have had there been no prospect of migration. This is largely in part due to higher educational attainment and training being prerequisites to migration and is independent of any effect coming from remittances or knowledge transfers. Batista, Lacuesta, and Vicente (2012) provide evidence of how the prospect of one's own future migration raises his level of education in Cape Verde, and Dinkelman and Mariotti (2016) found that migration leads to a long-term (over twenty years or more) increase in the educational attainment of men from Malawi. Theoharides (2018) presents evidence of this in the Philippines where migration was found to increase secondary school enrolment at the provincial level. Abarcar and Theoharides (2020) found that postsecondary enrolment in nursing increased in response to nursing demand changes in the US, and while passing rates decreased for the nursing licensure exam, the increase in licensed nurses far outweighed the number of those that departed. Khanna and Morales (2017) document the same occurrence in India where students enrolled in engineering schools to gain employment in the US' growing IT industry. The engineers who remained in India brought forth the unprecedented growth of the Indian IT sector. In addition, remittances have been documented to improve household education spending (Tabuga, 2007) and encourage human capital formation (Cabuay, 2017). These developmental implications make it unsurprising that most studies look at the case of developing countries as migrant senders.

The focus of this study is to provide evidence for the proposition put forth by Stark et al (1997, 1998) – that a country with a prospect of migration has greater human capital formation than a country without a prospect of migration. Additionally, it is notable that the literature on the developmental impacts of migration on developing origin countries often focus on the direct effects of migration. Most studies only look at the effect *on* households *with* a migrant member. It is quite surprising that there is very little literature on the spillover effects of migration, that is, the effects of migration on households *without* a migrant member. Albeit possibly only tangential, this study could also be tied to the literature on role-model effects since observing a migrant household's presence and lifestyle may influence a community's outlook and drive the aspirations of others to acquire human capital to allow them to migrate as well. By looking at this relatively unstudied aspect, this paper aims to weigh in on the debate regarding the impacts of migration on communities in general by directly looking at the effect of migration on non-migrant households' outcomes. In providing evidence for spillover effects, this study takes the approach of using geographical proximity to a migrant household and defining networks based on migrant clustering. Networks are innovatively established using a spatial statistics technique – hotspot analysis with GOGG and the GOGi*. This study aims to contribute to the growing literature on neighborhood effects as well with this creative application of geographic techniques. While I mention the potential contribution to role-model effect literature, I refrain from making any heavy comment on this since tracing role model effects require identifying key personnel in an agent's social network (Kofoed and McGovney, 2019; Tanaka, 2008; Lyle, 2007; Neumark and Gardeckil, 1998), and the true structure of households' social networks are unobservable in the data.

Why use geographical proximity and clustering to proxy for "migration prospects" in looking at migrant spillover effects? In justifying the use of geographical characteristics, this study appeals to the simple proposition being tested in neighborhood effects studies: "place matters" (Graham, 2018). Our environment, comprised of our surroundings (e.g. institutions) and our connections (neighbors, peers), are effectively non-market interactions which may influence our behavior and outcomes (Topa and Zenou, 2015). Moreover, closer proximity typically means higher probability of contact, hence leading to more interactions which implies greater access to information and opportunities (Helmers and Patnam, 2014).

In this paper, I assert that the prospect of migration stems not only from the knowledge that “migration is possible”, but also from seeing the behavior and outcomes of migrant households, and this only grows stronger the closer the proximity to the migrant household is. The main research question is then expressed as: *are non-migrant households more likely to enroll their children (possibly in hopes of probable labor migration in the future) when they are living in proximity to (and likely directly observing and interacting with) migrant households?* This study investigates the impact of migrant proximity and migrant clustering/neighborhood on the enrolment of school-aged individuals in non-migrant households using a unique dataset that allows the tracking and plotting of household locations via GIS and a unique application of spatial statistical techniques to identify migrant peer networks. This study is exploratory or positive in nature. While I make no claim as strong as arguing for causality, I utilize a strong enough identification strategy claiming that residential location choices are quasi-random after controlling for sorting into administrative groupings and consider all factors to improve the precision of my estimates and attempt to address various confounding factors.

Having a long history of international migration and one of the largest migrant diasporas in the world to date, the Philippines makes an interesting case among developing countries to further study the welfare impacts of international migration. The Philippines has identified international migration as a key driver of growth and development. In 2017, the total migrants around the world coming from the Philippines numbered approximately 6 million with remittance inflows reaching USD33 billion, making up about 14.3% of the country’s GDP (Ratha et al, 2018). Because of the well-known impacts of migration, the concept of international migration and the OFW have become so commonplace that many Filipinos aspire to migrate or work abroad.

I find that there are no discernible effects on primary and secondary enrolment, but tertiary enrolment tends to be higher with greater migrant proximity. This effect increases with more migrants around a closer area, and even more so when the household is in area identified to be a hotspot of migrants. I find similar results when I use conventional neighborhood effects variables based on migrant composition at administrative levels. In looking at possible channels through which education spillovers may occur, I find no evidence that non-migrant households engage in more entrepreneurial activity, and only find suggestive evidence that non-migrants benefit with the receipt of community remittances.

The remainder of this chapter is organized as follows. Section 4.2 reviews the literature on the spillover effects of migration, and briefly reviews how proximity and neighborhood may influence behavior and outcomes. Section 4.3 describes the data, the conventional strategies, and problems in estimating proximity and neighborhood effects, the empirical and identification strategies, and how I offer to address the common problems of estimation. Section 4.4 reports descriptive statistics, the primary results, and channels through which spillovers may affect non-migrant households' enrolment. Lastly, section 4.5 concludes.

4.2 Review of Literature

In studying the effects of migration on host country human capital formation, Stark et al (1997, 1998) offered a theoretical explanation of how the brain drain may be accompanied by a brain gain, and under what conditions host countries may end up with higher human capital formation than when there is no prospect of migration. When the returns to education are much higher in a foreign country, even just the prospect of migrating can alter the incentive structure in the sending country, thus influencing the human capital investment decisions of people. This may be seen in Theoharides (2018) who found higher migrant demand from abroad led to an increase in secondary school enrolment in Philippine provinces. Because the analysis used in the study was at the local labor market level, she mentions that the increase in enrolment reflects both impacts on migrants' households and spillovers to non-migrant households. This may also be seen for particular occupations. Abaracar and Theoharides (2020) exploited variations in the US Visa Policy regarding the demand for nurses from the Philippines. They found that the surge in the demand for nurses in 2000 led to an increase in enrolment in nursing, leaving the Philippines with a larger pool of licensed nurses even after many have already migrated to the US.Batista, Lacuesta and Vicente (2012) constructed a structural model where the probability of one's own future migration positively impacts secondary education decisions, implying how the prospect of migration may influence one's human capital decisions. Similarly, while not commenting on the impacts on non-migrant households, Böhme (2015) found that migration raises the educational aspirations that caregivers have for children in migrant-sending households. On the contrary, the study by McKenzie and Rapoport (2011), while not focusing nor commenting on the spillover effect, found that the prospect of migration from Mexico to the United States leads to lower educational attainment of 16-18 year old children. They attribute this to boys' current migration and girls' increased housework. In addition, they note the low skill requirements (and often illegal immigration) of Mexican immigrants to the US, so given the prospect of migration, children of migrants need not study more to be able to work in the US. Using the same dataset, the China-focused studies of

Feng (2018) and Wang, Cheng, and Smyth (2018) found conflicting results, although they look at the impact of internal migrant students (rather than international) on the academic achievement of their peers at the destination (rather than origin). Feng (2018) reported lower math scores for non-migrant peers at the middle school level, noting that because of migrants, teachers adopt worse pedagogical practices (more likely to use transmissive styles rather than interactive styles). The study of Wang et al (2018) focuses on the high school level, and found a small, positive effect for non-migrant students' test scores in Chinese.

A lot of other studies look at other spillover effects of migration in the origin country. While not strictly on current migrants, Hausmann and Nedelkoska (2018) investigate the impact of return migration from Greece on the labor market outcomes of non-migrants in Albania. They argue that return migrants' skills are non-homogenous with non-migrants because of the skills they acquire from the host country. They found that having more return migrants in a province increases the wage of lower-skilled non-migrants, and although it is associated with lower employment in the formal sector (a substitution effect), they detect higher labor force participation and employment for non-migrants overall. They associate this with return migrants' propensity to start new agricultural businesses, all the while employing non-migrants, hence lifting them out of non-participation. In their study of Senegal, Kveder and Beauchemin (2015) postulate that migration has an indirect role for non-migrants' investment behavior, such that migrants may be a source of new ideas, credit and even co-insurance. However, they found that there is no significant change in the investment decisions of non-migrants with access to a migrant network. The study of Wei, Liu, Lu, and Yang (2017) investigate the impact of foreign direct investments of ethnic Chinese-invested firms (ECIF) and return migrants on the productivity of indigenous firms. They found that investments made by ECIF raises the productivity and investment in R&D of indigenous firms, although they are less likely to export. They maintain the idea that return migrants are knowledge brokers that maintain relations outside China and bring new technology and channels that allow firms to target the international market. They find that firms in industries with a higher share of return migrants tend to have higher productivity, export orientation and intensity, and R&D investment. From a macroeconomic perspective, Figueiredo, Lima, and Orefice (2020) found that higher bilateral migration between a high-protection and low-protection country leads to higher bilateral imports. They attribute this to migrants' preference for origin country goods and bringing with them additional information on their origin country which lowers the cost of trade. Since the analysis is on a country level, one may posit that the higher bilateral imports may have an impact on non-migrants at home, especially those working in sectors producing tradeable goods. In a qualitative, demographic study on Tonga, Fukuyama, Watanabe, Umezaki and Ohtsuka (2009) found that international migration lowered the fertility of women who stayed behind, attributing this to the weaker desire to marry and when they are separated from their partners. However, they do not link this with the prospect of migration.

A person's environment plays a crucial role in shaping his life. These non-market interactions can influence his behavior and outcomes, and the strength of this influence may be determined by his social and physical space and his proximity to these factors. Simply put, the characteristics and outcomes of one's neighbors may have an impact on a person's behavior (Graham, 2018). Neighborhood effects are linked to the composition of one's residential neighborhood – a concept of physical space – be it in terms of race, origin or educational background, and even the quality of institutions and amenities available in the area, although this sometimes overlaps with network effects which is linked to the structure of a person's connections in abstract social space (Topa and Zenou, 2015). In the same sense, social and physical (geographic) proximity are two inevitably-intertwined concepts since interactions within or across networks and neighborhoods may be easier or have greater intensity if agents are closer to each other (Helmers and Patnam, 2014). These interactions may have market implications as they influence the flow of information (job openings, new technologies), alter preferences, offer risk-sharing devices, and facilitate complementarities in production and consumption (Topa and Zenou, 2015). On a personal level, these interactions may have psychological effects such as imitative behavior, interdependence of outcomes, and the alteration of the subjective perception of the returns to a certain behavior (Helmers and Patnam, 2014) similar to the suggestions in Stark et al (1997, 1998).

A brief look at some recent studies investigating proximity effects reveals applications in different contexts. Bertoli and Grembli (2016) exploit the exogenous variation of cities in Italy legally allowed to have a hospital based on population size to show that closer proximity to cities with hospitals have a life-saving effect in reducing fatalities associated with road accidents. O'Malley, James, MacKenzie, Byun, Subramanian, and Block (2017) test whether proximity to fast food establishments have any impact on individuals' body mass index (BMI) while comparing the effect for residential and workplace neighborhoods. They found that BMI is higher for females with greater residential proximity to fast food establishments and higher exposure these establishments in their home-work commute. They find a similar effect for males but only for workplace proximity. Cummings, Walker and Cotti (2017) found that areas that are closer to casinos tend to have lower lottery sales, a well-established fact that casinos and lotteries are gambling substitutes. Montolio and Planells-Struse (2015) offer a unique take on proximity: they argue that the phenomenon of being stopped by police for routine and traffic checks is exogenous and may be interpreted as a "visual" kind of proximity or "visibility" of an institution of security. They find that individuals that have not been recently victimized by any crime report lower perception of crime risk when they have been stopped by police, but those that have been recently victimized feel greater insecurity. On the other hand, some studies do not detect proximity effects. The study of Totadri, Trehan, Kaur, and Bansal (2019) in the United Kingdom found that the distance to treatment centers has no effect on children's survival rate from acute lymphoblastic leukemia. The study of Wetwitoo and Kato (2019) in Japan found that proximity of a prefecture or municipality to a high-speed railway station has no significant impact on the area's regional GDP and tax per capita.

Similarly, studies investigating neighborhood effects have great variation as well. The aforementioned studies of Feng (2018) and Wang et al (2018) on the spillover effects of internal migrants on their non-migrant school peers' academic performance are essentially neighborhood effects studies. They employ the same identification strategy where they exploit the variation in migrant composition of classes expressed as the percentage of migrant peers across classes in schools. They make use of the random assignment of students to classes as their identification strategy despite sorting that may occur when parents choose schools for their children. The study of Bayer, Ross, and Topa (2008) in Boston investigate the role of informal hiring networks on labor market outcomes. They search for a referral effect by looking at how the probability of neighbors working in the same location is affected by whether the two neighbors living in the same neighborhood live on the same block as opposed to nearby blocks. They find evidence of a referral effect which becomes larger when neighbors have similar sociodemographic characteristics. Altonji and Mansfield (2018) investigate how parents' choice of school and surrounding community affect the long-run educational and labor market outcomes of children in North Carolina. They find that moving to a superior school (top 10%) significantly increases the probability of high school graduation and enrolment in a 4-year college, as well as higher adult wages. Graham (2018) sought to understand the effects of racial segregation on long-run life outcomes in the US and found that minority adolescents that grew up in highly segregated cities fared worse in terms of academic performance and earnings compared to their white neighbors. Patacchini and Zenou (2012) look at how ethnic networks could influence employment outcomes and found that the likelihood of an individual to get a job through social networks increases with his ethnic group's employment rate in the same as well as surrounding regions. However, the effect of neighboring areas decreases with greater distances. Helmers and Patnam's (2014) study in India used the geographic information of households to establish the positive role of peer groups in children's cognitive skill development. They exploit the spatial contiguity among children assuming that those who live next door are likely to be part of a child's peer group and hence affect his outcomes more than those who live farther away. They find that a child's cognitive ability positively correlates with that of his peers as well as their other characteristics.

Lyle's (2007) study is an intersection of neighborhood effects and role model effects. He exploits the random assignment of cadets to companies in West Point to look at peer effects while identifying role model effects using the random assignment of mentors to cadets. He acknowledges the same issues in estimating neighborhood effects put forth by Manski (1993) and finds that there are no effects on academic performance but a role model effect exists for some cadets majoring in the same specialization as their mentors as well as those who decide to remain in the army. Kofoed and McGovney (2019) exploits the same natural experiment as with Lyle (2007), and further tests the effect of the length of exposure to cadets' assigned mentors in West Point. They find evidence for a higher likelihood to pick the same branch as their mentors' when their mentor is of the same gender (for females) and same race (for blacks). Nixon and Robinson (1999) find that higher proportions of female faculty and professional staff in high schools increase female students' years of schooling, likelihood to graduate high school, and enroll in and graduate from college. This is somewhat echoed in Koch and Zahedi (2019) where it was found that a higher proportion of black faculty in college leads to higher graduation rates for black students. On the other hand, Neumark and Gardecki (1997) find no support for a female dissertation chair, a higher proportion of female faculty, or a better ratio of female faculty to female students, leading to improved placement in female graduate students' first jobs. They do, however, find evidence for shorter time spent in graduate school for female students. Tanaka (2008) also finds a partially pessimistic role model effect in Japan. It was found that part-time maternal employment and self-employment lead to lower years of schooling for boys and girls. However, while full time maternal employment negatively impacts boys, there is no effect on girls, and there is even intergenerational transmission of this employment status from mother to daughters.

This study seeks to contribute to the literature on role model effects given that no study has identified international migrants as possible role models. Strictly speaking, role models – usually exemplars that set the bar for behavior, achievement, and aspirations for people – are typically determined by identifying key personnel in a person's social network structure. While this study cannot identify migrants within households' social structures directly, given how proximity may be linked with social interaction, observing the presence or clustering of migrants in a geographical area may arguably be considered a "role model" for the household, particularly in the Philippines where international migrants are put on a pedestal and drive the aspirations of people to migrate.

4.3 Data and Methodology

4.3.1 Data description

This study uses the 2015 CBMS survey of the PEP-CBMS. The dataset compiles information for 103,316 individuals in 22,826 households. The dataset is the result of a collaboration between PEP-CBMS and the De La Salle Philippines (DLSP) schools across the country. It is comprised of a *census* of all households and individuals in participating *barangays* (villages) linked to DLSP. While all agents in a village are included, not all villages in a city are covered. And while barangays are chosen in every island group, the dataset is not representative of the entire country as it does not include all provinces or even regions. The dataset is a census of all households in 20 participating barangays across 6 provinces (2 of which are technically districts) in 4 regions. Table 4.A.1.1 in the Appendix presents the participating barangays and groups them with the regions and provinces they represent. Because of the highly purposive design used in the sampling of the data, the distribution of observations is hugely disproportionate with majority of the observations coming from Negros Occidental and the city of Marikina. I exercise caution in the analysis and cluster all standard errors at the *barangay* level since selection into the sample was made at this level and account for the wide disparity in the distribution of observations.

Of the 103,316 individuals in the sample, 40,422 (39.12%) are of school age (5-24), where 30,544 are those who live in households without migrants (75.56% of school age individuals). A notable limitation of the data is that only contemporaneous migrants may be identified, and no history of migration is available. Table 4.1 reports the distribution of school-aged individuals into school age groups. Primary-aged individuals (5-11 years old) make up 34.74% of the school age sample. These individuals are expected to be enrolled in primary school (Kindergarten up to Grade 6). Secondary-aged individuals (12-15 years old) only make up 20.36% of the subsample. These individuals are expected to be enrolled in high school (1st year to 4th year, which may be equivalent to Grade 7 plus 3 years of middle school in other countries). The largest portion (34.74% of the subsample) of the school-aged sub-sample are tertiary-aged individuals (16-24). These are typically fresh high school graduates who may work, or continue to either post-secondary education (trades, technical-vocational courses) or higher education (university or college) and even post-graduate education. The reason I make this large bracket for this age group is that individuals of this age in the Philippines are usually at a junction between further education, work, or other aspirations. I also extend this bracket to accommodate the relatively newly implemented K-12 program in 2013, which increased the age that individuals may remain in school. However, to address potential measurement error in making this age range too wide, I divide the tertiary age sample into those aged 16-20 to represent those more likely to be in school, and those aged 21-24 to represent those more likely to work. This is presented in the robustness section of the results. It may be noted that the primary and secondary net enrolment rate are 97.03% and 96.08%, respectively, per the imposed development goal of universal basic education. Therefore, I do not expect a large impact (if any at all) when I estimate the effect on primary and secondary enrolment. The tertiary net enrolment rate on the other hand was at 40.39%, indicating that the choice of going to school at this age is not as straightforwardly determined, and that opportunity costs for sending a working age member of a household to school is high.

Table 4.1. Distribution and net enrolment rates of school aged individuals.

School Age	# of individuals	% of school age individuals	# of enrolled in school age	Net enrolment rate (% of school age)
Primary (5-11)	12,173	34.74	11,811	97.03
Secondary (12-15)	7,135	20.36	6,855	96.08
Tertiary (16-24)	15,736	44.90	6,356	40.39
Total	30,544	100	25,022	71.40

Source: Author's calculation, CBMS 2015 Data

Geographic data were collected from PhilGIS (philgis.org) which compiles GIS data (shapefiles) from various (free) sources. The *barangay* administrative boundaries shapefiles were taken from www.gadm.org. The road shapefile was taken from Geofabrik GmbH-OpenStreetMap. The Department of Education school locations shapefile was taken from https://deped.carto.com/datasets, and the shapefiles for airports and seaports were created by PhilGIS' administrator, Xavier Fuentes. All geographic data is projected using the World Geodetic System 1984 (WGS 1984) in longitude and latitude.

Table 4.2 reports some descriptive statistics for the school-aged sample. Panel A summarizes a few demographic and socioeconomic indicators. Noticeably, the ratio of males to females in the sample is roughly even (50.8% are males). Only 47.24% of the sample own the house and lot they reside in. 61.38% are residing in urban areas. Panel B reports the distance of each non-migrant household to the nearest feature (whether infrastructure or institution) calculated as Euclidean distance by ArcMap's "Near" tool.

Table4.2. Descriptive statistics for school-aged individuals

Panel A. Demographic and socioeconomic characteristics

Variable	Measurement	Mean	Std. Dev.	Min	Max
Sex	Binary, = 1 if male	0.508	0.499	0	1
Age	Years	14.492	5.748	5	24
Wealth Index	Real-valued, normalized index of asset ownership	-0.301	2.385	-4.081	8.244
Tenure	Housing tenure, Binary, = 1 if own house and lot	0.472	0.499	0	1
Urban	Binary, = 1 if household is in an urban area	0.614	0.487	0	1

Panel B. Distance to nearest infrastructures/institutions

Primary Road	Euclidean distance in meters	4,346.90	4,746.34	0.022	15,804.3
Airport	Euclidean distance in meters	16,153.38	6346.21	1,921.91	55,384.7
Seaport	Euclidean distance in meters	14200.02	6031.30	637.09	37,985.9
DepEd School	Euclidean distance in meters	654.14	529.41	2.035	3,586.13
Prov. Capital	Euclidean distance in meters	14,870.68	4,845.89	1,938.67	34,978.2
Nat'l Capital	Euclidean distance in meters	249,235.1	245,921.2	1,938.67	777,810

Source: Author's calculation, CBMS 2015 Data.

4.3.2 Proximity and neighborhood effects

Prior to presenting the empirical strategy to estimate migrant proximity and neighborhood spillover effects on non-migrants, I first give a brief review of how previous studies have estimated proximity and neighborhood effects as well as the known issues of identification. This allows me to justify the specification of the model and how I attempt to address the issues of identification.

In the studies directly testing for proximity effects I reviewed in the previous section, proximity expressed as *distance* (i.e. meter, kilometers) appears to be the most used and most straightforward approach. Distance may be calculated as Euclidean distance (straight line distance) either connecting two distinct points or connecting a distinct point to the centroid of an area (Totadri et al, 2019; Wetwitoo and Kato, 2019; Bertoli and Grembli, 2016). Alternatively, network distance may be used wherein the distance is calculated based on established pathways (e.g. roads) between two points (O'Malley et al, 2017). Some studies establish proximity by calculating travel times between two points, often assuming a person drives (Cummings et al, 2017; Patacchini and Zenou, 2012). Other studies use a very loose definition of proximity where they use an indicator variable to imply access to a point of interest. Montolio and Planells-Struse (2015) used an indicator for "being stopped by police" to denote how "visible" the police force is to a person, whereas Kveder and Beauchemin (2015) used an indicator if the person has a migrant in his close social network to proxy for social proximity. With regards to identification, distance is often arguably considered exogenous, however, issues may arise depending on the location of a point of interest. That is, the choice of setting up a hospital, or choosing to reside in an area may be influenced by unobservable characteristics. So, to be able to infer that distance is exogenous requires that the location of points be plausibly exogenous as well.

The estimation of neighborhood and network effects traditionally follow a typical specification (Topa and Zenou, 2015): the outcome or behavior of an individual is expressed as a function of his observable characteristics as well as his household's characteristics, observable characteristics of his neighborhood which usually reflect the institutional factors or the composition of people in the neighborhood, and mean outcomes in a neighborhood. Examples of neighborhood effects reflecting composition may be seen in the studies of Feng (2018), Wang et al (2018), Hausmann and Nedelkoska (2018) and Wei et al (2017), where they used the proportion of migrants (or return migrants) in an area to proxy for migrant composition. Examples that use the characteristics of the neighborhood include Altonji and Mansfield (2018) who used school ranking, Graham (2018) who used a measure of the degree of segregation in a city, and Patacchini and Zenou (2012) who used the employment rate of ethnic groups in each area.

The traditional way of estimating neighborhood effects, however, naturally suffers from an identification problem precisely because agents are expected to affect each other's outcomes, and any co-movement in the outcomes and characteristics of these agents are typically indicative of this problem (Graham, 2018; Topa and Zenou, 2015). This was originally put forth by Manski (1993) as the "reflection problem", which is an endogeneity or simultaneity problem (outcomes of different agents are correlated) and is the first of three problems making it hard to separately identify the parameters of the traditional model. The second problem is known as the "sorting problem" which comes from exogenous or "contextual" effects that occur when the outcome of an individual is influenced by the characteristics of others and may lead to selection into neighborhoods and networks. The last problem is known as "correlated effects" where an individual and his neighbors are subjected to the same shocks or amenities (e.g. institutions, access).

Topa and Zenou (2015) present a great discussion on the strategies that studies have taken to resolve identification problems. They classify them into two major strands of literature: the experimental or quasi-experimental approach and the non-experimental approach. The use of the experimental approach requires exploiting exogenous variation in the location of residence. These typically come from policies like relocation programs or resettlement programs which may randomly assign households to neighborhoods, or those that may cause exogenous variation in housing or land prices. These setups allow researchers to isolate the effect purely coming from the change in neighborhood. A classic example of such a program is the Moving to Opportunity program in the US which relocated families from poor to low-poverty neighborhoods via housing vouchers. Feng (2018) and Wang et al (2018) exploit a law imposed in China that requires the random assignment of students to classes, then controlling for sorting using school (or grade by school) fixed effects or clustering standard effects by school (sorting when parents choose the school their children would attend).

The non-experimental approach relies in arguing that the assignment of agents to an area is quasi-random, that is, location choice is driven by factors orthogonal to unobservable characteristics. This approach often requires geographical information of observations rather than just a classification or indicator of which neighborhood they are a part of. Bayer et al's (2008) identification strategy relied on the lack of correlation of unobservables within blocks after accounting for the broader reference group (neighborhood level). They argue that because of the thinness of the housing market and the inability of people to identify block-by-block variation within the neighborhood, individuals have little to no choice in the block they will reside in, hence location may be considered quasi-random. Patacchini and Zenou (2012) applied spatial data analysis techniques by introducing proximity bands of an agents location to other neighborhoods using driving time, and used area fixed effects and an IV regression to control for endogenous sorting. Helmers and Patnam's (2014) study offers perhaps one of the strongest approaches in disentangling the parameters of interest. Because they can pinpoint the exact geographic location of a household, they can identify a child's peer group as either the *k* nearest neighbors or the children within a specified community classification. They then proceed to compute for each child, the average outcome of their peer group to represent the endogenous effect, and the average characteristics the peer group to represent exogenous effects, which is a strategy endorsed by Altonji and Mansfield (2018). However, Helmers and Patnam's (2014) raised a potential problem when each child's peer network structure is misspecified because of random sampling. A problem may occur if, in the course of random sampling, key (or the true nearest) neighbors in a child's network may have been excluded, thus leading to a misspecification in the spatial weighting matrix. The network may be underspecified if the true nearest neighbors are excluded, would be indicated by low clustering but high spatial autocorrelation, and would lead to a downward bias in estimates. The network may be over specified if irrelevant neighbors are included, would be indicated by high clustering but low spatial autocorrelation, and would lead to an upward bias in estimates.

To briefly summarize the general approach the discipline has taken to address the identification problems in estimating neighborhood effects: endogenous effects, while ideally addressed by natural experiments causing random assignment, may somewhat be adequately addressed with the inclusion of an average of outcomes in the neighborhood (per Helmers and Patnam (2014)). Exogenous effects may be addressed with the inclusion of neighborhood-level averages of individual or household characteristics or a suitable instrument (Altonji and Mansfield, 2018), conditioning location on covariates (Graham, 2018), or may partially be addressed with the inclusion of area fixed effects (Patacchini and Zenou, 2012). Correlated effects, on the other hand, may be the most straightforwardly addressed issue with the inclusion of area-level fixed effects to absorb area-level shocks or amenity effects.

4.3.3 Identification strategy

In investigating whether there are proximity and neighborhood spillover effects for non-migrants, two major issues may confound identification. First, is that non-migrant households may be sorting into locations where they can be near migrants (presumably to benefit from them indirectly), hence non-migrants that are near migrants may have selection on unobservable characteristics. This behavior implies that non-migrants may become more willing to pay to live near migrants and may have a considerable impact on housing prices. Second, is that an area's wealth typically has intense correlation with both the migrants in an area and the likelihood of enrolment (richer areas tend to have more migrants and higher enrolment rates). This may be indicated by non-migrants having higher income and expenditure around migrants. This makes it difficult to disentangle migrant proximity and clustering effects from wealth effects.

To address these issues, I employ an identification strategy similar to Bayer et al (2008) and is somewhat similar in spirit with Feng (2018) and Wang et al (2018). Although I do not exploit any natural experiment, I assume, and henceforth argue, that *the location of people and migrants may be deemed random after considering the sorting of people into broader neighborhood classifications*. That is, people will sort into provinces, *barangays* and *purok*, but *where they are situated in even smaller geographic areas may be considered quasi-random*. Therefore, the identification strategy is hinged on two things: 1.) that geographic areas even smaller than *purok* exist and can be determined using proximity-based networks, and 2.) that housing prices and wealth in *purok* should generally be evenly distributed and uncorrelated with the proximity to a migrant household.

In ensuring the first requirement, I adopt a strategy similar to Helmers and Patnam (2014) geographic proximity-based peer network. A unique feature of the CBMS dataset is the geographic location of households (XY coordinates expressed as longitude and latitude) which allows me to establish a geographic proximity-based network between a non-migrant household and the nearest migrant household. I used ArcMap (ArcGIS) to calculate distance to the nearest migrant for every non-migrant household (more details on the spatial transformation used and this procedure in the next section). Geographic proximity is a reasonable basis in to establish networks since physical spaces often overlap with social spaces (Topa and Zenou, 2015) and proximity may determine social interaction (Helmers and Patnam, 2014).

After establishing the proximity-based structure of non-migrant-migrant pairs, I then show that housing prices, which I proxy using imputed rent (a variable defined in the CBMS dataset as a household's estimated willingness to pay to stay in their current residence), and total expenditures do not respond to the distance a non-migrant has to the nearest migrant once *purok* of residence is controlled for. The intuition behind this strategy is that, *after sorting into purok, if a household's willingness to pay to stay in their current residence is not statistically associated with their distance to the nearest migrant, then non-migrants are not "flocking" or are not sorting into their residences to be near migrants*. A similar thing may be said about total expenditures. If a non-migrant household's total expenditure does not respond to the distance to the nearest migrant, it may be said that their location of choice in relation to migrant households does not create any structural differences in wealth. Table 4.3 presents OLS estimates of the test regarding the relationship between distance to the nearest migrant (the computation of this variable is elaborated in more detail in the following section) and imputed rent and total expenditures.

Columns (1) and (4) show the effect that proximity to the nearest migrant has on imputed rent and total expenditures. It may be seen that as a non-migrant lives closer to a migrant household, they tend to have a higher willingness to pay to reside in their current dwelling and higher total expenditures. However, after controlling for sorting (which is the inclusion of *purok* dummies akin to Patacchini and Zenou's (2012) strategy), it may be seen that proximity to the nearest migrant has statistically no effect on non-migrant's imputed rent or total expenditures (Cols. (2) and (5)). I check for robustness of this result to the inclusion of various control variables and find that the lack of any significant correlation persists (Cols. (3) and (6)). I take this now as evidence to support the identifying assumption that, after considering the broader network, non-migrants are not flocking to where migrants are. In other words, *after controlling for purok, the geographic location of non-migrants is quasi-random*. As an additional measure, I also check for any systemic pattern on sorting based on nearest migrant household characteristics (columns (7) to (12) of Table 4.3). Non-migrants may be sorting towards higher educated migrant household heads or those that receive remittances as they may receive benefits from these, so this possible feedback may confound the proximity and neighborhood effects on enrolment. Columns (7) and (10) report that, prior to controlling for sorting, the proximity to the nearest migrant is positively associated with higher migrant household head education (which indicates sorting behavior) but negatively on the likelihood that the nearest migrant household receives remittances (which is counterintuitive). However, after controlling for *purok* dummies (Columns (8), (9), (11) and (12)), it may be seen that any systematic difference disappears which reinforces the identifying assumption.

In this study, I generate a binary migrant hotspot variable which indicates whether non-migrants belong to a statistically significant hotspot of migrants (the process of generating this variable will be elaborated in greater detail in the following section). The inverse distance to nearest migrant is used as a running variable and is tangentially correlated to the hotspot variable. Although the proximity variable may already be considered quasi-random, as an added measure, I check for any sorting based on migrant hotspot in the same vein as the results presented in Table 4.3 (results reported in Table 4.A.1.2 of the Appendix). For all four outcomes, even without controlling for *purok* dummies, the impact of being in a migrant hotspot is statistically insignificant. When controlling for *purok* dummies, the same may be said for all except total expenditures where the effects are negative. I believe this is not alarming as this relationship runs counterintuitively to the expectation that non-migrants sort into richer neighborhoods. With these checks, I argue with the identifying assumption that after controlling for sorting into *purok*, the geographic location of non-migrants within these small administrative areas may be considered quasi-random. I then utilize a spatial approach in estimating proximity and neighborhood spillover effects.

Table 4.3. The effect of proximity to nearest migrant on imputed rent and total expenditures and select nearest migrant characteristics before and after controlling for sorting into *purok*.

Dependent Variable	Imputed Rent			Total Expenditures			Nearest Migrant Years of Schooling			Nearest Migrant Remittances		
	No control	*Sorting controlled*		*No control*	*Sorting controlled*		*No control*	*Sorting controlled*		*No control*	*Sorting controlled*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ln (idist_nmig)	428***	-82.91	-74.77	241***	-67.73	-103.1	0.41***	0.0232	0.0279	-0.0356*	-0.0049	-0.0046
	(77.21)	(53.92)	(60.34)	(61.76)	(74.03)	(66.77)	(0.123)	(0.0562)	(0.0563)	(0.0181)	(0.0108)	(0.0119)
Purok dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Controls^	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	89,887	89,887	89,887	51,580	51,580	51,580	67,459	67,459	67,459	89,887	89,887	89,887
R-squared	0.017	0.100	0.108	0.000	0.012	0.012	0.032	0.334	0.336	0.012	0.243	0.248

Source: Author's computation, CBMS 2015 Dataset

Note: Standard errors (in parentheses) are clustered on a *barangay* level. ***, **, * denote significance levels at 1%, 5%, and 10%. *ln (idist_nmig)* stands for the natural log of the inverse distance to the nearest migrant used to denote the incremental change in the proximity to the nearest migrant.

^ include individual characteristics (sex, age), household geographical characteristics (log of inverse distance to nearest primary road, airport, seaport, school, province capital and national capital), nearest migrant characteristics (indicators for owning their house & lot and remittances, level of remittances and wealth).

4.3.4 A spatial approach to proximity and neighborhood spillover effects

In estimating migrant proximity and neighborhood spillover effects, I employ an empirical strategy similar to Helmers and Patnam (2014) in that I use the geographic location of households to establish nearest-neighbor networks. This strategy is justified in that proximity often triggers greater interactions hence should have an impact on behavior and outcomes. Figure 4.1 shows a partial snapshot of the distribution of households across a few barangays in the province of Negros Occidental (household distribution in other provinces are presented in Figures 4.A.1.1 – 4.A.1.6 in the Appendix). Given that only a few neighborhoods have been selected into the sample, there may be a shortfall in using conventional methods of measuring neighborhood effects based on administrative boundaries in that not all neighborhoods are well-represented. Making use of the geographical location of households allows the establishment of networks between non-migrants and migrants even within smaller neighborhoods.

Since the CBMS and geographic data were originally encoded using the WGS1984 geographic coordinate system (which uses decimal degrees (i.e. longitude, latitude) for angular units), I project the data onto a Transverse Mercator projected coordinate system: the WGS1984 Universal Transverse Mercator Zone 51N[22]. This allows the use of more easily interpretable metric distance values rather than decimal degrees.

In preparing the proximity variable used in the estimating equation, I use the "Near" function for every non-migrant household to identify the nearest migrant household. The distance (in meters) is then calculated as the Euclidean (straight line) distance between the two. I then take the inverse distance (1/d) to represent the degree of closeness rather than separation, and then apply natural log transformation to later facilitate ease in the interpretation of effects of percentage changes. The proximity variable is the log of inverse distance between a non-migrant and the nearest migrant. By the identification strategy presented earlier, this variable is plausibly random. However, by itself, it lacks features that allow us to identify characterizations such as a critical distance wherein I may expect relevant interactions to occur. In other words, I may find that proximity to a migrant may be relevant in determining a non-migrant's outcomes, but at what level of proximity will they be more likely to interact?

[22] Projection from WGS1984 to UTM is the process of taking the images sprawled on a sphere and projecting it onto a flat surface.

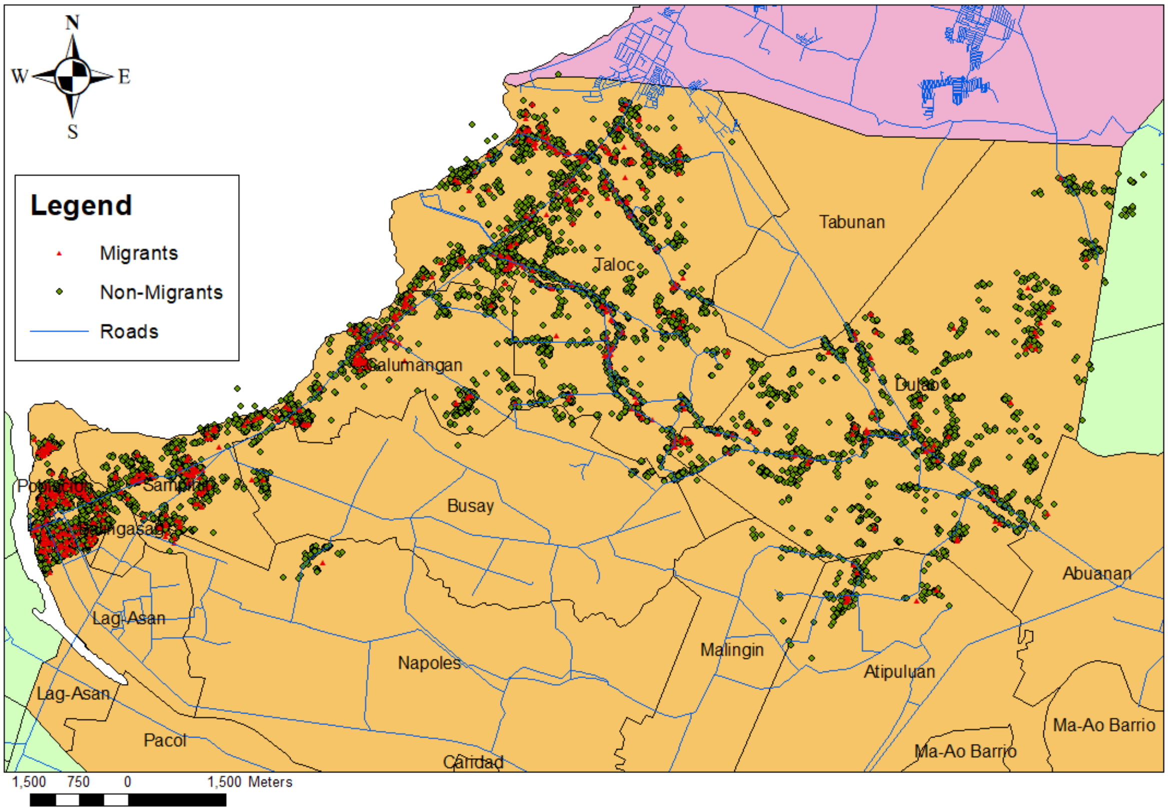


Figure 4.1. Example of the geographic distribution of non-migrant and migrant households.

Source: Household locations taken from CBMS (2015). Administrative boundaries and roads taken from PhilGIS.

In coming up with this critical distance, I use the Getis-Ord (1992) General G (GOGG) statistic which measures the degree of clustering for high or low values, but in this case, values are {0,1} with "1" denoting migrant households. GOGG is also used to assess the overall spatial association (the pattern and trend of data) within an area, allowing the identification of a distance of spatial autocorrelation when all features draws from nearest neighbors no matter how far and also while setting fixed distance bands. Simply put, GOGG identifies whether a relevant distance exists when households are able to interact with all other households in an area, and may also identify whether there exist spatial autocorrelation exist within specified distances (Appendix 4.A.2 presents the calculation behind the GOGG). In calculating the GOGG for each *barangay*, it is found that across *barangay*s, spatial autocorrelation (the clustering of migrant households) occurs at 100m and 50m distances. Although the GOGG also automatically identifies the maximum distance at which statistically significant clustering occurs, I forego the use of this as the size of areas play a direct influence, and these distances are not comparable across *barangays* (some barangays have a critical distance of up to 700m). Table 4.A.1.3 in the Appendix summarizes the findings of the GOGG computed for each *barangay*. I then test for the effect of having a migrant within this critical distance on the non-migrant. I do this by generating buffer rings with radii of 100m and 50m around each non-migrant household and conducting a spatial join to count the number of migrants completely contained in the buffer. A binary variable is then generated where it takes value of 1 when the number of migrants within the buffer is positive and 0 otherwise.

In estimating the neighborhood effect, it may be interesting to look at the migrant network around the area of the non-migrant. I use the number of migrants around the 100m and 50m buffers around non-migrant households as a proxy for a "visible" network of migrants. As an alternative proxy for a neighborhood effect, I perform Hot Spot Analysis which identifies hot and cold spots using the Getis-Ord (1992) Gi* (GOGi*). Hot spots are statistically significant spatial clusters of high values, and cold spots are statistically significant spatial clusters of low values. The difference between the GOGG and the GOGi* is that the GOGi* looks at clustering around each feature in the context of its neighboring feature. The tool generates z-scores and having a high z-score may indicate clustering, but this will only be statistically significant if it is surrounded by other features with high values as well. The local sum for a feature and its neighbors is then compared proportionally to the sum of all features. The tool then generates and classifies each feature into bins based on statistically significant hot and cold spots[23] (the calculation behind the GOGi* is presented in Appendix 4.A.3). I then generate a binary variable that takes the value of 1 when a household is classified into any bin that indicates it is part of a hotspot that is statistically significant at any level, given either a fixed distance band of 100m or 50m. As an example of the result, Figure 4.2 shows a snapshot of the hotspot analysis conducted on the set of barangays in Negros Occidental as in Figure 4.1.

Hot Spot Analysis using the GOGi* is an innovative alternative to the identification of neighborhoods or the density/clustering of a network, and hence an innovative way of estimating neighborhood effects. It offers flexibility in determining neighborhoods based on the surroundings of a feature. Paired with the GOGG, it allows for the determination of a household's peer network structure while allowing spatial autocorrelation to guide the range at which I may expect to see meaningful interactions. Furthermore, the use of GOGG and GOGi* may be suitable when working with data where geographic information of points is available, and the number of neighborhoods based on administrative

[23] Bins have the following values {-3, -2, -1, 0, +1, +2, +3}, where negative values represent cold spots (concentration of low values) and positive values represent hot spots (concentration of high values). A bin of 0 represents complete spatial randomness. 1,2,3 represent significance at the 10%, 5%, and 1% levels, respectively. E.g., the +2 bin would represent that the feature is part of a hotspot with 5% level of significance.

boundaries is small. This analysis may also be more meaningful when we may expect relationships to appear given very close proximity.

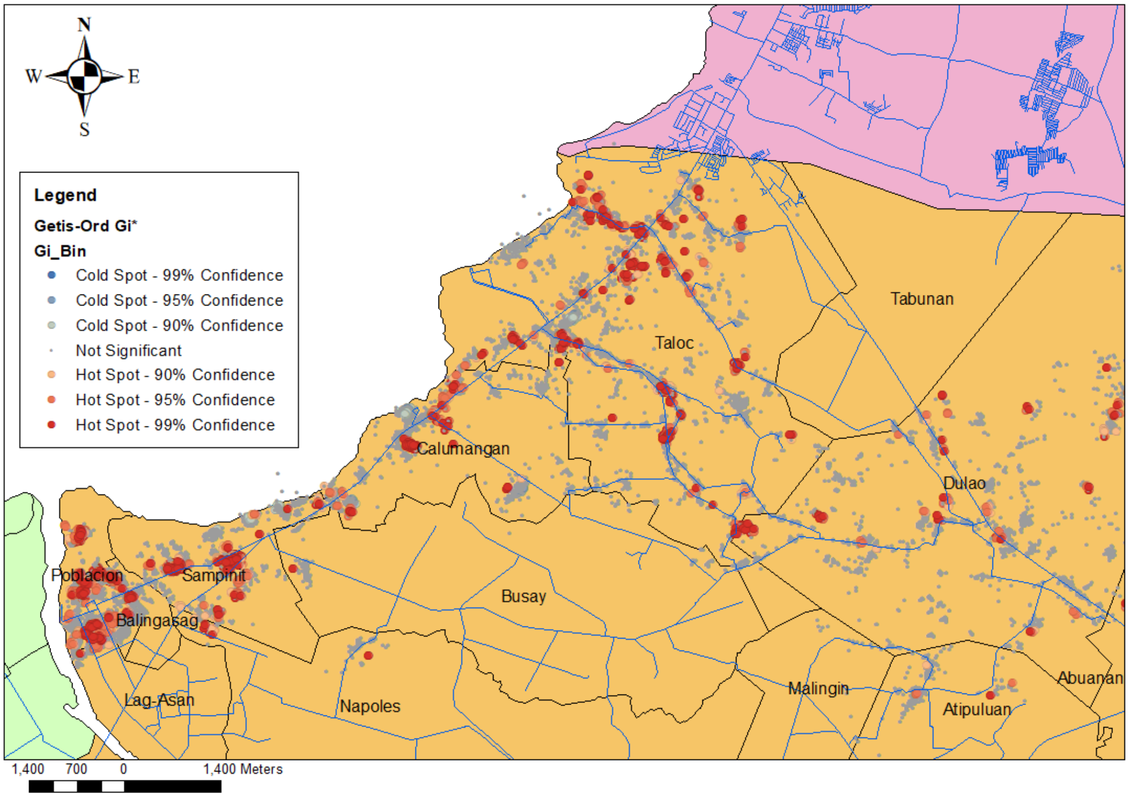


Figure 4.2. Example of the hotspot analysis on the presence of migrants.
Source: Household locations taken from CBMS (2015). Administrative boundaries and roads taken from PhilGIS.

4.3.5 Estimating equation

Using the abovementioned identification strategy and representation of proximity and neighborhood effects, the following equation is estimated:

$$Y_{ijp} = \alpha \; + \; \delta \cdot D_{ij} \; + \; \beta \cdot \{M_i\} \; + \; \boldsymbol{\pi X_i} + \boldsymbol{\gamma Z_j} + \boldsymbol{\varepsilon_p} + u_{ijp} \qquad (4.1)$$

Where Y_{ijp} is the binary enrolment status of the *i*th school-aged individual[24] residing in (interchangeably) household *i* nearest to the *j*th migrant in *purok p*, = 1 if currently attending school and 0 otherwise. D_{ij} represents the proximity between household *i* and nearest migrant *j* It follows that δ is a coefficient of interest and represents the migrant proximity spillover effect. The vector $\boldsymbol{\varepsilon_p}$ represents *purok* dummies and accounts for the identification strategy that locational distribution is quasi-random after controlling for the broader neighborhood. The first estimation of equation (4.1) focuses solely on proximity spillovers, D_{ij}, and so $\{M_i\}$ is excluded.

Succeeding iterations will have different $\{M_i\}$ based on different measures of spillover effects coming from migrant presence and neighborhood clustering. $\{M_i\}$ is enumerated as follows: 1.) migrant presence ($M^r_{presence,i}$, $r \in \{50{,}100\}$) – a binary variable, = 1 if there is a migrant household within a 100m and 50m radius around the non-migrant household and 0 otherwise; 2.) migrant count ($M^r_{count,i}$, $r \in \{50{,}100\}$) – count variable, number of migrant households within a 100m and 50m radius around the non-migrant household; and 3.) migrant hotspot ($M_{hot,i}$, $r \in \{50{,}100\}$) – a binary variable, = 1 if the non-migrant household belongs to a cluster of households considered a statistically significant hotspot for migrant households with a fixed distance band of 50m or 100m and 0 otherwise. Again, testing $M^r_{presence,i}$ is interesting to see if there is a critical distance where a proximity effect may appear. $M^r_{count,i}$ tests the possible neighborhood effect through a migrant network and will allow the interpretation of a marginal increase in the number of migrant households within a relevant distance. $M_{hot,i}$ is of particular interest as it is a neighborhood effect measuring migrant clustering relative to the position of the *i*th non-migrant household. It indicates whether the non-migrant household is in a spatially determined neighborhood where migrant households are concentrated (hence, hotspot). D_{ij} is included as a running variable in each $\{M_i\}$ equation as well as the vector $\boldsymbol{\varepsilon_p}$ for identification.

α is a constant. $\boldsymbol{X_i}$ is a vector of individual and household characteristics in the non-migrant household. This includes the school-aged individual's sex (= 1 if male, 0 if female) and age (count), and geographic characteristics of the non-migrant household: log of inverse (Euclidean) distances to the nearest primary road (defined as a main road), airport, seaport, school, the provincial capital[25], and the national capital (Manila). $\boldsymbol{Z_j}$ is a vector of characteristics of the nearest migrant household. This includes house and

[24] School age is classified primary/elementary (5-11), secondary/high school (12-15), and tertiary/post-secondary and college (16-24).
[25] Euclidean distance between non-migrant households and centroid of provincial capitals: Batangas City (Batangas), Imus (Cavite), Bacolod (Negros Occidental), Oroquieta (Misamis Occidental), City of Manila (Manila and Marikina)

lot ownership (= 1 if they own the house and lot, 0 otherwise), remittance receipt (= 1 if they receive remittances, 0 otherwise), remittance level (continuous), and a normalized index of wealth based on asset ownership (continuous).

While this paper is not a neighborhood effects paper in the strictest sense – that I am more interested in correlated effects (migrant households can be likened to institutions that non-migrants are exposed to) rather than social effects (non-migrants affecting non-migrants) – the identification strategy of including *purok* dummies should be able to address any concerns arising from contextual (sorting) and correlated effects especially in disentangling pure wealth effects from the proximity and clustering spillovers. I do not include variables to account for simultaneity among non-migrant households as the migrant spillover variables may cause a feedback effect to both the average outcomes of a network (the term used by Helmers and Patnam [2014] to account for the reflection problem) and the main dependent variable. The control variables are added to improve the precision of estimates. With regards to the network misspecification problem raised by Helmers and Patnam (2014), I believe it is reasonable to assume that there would be no over- or under-specification since the CBMS is a census of all households in each *barangay*. As for the actual structure of networks, the combined use of proximity measures and clustering/neighborhood measures are meant to provide a representation for these networks.

I disaggregate the sample into children aged 5-11 (primary school/elementary), 12-15 (secondary/high school), and 16-24 (post-secondary and tertiary/higher education) and use OLS to estimate the expected relationships.

4.4 Results

4.4.1 Main results

Table 4.4 reports the coefficients of the proximity (Panel A) and neighborhood variables (Panel B) from estimating equation (4.1). Columns (1)-(4) show the results for primary school-aged individuals. It may be seen that the marginal contributions of the distance variable are very minute. The signs of coefficients of the migrant presence and migrant count variables are not robust over changing radii. The coefficient of the hotspot indicator is counterintuitive but statistically insignificant as is all other coefficients. Inspecting columns (5)-(8) for the results on secondary school-aged individuals, a similar landscape appears. All proximity effect coefficients report negative, albeit statistically insignificant effects. Whereas all neighborhood effect coefficients, although positive, are also statistically insignificant. The same conclusion may be drawn for both subsamples: there are virtually no migrant proximity and neighborhood spillover effects on primary and secondary enrolment. While seemingly pessimistic, this may well be expected. Recalling from Table 4.1 that the figures for primary and secondary net enrolment rates are near universal (97.03% and 96.08%, respectively). This may in part be due to policies in place enforcing enrolment in basic education. With this lack of variation, it is not surprising that migrant spillovers have little to no effect.

Columns (9)-(12) of Table 4.4 presents some evidence of migrant proximity and neighborhood spillover effects. Looking at the coefficient of D_{ij}, it is seen that non-migrant households that are closer to migrant households tend to have higher enrolment rates. Furthermore, the coefficient appears robust to the inclusion and exclusion of various controls. I take caution, however, in giving an interpretation based on a marginal change. Since the specification is a linear-logarithmic probability model, a 10% increase in D_{ij} is what would lead to a $\hat{\beta}$ unit change in the probability of enrolment. If the distance between all non-migrants and migrants are closed by 10%, the non-migrant enrolment rate may increase by 0.00675 percentage points (from col. (12)), which translates to approximately 104 more individuals enrolled in a form of post-secondary or higher education for the entire sample. It may then be said that non-migrants are more likely to enroll when they live closer to a migrant household.

What may be said about having a migrant household within specific ranges of proximity? It may be seen that coefficients of $M^r_{presence,i}$ are not consistent over alternative radii specifications, nor are they statistically significant. It is likely that simply having a migrant within a certain range is not enough to influence behavior. However, this may not be enough to conclude that the concept of a critical distance does not exist. Looking at the coefficients for $M^r_{count,i}$, there is suggestive evidence that within the specified ranges, what matters more may be the number of migrants within an area. The coefficients for the migrant count variable are consistently positive for all radius and model specifications, yet it is only significant given a 100m radius when controlling for demographic and socioeconomic factors, and only significant given a 50m radius with the full specification. The coefficients depict characteristics that are consistent with most distance effects. That is, distance may act as a running variable where an effect must be the same albeit monotonically adjusting (i.e. dissipating effect over farther distances) over different levels as demonstrated in Patacchini and Zenou (2012). It may be seen that the marginal effect of an additional migrant in the area is stronger for closer proximity. This is considerably a prelude to potential network and neighborhood effects.

Table 4.4. Migrant proximity and neighborhood spillover effects on non-migrant households' enrolment status.

Specification:	**Primary** (n=12,047)				**Secondary** (n=7,051)				**Tertiary** (n=15,520)			
	Basic	$+\boldsymbol{X_i}$	$+\boldsymbol{Z_j}$	Full	Basic	$+\boldsymbol{X_i}$	$+\boldsymbol{Z_j}$	Full	Basic	$+\boldsymbol{X_i}$	$+\boldsymbol{Z_j}$	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Proximity effects.												
D_{ij}	6.60e-05	0.000342	5.65e-05	0.000343	-0.000953	-0.000896	-0.000985	-0.000926	0.00722**	0.00603**	0.00809**	0.00675**
	(0.00173)	(0.00201)	(0.00176)	(0.00202)	(0.00272)	(0.00251)	(0.00270)	(0.00249)	(0.00288)	(0.00244)	(0.00290)	(0.00257)
$M_{presence,i}^{100}$	-0.00828	-0.00863	-0.00844	-0.00884	-0.00511	-0.00480	-0.00441	-0.00397	0.0201	0.00164	0.0198	0.000960
	(0.00765)	(0.00798)	(0.00761)	(0.00793)	(0.00830)	(0.00773)	(0.00850)	(0.00785)	(0.0124)	(0.0123)	(0.0123)	(0.0124)
$M_{presence,i}^{50}$	0.00478	0.00442	0.00490	0.00456	-0.00290	-0.000900	-0.00263	-0.000629	-0.00934	-0.0187	-0.00873	-0.0182
	(0.00555)	(0.00546)	(0.00550)	(0.00542)	(0.00882)	(0.00880)	(0.00861)	(0.00861)	(0.0200)	(0.0131)	(0.0198)	(0.0130)
Panel B. Neighborhood effects												
$M_{count,i}^{100}$	-0.000251	-0.000246	-0.000265	-0.000258	0.000362	0.000312	0.000347	0.000286	0.00124	0.00120**	0.00105	0.00109**
	(0.000480)	(0.000450)	(0.000495)	(0.000466)	(0.000666)	(0.000634)	(0.000695)	(0.000664)	(0.000793)	(0.000538)	(0.000789)	(0.000507)
$M_{count,i}^{50}$	0.000484	0.000478	0.000492	0.000497	0.000418	0.000306	0.000328	0.000202	0.00179	0.00219	0.00168	0.00223*
	(0.000568)	(0.000491)	(0.000594)	(0.000517)	(0.000802)	(0.000806)	(0.000831)	(0.000836)	(0.00145)	(0.00139)	(0.00140)	(0.00127)
$M_{hot,i}$	-0.00835	-0.00808	-0.00865	-0.00839	0.00109	0.00414	0.000960	0.00394	0.0327**	0.0287**	0.0294*	0.0264**
	(0.00651)	(0.00672)	(0.00660)	(0.00680)	(0.00456)	(0.00409)	(0.00440)	(0.00423)	(0.0144)	(0.0106)	(0.0152)	(0.0115)

Source: Author's computation, CBMS 2015 Data.

Note: Standard errors clustered at *barangay* level to account for sampling design. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively. Each cell represents a separate regression equation. All regressions include *purok* dummies to account for identification strategy. All $\{M_i\}$ regressions include D_{ij} as a running variable. "Basic" regressions include only the proximity and neighborhood effects variables. "$+\boldsymbol{X_i}$" regressions include the basic model plus non-migrant individual and household controls: sex, age, log of inverse distance to nearest primary road, airport, seaport, DepEd school, provincial capital, and national capital. "$+\boldsymbol{Z_j}$" regressions include the basic model plus nearest migrant household controls: house and lot ownership, remittance indicator, remittance level, and wealth index. "Full" regressions include all controls. All equations estimated with OLS.

Looking at the coefficients for $M_{hot,i}$, it may be seen that the coefficients are positive, statistically significant, and robust to all model specifications. A tertiary education-aged individual in a non-migrant household that located in a concentration of migrant households has an approximately 2.64% higher likelihood of being enrolled. This translates to about 409 more individuals enrolled in post-secondary or higher education across all migrant clusters in the sample. This is indicative of migrant neighborhood spillover effects through the presence of migrant clusters.

In sum, there is correlated evidence at the very least, that the prospect of migration can raise the level of human capital in an area. This lends strength to the role model hypothesis as well: being able to interact with migrants can alter a person's aspirations and incentive structure, increasing his perceived returns to higher education. Not only does living in a migrant cluster increase the likelihood of tertiary enrolment, but this may be enhanced further the closer one lives to a migrant through the supposed higher likelihood of interacting with the migrant household.

4.4.2 Robustness to alternative measures of neighborhood effects

As a check of robustness to conventional measures of neighborhood effects, I look at how the enrolment status of non-migrant school age children may vary with migrant composition at the *purok* level. To represent migrant composition, I test three alternative definitions. First, I look at the proportion of individuals in migrant households relative to the sample population in each *purok*. This would allow me to look at the effect of migrants in general. Then I define migrant composition at the level of school-aged peers. I use *purok* level proportion of migrant peers defined as the proportion of individuals in an age group that are part of migrant households[26]. I also look at the *purok* level migrant peer net enrolment rate (NER)[27]. The specification is as follows:

$$Y_{ijpk} = \alpha \; + \; \tilde{\beta} \cdot \left\{ \widetilde{M_p} \right\} \; + \; \boldsymbol{\pi X_i} + \; \boldsymbol{\gamma Z_j} + \; \boldsymbol{\varphi_k} + u_{ijp} \tag{4.2}$$

[26] % of migrant peers in a *purok* is defined as $\frac{\#\, of\ migrant\ individuals\ of\ an\ age\ group}{\#\, of\ individuals\ of\ an\ age\ group}$, computed for all age groups in each *purok*.

[27] Migrant peer net enrolment rate is defined as $\frac{\#\, of\ migrant\ individuals\ of\ an\ age\ group\ that\ are\ enrolled}{\#\, of\ migrant\ individuals\ of\ an\ age\ group}$, computed for all groups in each *purok*.

Which is essentially the same as equation (4.1) with the exception that the variables of interest are now $\{\widetilde{M_p}\}$ which is set of measures mentioned previously (% of migrant households, % of migrant peers in an age group, and migrant peer NER). Including *purok* dummies will likely absorb the any *purok* level variation hence province dummies $\boldsymbol{\varphi_k}$ for *k* provinces are used instead. Natural logarithmic transformation will be applied to $\{\widetilde{M_p}\}$ to help facilitate interpretation of marginal changes in the proportion of migrants.

Table 4.5 reports the results of the robustness check using *purok* level migrant composition. Looking at effects for primary and secondary education aged individuals, a direct contrast may be seen with the results presented in Table 4.4. For primary education (columns (1) and (2)), a positive and significant effect appears only for the migrant peer NER. Having more migrants in general or in their peer group has no impact on their enrolment rate. Perhaps seeing more migrant peers enrolled are what have a more distinct impact in raising non-migrant primary enrolment rates. As for secondary education-aged individuals (columns (3) and (4)), impacts of having higher migrant composition is more readily visible in all measures. The coefficient for migrant peer composition, however, is not robust to the inclusion of control variables. Looking at the effects for tertiary education-aged individuals (columns (5) and (6)), a similar picture may be seen with that of the findings from the primary model. An increase in the proportion of migrant households and migrant peers in the age group appear to be associated with an increase in the probability of enrolment of non-migrants. Surprisingly, the effect seems to appear only for the density of migrants in the area rather than whether their migrant peers are enrolled. I note a few limitations on these estimates. Unobserved characteristics may still be driving non-migrants to sort toward areas with more migrants, and the use of NER may have a profound simultaneity issue since the enrolment of individuals may drive the enrolment of others as well.

In trying to enhance the precision of the estimates, I perform two additional robustness checks to flesh out certain nuances of the model. First, to rule out the possibility that non-migrant households may be receiving remittances from abroad (this is explored as a channel in a later subsection), I run the full-control specification of equation (1) restricting it to the sub-sample of non-migrant households that did not receive remittances (Columns (1) to (3) in Table 4.A.1.4 in the Appendix). There appears to be no novel difference (no change in statistical significance), save for slightly smaller coefficients of the proximity variables and slightly larger coefficients for the neighborhood variables.

The second check I perform addresses the potential measurement error in the tertiary age subsample. The tertiary age range (16-24) may be too wide that it captures two unobserved cohorts: the fresh graduates from high school (16-20) and those that may have finished college or university and may have already be working (21-24). I divide the tertiary age subsample further into these groups and estimate equation (4.1). The results for the full-control specification are reported in columns (5) and (6) of Table 4.A.1.4 in the Appendix, comparing it with the full cohort results from Table 4.4 reported in column (4). Three distinct findings appear from this exercise. First, the positive proximity effect captured by D_{ij} in the full subsample seems to be driven by the 16-20 subgroup as there is a much larger, positive coefficient, but no significant effect for the 21-24 subgroup. This may imply that the proximity spillover is more relevant to new high school graduates, perhaps more likely encouraging them to enroll in college or university. Second, the neighborhood spillover effect captured by $M^{r}_{count,i}$ in the full subsample is only evident in the 16-20 subgroup but is inconsistent with distance properties since statistical significance is lost from 100m to 50m. Third, the positive neighborhood spillover effect captured by $M_{hot,i}$ is only evident for the 21-24 subgroup. This may indicate that belonging to a migrant community encourages the older non-migrant subgroup to pursue higher or even graduate education.

Table 4.5. *Purok*-level migrant composition as robustness check for neighborhood effects

	Primary		**Secondary**		**Tertiary**	
	Basic	Full	Basic	Full	Basic	Full
Specification:	(1)	(2)	(3)	(4)	(5)	(6)
% of migrant households	0.00457	0.00153	0.0128**	0.00776**	0.0282***	0.0211**
	(0.00323)	(0.00302)	(0.00521)	(0.00317)	(0.00901)	(0.00952)
	n= 11,849		n=6,988		n=15,387	
% of migrant peers	0.00391	0.000747	0.0128**	0.00640	0.0282***	0.0206***
	(0.00275)	(0.00283)	(0.00525)	(0.00604)	(0.00629)	(0.00570)
	n=10,889		n=5,855		n=14,424	
migrant peer NER	0.0648**	0.0653**	0.0849*	0.0848*	0.0108	0.00338
	(0.0306)	(0.0303)	(0.0426)	(0.0466)	(0.0242)	(0.0235)
	n=10,889		n=5,852		n=13,523	

Source: Author's computation, CBMS 2015 Data.

Note: Standard errors clustered at *barangay* level to account for sampling design. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively. Each cell represents a separate regression equation. All regressions include province dummies. "Full" regressions include non-migrant individual and household controls: sex, age, log of inverse distance to nearest primary road, airport, seaport, DepEd school, provincial capital, and national capital, and nearest migrant household controls: house and lot ownership, remittance indicator, remittance level, and wealth index. All equations estimated with OLS.

4.4.3 Heterogeneity

I further investigate possible nuances in the spatial spillover effects by testing for heterogeneities according to rural-urban classification and gender. Table 4.6 reports the full-control estimates of equation (4.1) for all age groups, disaggregated further according to subsample.

Columns (1), (5) and (9) report the findings for non-migrants in rural areas for primary, secondary and tertiary aged individuals, respectively. Findings are highly inconsistent. Neither D_{ij} nor $M_{presence,i}^{100}$ have any effect on any group. $M_{presence,i}^{50}$ appears positive for primary and negative for tertiary, but both are inconsistent with distance properties. Only $M_{count,i}^{100}$ is positive and significant for secondary but is also inconsistent with distance properties. Lastly, $M_{hot,i}$ is only significant for tertiary but the marginal effect (4.65%) is larger than that of the full tertiary sample (2.64%). This may hint on a story that migrant networks may be more encouraging of higher educational aspirations in rural areas. When looking at the results for urban areas (columns (2), (6) and (10) for primary, secondary, and tertiary, respectively), the only significant findings are that $D_{ij}$and $M_{count,i}^{100}$have positive impacts for tertiary, and $M_{hot,i}$ is only significant but negative for primary. The findings for tertiary are to be expected, but further investigation is needed for why a migrant hotspot discourages primary enrolment in an urban setting, especially since the enforcement of universal education is usually stronger in urban areas. It may be said that proximity and neighborhood effects have varying impacts between urban-rural classifications.

Similarly, looking at the gender dimension reveals that there are only a few significant coefficients. First, $D_{ij}$is only significant and positive for tertiary-aged females, while $M_{presence,i}^{100}$ is not significant for any subgroup. $M_{presence,i}^{50}$ is significant and positive only for primary-aged males (however inconsistent with distance properties) but is surprisingly negative (and consistent with distance properties) for both secondary- and tertiary-aged females. This phenomenon is arguably peculiar and warrants further investigation. $M_{count,i}^{50}$ is significant (but not $M_{count,i}^{100}$) for secondary- and tertiary-aged females, showing positive coefficients, although the result for secondary is inconsistent with distance properties. Lastly, $M_{hot,i}$ appears to only be significant and largely positive (3.07%) for tertiary-aged males. Like the earlier heterogeneity, it may be said that there is no clear trend across subgroups and only nuanced patterns of proximity and neighborhood spillovers over different heterogeneities may be apparent.

Table 4.6. Heterogeneity of migrant proximity and neighborhood spillover effects on non-migrant households' enrolment status by rural-urban classification and gender.

	Primary (n=12,047)				**Secondary** (n=7,051)				**Tertiary** (n=15,520)			
	Rural	Urban	Male	Female	Rural	Urban	Male	Female	Rural	Urban	Male	Female
Specification:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Proximity effects.												
D_{ij}	-0.0022	0.0015	-0.0011	0.0021	0.0009	-0.0012	-0.0017	0.0008	0.0039	0.0081**	0.0056	0.0069*
	(0.0029)	(0.0024)	(0.0029)	(0.0015)	(0.0049)	(0.0027)	(0.0035)	(0.0029)	(0.0065)	(0.0027)	(0.0038)	(0.0036)
$M_{presence,i}^{100}$	-0.0016	-0.0181	-0.0082	-0.0074	0.0003	-0.0160	-0.0033	-0.0026	0.0243	-0.0211	0.0029	-0.0005
	(0.0084)	(0.0134)	(0.0131)	(0.0084)	(0.0068)	(0.0154)	(0.0152)	(0.0075)	(0.0149)	(0.0238)	(0.0135)	(0.0192)
$M_{presence,i}^{50}$	0.0142*	0.0003	0.0142**	-0.0067	-0.0170	0.0074	0.0136	-0.0146*	-0.029**	-0.0107	-0.0127	-0.0238*
	(0.007)	(0.0062)	(0.00641)	(0.0058)	(0.0173)	(0.0119)	(0.0169)	(0.0084)	(0.0091)	(0.0180)	(0.0168)	(0.0133)
Panel B. Neighborhood effects												
$M_{count,i}^{100}$	-0.0015	-0.0003	0.0001	-0.0007	0.0035*	0.0003	0.0005	-3.27e-05	0.0059	0.0011*	0.0012	0.0009
	(0.0014)	(0.0005)	(0.0009)	(0.0005)	(0.0015)	(0.0007)	(0.0011)	(0.0004)	(0.0039)	(0.0005)	(0.0009)	(0.0006)
$M_{count,i}^{50}$	0.0032	0.0003	0.001	-0.0002	-0.0034	0.0006	-0.0005	0.0010*	-0.0042	0.0027	0.0021	0.0024**
	(0.00417)	(0.0006)	(0.001)	(0.0007)	(0.0066)	(0.0008)	(0.0015)	(0.0006)	(0.0094)	(0.0016)	(0.0022)	(0.0009)
$M_{hot,i}$	0.0123	-0.017**	-0.0140	-0.0036	0.0035	0.0027	0.0093	-0.0021	0.0465**	0.0197	0.0307*	0.0200
	(0.0141)	(0.0058)	(0.0121)	(0.0085)	(0.0084)	(0.0051)	(0.0091)	(0.0065)	(0.0151)	(0.0131)	(0.0177)	(0.0134)
No. of obs.	5,094	6,953	6,125	5,922	2,824	4,227	3,640	3,411	5,596	9,924	7,832	7,688

Source: Author's computation, CBMS 2015 Data.

Note: Standard errors clustered at *barangay* level to account for sampling design. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively. Each cell represents a separate regression equation. All regressions include *purok* dummies to account for identification strategy. All $\{M_i\}$ regressions include D_{ij} as a running variable. All regressions are full specification: proximity and neighborhood effects variables, non-migrant individual and household controls: sex, age, log of inverse distance to nearest primary road, airport, seaport, DepEd school, provincial capital, and national capital, and nearest migrant household controls: house and lot ownership, remittance indicator, remittance level, and wealth index. All equations estimated with OLS.

4.4.4 Channels

As a test of channels through which migrant proximity and clustering may affect non-migrants' enrolment, I look at whether working age non-migrant adults (defined as those aged 25-64) have a higher propensity to engage in entrepreneurial work and receive remittances from OFWs. The choice of these channels is in a way suggested in Topa and Zenou (2015). Non-migrants would benefit from interacting with migrants by possibly receiving information, knowledge spillovers, and even a source of credit. However, at the time of writing, these other channels are not testable as no data is available on information networks and knowledge spillovers or direct measures of informal credit.

To proxy for a source of credit, I use an indicator of entrepreneurial activity. Engaging in entrepreneurial activity may be an indication of possessing capital, which may have implicitly come from a neighborly source. I define this as a binary variable equal to 1 if the individual is engaged in any entrepreneurial activity and 0 otherwise. Alternatively, a more direct channel of benefit would be remittances. Inspecting the data reveals that there is a small portion of non-migrant households (without OFWs) that receive remittances from OFWs. This may be indicative of community remittances often performed as a form of aid or debt repayment. Community remittances is represented as a binary variable equal to 1 if the non-migrant household receives remittances and 0 otherwise. In testing these channels, I estimate the same specification as equation (4.1) with the outcomes being entrepreneurial activity and community remittances for working adults (aged 25-64).

Table 4.7 reports the findings for entrepreneurial and remittance channels. Looking at the entrepreneurial activity regressions, it may be said that there is barely any spillover effect coming from migrant proximity and neighborhoods. There is no significant association coming from the proximity and clustering variables. The small, negative coefficient for $M_{count,i}^{100}$ may be an exception being the only one significant across specifications albeit at only the 10% level. This may suggest that competition in entrepreneurial activity occurs with more migrants in an area, but I take caution in trying to provide a further explanation for this because the sign is not robust to changes in alternative radius specifications. In a way, effects across distance should generally be consistent albeit monotonically changing as demonstrated by Patacchini and Zenou (2012).

When looking at the community remittance regressions, evidence of any channel appears scant. There is no significant effect coming from the distance and clustering variables. For proximity effects, only $M_{presence,i}^{100}$ has a positive, significant coefficient that is robust to the inclusion of control variables. However, I exercise caution in interpreting this result since the effect is not robust to a change in the effective radius. While the coefficient of $M_{presence,i}^{50}$ is statistically insignificant, it also posts a (counterintuitive) negative sign. I cannot hastily conclude that non-migrant adults are more likely to receive community remittances with a migrant around 100 meters if looking for the same impact on a nearer distance reveals an opposite relationship.

Table 4.7. Entrepreneurial activity and community remittances for working adults aged 25-64.

	Entrepreneurial Activity (n=20,536)		Community Remittance (n=41,801)	
	Basic	Full	Basic	Full
Specification:	(1)	(2)	(3)	(4)
Panel A. Proximity effects				
D_{ij}	0.00107	0.000191	0.000429	0.000374
	(0.00235)	(0.00251)	(0.00102)	(0.00115)
$M^{100}_{presence,i}$	0.00126	0.000685	0.00821**	0.00829**
	(0.00763)	(0.00799)	(0.00390)	(0.00391)
$M^{50}_{presence,i}$	-0.00363	-0.00323	-0.00266	-0.00224
	(0.00445)	(0.00499)	(0.00659)	(0.00664)
Panel B. Neighborhood effects				
$M^{100}_{count,i}$	-0.000959*	-0.00119*	0.000332*	0.000263
	(0.000513)	(0.000578)	(0.000163)	(0.000178)
$M^{50}_{count,i}$	4.43e-05	0.000100	0.000822**	0.000667
	(0.000984)	(0.00102)	(0.000333)	(0.000391)
$M_{hot,i}$	0.00423	0.000778	0.00531	0.00562
	(0.00652)	(0.00806)	(0.00351)	(0.00368)

Source: Author's computation, CBMS 2015 Data.

Note: Standard errors clustered at *barangay* level to account for sampling design. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively. Each cell represents a separate regression equation. All regressions include *purok* dummies to account for identification strategy. All $\{M_i\}$ regressions include D_{ij} as a running variable. "Full" regressions include non-migrant individual and household controls: sex, age, log of inverse distance to nearest primary road, airport, seaport, DepEd school, provincial capital, and national capital, and nearest migrant household controls: house and lot ownership, remittance indicator, remittance level, and wealth index. All equations estimated with OLS.

Perhaps a more convincing piece of evidence is revealed by $M^{r}_{count,i}$ variable which reveals shows positive and significant coefficients for both radius specifications. It also exhibits a key characteristic I look for in proximity effects, that the effect tends to grow with closer proximity. Still, caution is necessary in interpreting this result since the results are not robust to the inclusion of control variables. It may be said that greater numbers of migrants in an area may be associated with a higher likelihood of receiving community remittances, and the effect is even more pronounced for greater proximity. Although this channel does not play directly with effects of the "prospect" of migration, the receipt of community remittances relaxes the liquidity constraints of a household, allowing it to divert more resources into enrolling working age individuals despite the high opportunity costs of post-secondary and higher education.

4.5 Conclusion

Understanding the spillover effects of migration is a subject that warrants more attention especially with the growing number of migrants around the world. Despite the significant brain drain literature that has criticized migration, recent theoretical and empirical works have been pointing toward a brain gain that occurs when the host country forms more human capital with the prospect of migration than without it. This is attributable to changes in people's incentive structure as well as their perceived returns to human capital. In studying the spillover effects that migrant proximity and clustering have on non-migrants' enrolment decisions, this paper provides evidence to further expand the brain gain literature. Moreover, this paper expands the frontier in the methods of studying neighborhood effects by uniquely applying techniques in spatial statistics that have been used infrequently in economics. Using a unique dataset, which reveals the geographical location of households within smaller administrative boundaries, that is the CBMS 2015 data, I am able to establish migrant peer networks based on proximity for non-migrants by identifying the nearest migrant neighbor. In addition, I use the GOGG to establish migrant peer networks by identifying a critical distance at which interactions are more likely to occur, and conjunctively apply Hot Spot Analysis using GOGi* to assign non-migrant households into migrant hotspots or clusters. In identifying proximity and neighborhood effects, I assume and argue that non-migrant households do not sort into areas near migrants after controlling for the broader neighborhood catchment. This strategy assumes that after controlling for *purok* dummies, which is the control for sorting and correlated effects, the geographical distribution of non-migrant households in the area is considerably random. Although I do not argue for anything as strong as causality, the model I estimate is carefully specified to help disentangle the proximity and neighborhood effects from confounding factors.

In sum, I find that although there is no impact for primary and secondary enrolment, the enrolment of tertiary education-aged individuals in post-secondary and higher education tends to be higher in closer proximity to migrants and tends to be even higher with greater proximity and a greater number of migrants. Furthermore, tertiary enrolment is also significantly higher when a non-migrant household is in an area where migrant households are clustered. These findings confirm both the existence of migrant spillover and role model effects. Decomposing the tertiary-aged group into fresh graduates from high school and those likely to begin working reveals potential nuances in their motivations for enrolment but in general reports similar results as the full sample. Moreover, I find similar results when I check for robustness using migrant composition at the purok level.

When checking for heterogenous impacts according to urban-rural classification and gender, no general pattern emerged although several nuances were revealed. Many of these are counterintuitive and require further investigation to provide an apt explanation. Looking at channels, it appears that greater entrepreneurial activity is not a channel through which migration may affect the enrolment of non-migrant households, or that it may be an imperfect proxy for informal sources of credit in the absence of a variable that directly measures informal borrowing. On the other hand, there is soft evidence that community remittances may be a channel, and while migration arguably has a direct impact on human capital formation that is separate from remittances, the receipt of community remittances may an avenue to relax any liquidity constraint experienced by non-migrant households given the high opportunity cost of sending a working age member to further education.

Although the findings in this study do not directly contribute to policy making, understanding the behavior of people, particularly their incentive structures and how these are influenced by external factors, may allow the exploitation of nudges in information to lead people toward a socially-favorable outcome. Making the prospect and benefits of migration more known may nudge individuals to favor pursuing higher education or studying a particular set of skills or trades rather than working right away. It follows thereafter that the home country will benefit in general thanks to a more highly educated workforce and citizenry.

I acknowledge a handful of limitations and raise avenues for future research. First, although the social and physical spaces of networks are arguably intertwined, without knowledge of the actual social network of the non-migrant it is hard to argue that proximity effects go through the social space. Although I use the concepts of “network” and “neighborhood” interchangeably, the effects I explore are more consistent with neighborhood effects rather than network effects since a person’s network often transcends geography and proximity especially with the advancement in communication technology. I do make an implicit assumption throughout the paper though, that the way neighborhoods and proximity may alter a person’s perceived returns to human capital is that their immediate physical space translates automatically to their social space and which then revises their incentive structure. Additionally, the analysis I can make is limited by the data being a cross-section, which, in empirical economic literature, is known to limit causal inference. Lastly, there is a need to look for stronger channels as to how migrant proximity and clustering may influence enrolment. Variables revealing migration aspirations or migrations histories may be telling of differences in incentive structures e.g. a person with a history of migration in the household may more likely be part of a migrant cluster even when a migrant in their household is not currently observable at the present. In addition, it may be interesting to investigate whether non-migrants are accumulating skills with high demand abroad when they are observing migrants in their vicinity. The intersection between migration and geographical concepts is broad and still leaves a lot for exploration.

Chapter 5
Conclusion

5.1 Thesis Highlights

International migration and remittances are a global phenomenon that has significantly influenced the behavior of people, particularly Filipinos, who aspire to migrate and remit back to their families. With an international migrant stock of 6 million and USD 33 billion worth of remittances accounting for 8.8% of GDP in 2020, the Philippines hails OFWs as “heroes” and has identified migration and remittances as key drivers for the nation’s growth.

This thesis is a compilation of three essays about migration and remittances in the Philippines. Chapter 2 found that following Typhoon Haiyan, more households received remittances although remittance levels were not higher. This holds true for lower income households, renters, and those with household heads of lower educational attainment. The results revealed that remittances behave independently from relief, although there is some evidence that they generally behave as substitutes and serve as complements during disasters. Furthermore, remittances were also higher in regions with poorer infrastructure and institutions. These results reinforce the role of remittances as informal aid and insurance for families, helping them cope with the risk of both the disaster and poor regional capacity. The major contributions of this paper are two-fold. First, while many studies have pointed out the countercyclical nature of remittances, this study distinctly identifies this effect using a natural experiment based on the randomness of the path of a single, debilitating disaster, accentuating how the localized impacts of single disasters may be captured . And second, the results of the extended analysis contribute new knowledge to a very scant body of literature about the interaction of remittances, relief, and a region’s facilitators.

Chapter 3 reported that greater cultural similarity, deeper migrant networks, and more selective immigration policies decreases the wage gaps with natives and enhances human capital transferability of immigrants, easing the labor market assimilation of Filipinos. On the contrary, cultural diversity and fractionalization hampers assimilation. The definitive contribution of this paper is the departure from the conventional approach to studying assimilation where immigrants of multiple origins are observed in a single host country. The study introduces a distinctive framework where immigrants of a single origin are observed in different host countries, thus highlighting how the institutional differences in these countries may influence assimilation.

Chapter 4 presented how tertiary enrolment for non-migrant households are higher when they reside close to a migrant household or when they belong to a migrant cluster. The evidence generated about these proximity and neighborhood spillover effects are an affirmation that migration prospects alone are enough to encourage human capital formation. While the results are mildly unsurprising, this study is the first to directly measure spillover effects of migrant households on non-migrant households. Furthermore, this exposition was done in a novel way as this study brings migration and geography to an intersection. Lastly, this study introduces a new, innovative way to capture neighborhood effects by borrowing techniques from spatial statistics. Evaluating interspatial autocorrelation and clustering allowed the identification of peer-network groupings without having to rely on administrative boundaries.

5.2 Policy Implications

The nature of each paper in this thesis is evidently more positive than normative. The objectives were designed to be explanatory, and the results were meant to reveal new facets of migration and remittances. I refrain from giving any substantial value judgments to avoid overextending the scope of my results. The choice to temporarily migrate or remit by itself is already riddled by selectivity, much less can they be induced or made mandatory. Instead, I offer light suggestions considering the many advantages of migration and remittances found in this thesis.

Efforts need to be made to reduce the stigma surrounding remittances. While irresponsible use of remittances was documented in the past, the expansion of its roles needs to be put to fore. The resilience of remittances proven in Chapter 2 need not be externally induced especially since it was found that remittances flow autonomously from relief and institutions especially during crises. Surely enough, developing regional infrastructures and institutions and enhancing their resilience would create benefits beyond facilitating remittance mobility. Drawing from the impacts of the differences in host countries' institutions found in Chapter 3, migration agencies need to communicate how moving to different host countries given the starting migrant skill base may have profound implications on their assimilation. Perhaps training or short courses on additional languages or handling diversity may aid in decreasing initial wage gaps and hasten assimilation. Lastly, Chapter 4 hints that it may be desirable to promote the prospect of migration to nudge people to invest in higher education. While the private benefits of higher education are typically higher than its social benefits, it is reasonable to suppose a country will see a net benefit in a more highly educated citizenry.

In terms of data, migration and remittances need to be more fully integrated within the PSA's major datasets, especially since migration and remittances are already major phenomenon. Although the PSA diligently collects the FIES and APIS, the sampling procedure needs to be improved to allow for deeper disaggregation. As it stands, the PSA's datasets only allow for disaggregation at the region level and regions do not have their own local government unit. A deeper disaggregation not only provides greater variation, but it also allows more realistic policy implications to be generated. Furthermore, there is a need to collect longitudinal data to provide more compelling, and possibly causal evidence of many phenomena. Moreover, there is a need to expand the variables and indicators that PSA's survey questionnaires cover. As it is, survey questionnaires across rounds lack innovation in that they ask the same set of questions for each round with no prospect nor ambition to increase the amount of information that is collected. The CBMS covers a wider range of variables and indicators, far more than any survey collected by the PSA, but it is heavily underfunded. Being able to appropriately disaggregate at lower administrative levels, track households over time, and cover more variables, would open a lot of possibilities for research and enhance the capacity of the country.

5.3 Avenues for Future Research

While writing each paper, a single, cross-cutting limitation, and hence an important avenue for future research stands out. The analysis in Chapter 2 and 4 were grossly limited by the datasets used. In the context of this thesis, better controls, tests for heterogeneity, or identification strategies, and hence stronger evidence may be developed with deeper data disaggregation, longitudinal structures, and information on migration histories and destinations. With regards to Chapter 3, there is a need to refine how the institutions are represented, measured, and classified. Currently, most of the indicators are only available at the country level. Greater variation, perhaps at subnational levels, should help drive a clearer story. However, given the complexity of this task, an interdisciplinary approach would be most desirable to capture the intricacies of culture, migration networks, and immigration policies. This would give better representations of host countries and may even facilitate the eventual extension of the study to the assimilation of migrants of other origins.

Overall, the trend of globalization and integration warrants the continued research on migration and remittances, although historically, these have mostly been about motivations and consequences. While the discipline may currently be waiting for the next breakthrough, newer facets keep being illuminated, thus expanding the roles and impacts that migration and remittances may have in people's lives.

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Appendices to Chapters

Appendix to Chapter 2

2.A.1. Additional tables and figures.

Table 2.A.1.1. List of Regions in the Philippines, by island group.

Island Group	Region Number/Code	Region Name
Luzon	1	Ilocos
	2	Cagayan
	3	Central Luzon
	4a	CALABARZON (Cavite, Laguna, Batangas, Rizal, Quezon)
	4b	MIMAROPA (Mindoro, Marinduque, Romblon, Palawan)
	5	Bicol
	13	National Capital Region (NCR)
	14	Cordillera Administrative Region (CAR)
Visayas	6	Western Visayas
	7	Central Visayas
	8	Eastern Visayas
Mindanao	9	Western Mindanao
	10	Nortern Mindanao
	11	Southern Mindanao
	12	Central Mindanao
	15	Autonomous Region of Muslim Mindanao (ARMM)
	16	Caraga administrative region (CARAGA)

Table 2.A.1.2. Full variable list and specifications used in estimation and other analyses.

Variable specifications in APIS 2011, 2013, 2014

Variable	APIS Code	Specification
A. Dependent Variables		
Remittance Participation	*remit*	= 1 if cash_abroad > 0 = 0 otherwise
Remittance Level	*cash_abroad*	Household average monthly remittance receipt, PHP
B. Treatment-Related and Extended Analysis Variables		
Affected	*affected_path*	= 1 if household was surveyed in regions along the path of Typhoon Haiyan (regions 4b, 6, 7, 8) = 0 otherwise
Year	*year*	= 2011, 2013, and 2014, pertaining to survey years
Relief	*recvd_disrlf*	= 1 if the household received disaster relief = 0 otherwise The disaster relief indicator does not specify the source of the relief, so it may be implied that it combines local and international forms of aid.
Good Communication Infrastructure	*good_c*	= 1 if computed communication index is ≥ 0 = 0 otherwise
Good Transport Infrastructure	*good_t*	= 1 if computed transportation index is ≥ 0 = 0 otherwise
Good Local Governance Institutions	*good_g*	= 1 if computed governance index is ≥ 0 = 0 otherwise
Good Banking Institutions	*good_b*	= 1 if computed banking index is ≥ 0 = 0 otherwise
C. Alternative Outcomes/Channels		
Total Income	*toinc*	Household average yearly income, PHP
Total Expenditure	*totex*	Household average yearly expenditure, PHP
Food Spending	*food*	Household average yearly food expenditure, PHP
Education Spending	*education*	Household average yearly schooling expenditure, PHP
Health Spending	*health*	Household average yearly health/medical expenditures, PHP
Domestic Remittances	*dremit*	= 1 if household received remittances from domestic source = 0 otherwise
D. Controls		

Own House and Lot	*own_house_lot*	= 1 if household dwelling in their own house and lot = 0 otherwise (renting, etc.)
Floor Area	*pufeq4b*	Floor area of housing unit, continuous variable
Familiy Size	*fsize*	Number of household members
No Grade Completed	*head_hgc_1*	= 1 if the household head has no grade completed = 0 otherwise
Pre-School	*head_hgc_2*	= 1 if the highest educational attainment of the household head is pre-school = 0 otherwise
Elementary Undergraduate	*head_hgc_3*	= 1 if the highest educational attainment of the household head is elementary undergraduate (Grade 1-6) = 0 otherwise
Elementary Graduate	*head_hgc_4*	= 1 if the highest educational attainment of the household head finished primary school (Grade 6) = 0 otherwise
High School Undergraduate	*head_hgc_5*	= 1 if the highest educational attainment of the household head is high school undergraduate (Grade 7-10) = 0 otherwise
High School Graduate	*head_hgc_6*	= 1 if the highest educational attainment of the household head finished secondary school (Grade 10/4th year high school) = 0 otherwise
Post-Secondary	*head_hgc_7*	= 1 if the highest educational attainment of the household head finished a post-secondary degree (technical/vocational) = 0 otherwise
College Undergraduate	*head_hgc_8*	= 1 if the highest educational attainment of the household head is college undergraduate (1st-4th year college/university) = 0 otherwise
College Graduate	*head_hgc_9*	= 1 if the highest educational attainment of the household head is a college/university graduate (3-5 years of college/university) = 0 otherwise
Post Baccalaureate	*head_hgc_10*	= 1 if the highest educational attainment of the household head holds a graduate degree or higher = 0 otherwise

Table 2.A.1.3. Regional institutional capacity indicators specification and sources.

	Variable	Specification	Source
Communication	Telephone Density Radio Stations Broadcast TV stations Cable TV Networks	Phone lines / 100 pop'n # of radio stations in 2013 # of broadcast stations # of Cable TV Networks	National Telecommunications Commission (in PSY, 2015)
Transport	Aircraft movement Air passenger movement Airports	# of flights # of passengers that have flown in and out of the region # of airports	Civil Aviation Authority of the Philippines (in PSY, 2015)
Governance	Calamity Funds	PHP	NDRRMC (in PSY, 2015)
	Internal revenue allotment	Revenue allotment per region, Million PHP	Department of Budget and Management (in PSY, 2015)
	Revenue collection	Total tax revenue collection per region, Million PHP	Bureau of Internal Revenue (in PSY, 2015)
Banking	ATM and Electronic Banking Banking Offices	# of ATMs and Electronic Banking Facilities # of branches/offices	*Bangko Sentral ng Pilipinas*

Table 2.A.1.4. T-tests of select characteristics comparing samples in affected areas after attrition.

	2013 Mean (Std. Err.) (1)	2014 Mean (Std. Err.) (2)	Difference (1) – (2)	t-statistic (Pr |T| > |t|)
Region 6				
Total Income	83,627.49 (3,631.33)	92,271.31 (3,466.99)	-8,643.83	-1.7186 (0.0859)
Total Expenditure	68,265.88 (2,510.18)	83,254.51 (3,740.35)	-14,988.63	-3.357 (0.0008)
Own House and Lot	0.4654 (0.0180)	0.4356 (0.0184)	0.0298	1.159 (0.2465)
Received Domestic Remittances	0.5319 (0.0180)	0.6274 (0.0179)	-0.0954	-3.7535 (0.0002)
Household Head Age	52.80 (0.5408)	53.06 (0.5405)	-0.2667	-0.3486 (0.7274)
Highest Grade Completed (Head)				
No Grade Completed	0.0261 (0.0058)	0.0274 (0.0061)	-0.0013	-0.1584 (0.8742)
Elementary Grad.	0.1616 (0.0133)	0.1561 (0.0134)	0.0055	0.2909 (0.7711)
High School Grad.	0.2177 (0.0149)	0.2178 (0.0152)	-0.00008	-0.0036 (0.9971)
Post-Secondary	0.05345 (0.0081)	0.0671 (0.0093)	-0.0136	-1.1117 (0.2664)
College Grad. Or Higher	0.0873 (0.0102)	0.0863 (0.0104)	0.0011	0.0722 (0.9425)
Region 7				
	2013 Mean (Std. Err.) (1)	2014 Mean (Std. Err.) (2)	Difference (1) – (2)	t-statistic (Pr |T| > |t|)
Total Income	114,878.9 (7,621.1)	111,584.2 (4,914.1)	3,294.74	0.3584 (0.7201)
Total Expenditure	90,728.9 (4,521.7)	95,089.7 (3,944.9)	-4.360.8	-0.7230 (0.4698)
Own House and Lot	0.5754 (0.0194)	0.6432 (0.0194)	-0.0678	-2.4698 (0.0137)
Received Domestic Remittances	0.5108 (0.0196)	0.4909 (0.0202)	0.0198	0.7013 (0.4832)
Household Head Age	51.59 (0.5727)	51.79 (0.5680)	-0.1985	-0.2459 (0.8058)
Highest Grade Completed (Head)				

No Grade Completed	0.0277 (0.0064)	0.0295 (0.0068)	-0.0018	-0.1882 (0.8507)
Elementary Grad.	0.1877 (0.0153)	0.1948 (0.0160)	-0.0071	-0.3189 (0.7499)
High School Grad.	0.1554 (0.0142)	0.1113 (0.0127)	0.0441	2.2999 (0.0216)
Post-Secondary	0.0123 (0.0043)	0.0343 (0.0074)	-0.0221	-2.6171 (0.0090)
College Grad. Or Higher	0.1000 (0.0117)	0.0981 (0.0121)	0.0018	0.1068 (0.9149)

Region 8

	2013 Mean (Std. Err.) (1)	2014 Mean (Std. Err.) (2)	Difference (1) – (2)	t-statistic (Pr |T| > |t|)
Total Income	96,990.1 (10,060.3)	82,429.6 (6,759)	14,560.4	0.9764 (0.3291)
Total Expenditure	76,951.7 (4,599.3)	72,858.8 (5,050.5)	4,092.9	0.5540 (0.5797)
Own House and Lot	0.5373 (0.0205)	0.73 (0.0257)	-0.193	-5.6451 (0.000)
Received Domestic Remittances	0.6153 (0.0200)	0.59 (0.0284)	0.0252	0.7285 (0.4665)
Household Head Age	51.56 (0.6321)	51.18 (0.8921)	0.3861	0.3539 (0.7235)
Highest Grade Completed (Head)				
No Grade Completed	0.0356 (0.0076)	0.02 (0.0081)	0.0156	1.2819 (0.2002)
Elementary Grad.	0.1746 (0.0156)	0.2167 (0.0238)	-0.0421	-1.5171 (0.1296)
High School Grad.	0.1288 (0.0138)	0.1433 (0.0203)	-0.0145	-0.6011 (0.5479)
Post-Secondary	0.0186 (0.0056)	0.02 (0.0081)	-0.0014	-0.1395 (0.8891)
College Grad. Or Higher	0.1153 (0.0132)	0.0933 (0.0168)	0.0219	0.9960 (0.3195)

Region 4b

	2013 Mean (Std. Err.) (1)	2014 Mean (Std. Err.) (2)	Difference (1) – (2)	t-statistic (Pr |T| > |t|)
Total Income	87,926.7 (4,274.6)	88,257.9 (4,792.4)	-331.29	-0.0511 (0.9593)
Total Expenditure	74,317.98 (4,246.3)	73,224.6 (3,435.8)	1,093.36	0.2000 (0.8416)
Own House and Lot	0.6507	0.6566	-0.0058	-0.1594

	(0.0261)	(0.0261)		(0.8734)
Received Domestic Remittances	0.6447	0.6145	0.0303	0.8099
	(0.0262)	(0.0268)		(0.4183)
Household Head Age	50.79	51.27	-0.4801	-0.4146
	(0.8118)	(0.8259)		(0.6786)
Highest Grade Completed (Head)				
No Grade Completed	0.0478	0.0331	0.0146	0.9577
	(0.0117)	(0.0098)		(0.3386)
Elementary Grad.	0.2687	0.2469	0.0217	0.6389
	(0.0242)	(0.0237)		(0.5231)
High School Grad.	0.1582	0.1566	0.0016	0.0560
	(0.0199)	(0.0199)		(0.9553)
Post-Secondary	0.0328	0.0391	-0.0063	-0.4376
	(0.0097)	(0.0106)		(0.6618)
College Grad. Or Higher	0.0716	0.0692	0.0024	0.1191
	(0.0141)	(0.0139)		(0.09052)

Source: Authors' computation, APIS 2013-2014.

Table 2.A.1.5. Summary statistics of family size and selected wealth variables across regions and affected areas

	Region	Total Income	Family size	Strong Roof	Light Roof	Salvaged Roof	Strong Wall	Light Wall	Salvaged Wall	Domestic Remittance
		Panel A. Affected Regions								
4B	MIMAROPA	88,091.59	4.31	0.72	0.27	0.01	0.61	0.37	0.01	0.63
	n=667	(83,693.80)	(2.20)							
6	W. Visayas	87,842.58	4.45	0.87	0.12	0.01	0.61	0.36	0.02	0.58
	n=1,497	(97,330.94)	(2.19)							
7	C. Visayas	113,282.49	4.60	0.88	0.10	0.01	0.69	0.28	0.03	0.50
	n=1,261	(163,069.35)	(2.46)							
8	E. Visayas	92,082.03	4.40	0.74	0.26	0.00	0.68	0.31	0.01	0.61
	n=890	(210,286.63)	(2.18)							
	ALL AFFECTED	**96,189.95**	**4.46**	**0.82**	**0.17**	**0.01**	**0.65**	**0.33**	**0.02**	**0.57**
	n=4,315	**(146,181.56)**	**(2.27)**							
		Panel B. Unaffected Regions								
1	Ilocos	105,882.05	4.47	0.93	0.06	0.01	0.83	0.15	0.01	0.49
	n=1,184	(110,285.77)	(2.28)							
2	Cagayan	122,005.59	4.34	0.94	0.06	0.00	0.90	0.10	0.01	0.38
	n=1,007	(125,098.16)	(2.07)							
3	C. Luzon	136,115.53	4.49	0.95	0.04	0.02	0.92	0.06	0.02	0.41
	n=1,733	(137,827.91)	(2.17)							
4A	CALABARZON	132,867.82	4.30	0.94	0.05	0.00	0.91	0.08	0.01	0.35
	n=2,137	(128,357.78)	(2.07)							
5	Bicol	86,719.54	4.81	0.67	0.33	0.01	0.68	0.30	0.02	0.66
	n=1,244	(133,033.82)	(2.43)							
9	W. Mindanao	92,301.37	4.47	0.76	0.23	0.00	0.69	0.29	0.02	0.62
	n=959	(263,191.06)	(2.05)							
10	N. Mindanao	96,960.76	4.78	0.91	0.08	0.01	0.76	0.23	0.01	0.56
	n=933	(104,054.13)	(2.25)							
11	S. Mindanao	108,716.30	4.29	0.85	0.13	0.01	0.65	0.33	0.02	0.48

	n=1,295	(136,315.70)	(2.13)							
12	C. Mindanao	98,965.23	4.48	0.87	0.13	0.00	0.57	0.43	0.00	0.46
	n=1,126	(241,683.72)	(2.25)							
13	NCR	182,441.03	4.23	0.96	0.03	0.01	0.96	0.04	0.01	0.29
	n=2,480	(160,148.59)	(2.06)							
14	CAR	136,381.31	4.57	0.97	0.02	0.01	0.96	0.03	0.01	0.42
	n=946	(169596.31)	(2.26)							
15	ARMM	65,610.85	5.44	0.65	0.35	0.00	0.56	0.44	0.00	0.51
	n=1,042	(46,649.55)	(2.09)							
16	CARAGA	94,803.02	4.51	0.68	0.31	0.00	0.80	0.19	0.01	0.68
	n=932	(108,435.66)	(2.32)							
ALL UNAFFECTED		**120,186.10**	**4.50**	**0.87**	**0.12**	**0.01**	**0.81**	**0.18**	**0.01**	**0.46**
n=17,018		**(154,902.61)**	**(4.46)**							
TOTAL		**115,332.43**	**4.49**	**0.86**	**0.13**	**0.01**	**0.77**	**0.21**	**0.01**	**0.48**
N = 21,333		**(153,478.33)**	**(2.21)**							

Source: Author's computation, APIS 2013-2014;

Note: Affected regions were identified as those along the path of the typhoon.

Means may not add up due to rounding. Standard deviations in parentheses. Figures for roof and wall materials represent proportion of subsample

Table 2.A.1.6. Distribution of highest grade completed of household heads across regions and affected areas

	Region	No Grade completed	Elementary Undergrad	Elementary Graduate	High School Undergrad	High School Graduate	Post Secondary	College Undergrad	College Grad or Higher	Post Grad
					Panel A. Affected Regions					
4B	MIMAROPA n=667	0.04	0.23	0.26	0.15	0.16	0.04	0.06	0.07	0
6	W. Visayas n=1,497	0.03	0.28	0.16	0.11	0.22	0.06	0.05	0.09	0
7	C. Visayas n=1,261	0.03	0.32	0.19	0.13	0.13	0.02	0.06	0.1	0
8	E. Visayas n=890	0.03	0.33	0.19	0.12	0.13	0.02	0.06	0.11	0.01
	AFFECTED	0.03	0.30	0.18	0.12	0.17	0.04	0.06	0.09	0.00
					Panel B. Unaffected Regions					
1	Ilocos n=1,184	0.01	0.13	0.26	0.09	0.3	0.03	0.08	0.08	0.01
2	Cagayan n=1,007	0.01	0.22	0.27	0.12	0.17	0.02	0.1	0.1	0
3	C. Luzon n=1,733	0	0.15	0.2	0.11	0.29	0.05	0.08	0.12	0
4A	CALABARZON n=2,137	0.01	0.13	0.18	0.15	0.27	0.06	0.09	0.11	0
5	Bicol n=1,244	0.01	0.21	0.28	0.16	0.15	0.02	0.08	0.09	0.01
9	W. Mindanao n=959	0.05	0.29	0.16	0.18	0.14	0.04	0.07	0.08	0
10	N. Mindanao n=933	0.02	0.24	0.14	0.21	0.18	0.03	0.09	0.1	0.01

11	S. Mindanao n=1,295	0.03	0.22	0.17	0.14	0.21	0.03	0.09	0.1	0
12	C. Mindanao n=1,126	0.05	0.21	0.19	0.13	0.2	0.04	0.08	0.09	0.01
13	NCR n=2,480	0	0.06	0.09	0.1	0.36	0.05	0.14	0.2	0.01
14	CAR n=946	0.06	0.2	0.14	0.13	0.19	0.04	0.09	0.13	0.02
15	ARMM n=1,042	0.14	0.29	0.17	0.16	0.13	0	0.06	0.05	0
16	CARAGA n=932	0.01	0.25	0.17	0.17	0.16	0.03	0.08	0.12	0.01
ALL UNAFFECTED n=17,018		0.03	0.18	0.19	0.14	0.23	0.04	0.09	0.11	0.01
TOTAL N = 21,333		**0.03**	**0.2**	**0.18**	**0.13**	**0.22**	**0.04**	**0.08**	**0.11**	**0.01**

Source: Author’s computation, APIS 2013-2014

Note: Preschool dropped due to significantly low value leading to 0.00 values when rounded to two decimal places; Affected regions were identified as those along the path of the typhoon.

Figures represent proportion of subsamples.

Table 2.A.1.7. Proportion of households receiving remittances and summary statistics of monthly remittance levels across regions and affected areas

		Remittance Participation		Monthly Remittance Levels		Receipt of Disaster Relief	
	Region^	**2013**	**2014**	**2013**	**2014**	**2013**	**2014**
4B	MIMAROPA n=335; 332	0.11	0.14	5,720.90 (24,686.97)	6,320.54 (24,825.53)	0.00	0.009
6	W. Visayas n=767; 730	0.21	0.22	10,188.58 (33,810.11)	10,662.12 (32,790.71)	0.007	0.339
7	C. Visayas n=650; 611	0.16	0.20	12,987.85 (52,650.10)	16,863.37 (56,248.29)	0.008	0.077
8	E. Visayas n=590; 300	0.15	0.25	10,080.22 (39,009.01)	6,539.41 (24,293.10)	0.002	0.276
ALL AFFECTED n=2,342; 1,973		**0.17**	**0.20**	**10,299.13 (40,216.62)**	**11,225.10 (39,380.31)**	**0.004**	**0.193**
1	Ilocos n=585;599	0.29	0.33	14,829.80 (41,174.37)	24,126.66 (70,272.85)	0.002	0.000
2	Cagayan n=502; 505	0.30	0.28	14,700.70 (34,470.84)	17,390.69 (55,287.90)	0.022	0.000
3	C. Luzon n=871; 862	0.30	0.29	23,720.12 (63,403.37)	25,035.27 (8,020.74)	0.005	0.007
4A	CALABARZON n=1,072; 1,065	0.23	0.25	16,058.86 (48,125.97)	18,637.56 (52,029.94)	0.005	0.003
5	Bicol n=626; 618	0.12	0.12	6,769.49 (37,899.17)	8,020.74 (44,494.15)	0.013	0.013
9	W. Mindanao n=478; 481	0.10	0.10	3,501.80 (15,199.25)	5,194.09 (28,688.94)	0.006	0.00
10	N. Mindanao n=459; 474	0.14	0.16	12,594.86 (47,425.37)	11,276.37 (42,745.02)	0.007	0.008
11	S. Mindanao n=637; 658	0.16	0.13	10,416.95 (59,761.61)	11,627.20 (63,621.92)	0.039	0.006
12	C. Mindanao n=566; 560	0.11	0.14	6,316.54 (29,762.50)	7,166.43 (37,909.26)	0.000	0.000
13	NCR n=1,244; 1,236	0.23	0.23	17,733.49 (58,132.52)	19,631.47 (55,485.26)	0.004	0.014
14	CAR n=476; 470	0.22	0.22	12,507.12 (37,869.97)	13,400.43 (44,260.56)	0.002	0.017
15	ARMM n=529; 513	0.15	0.09	1,917.22 (8,257.34)	1,502.34 (7,469.30)	0.013	0.000
16	CARAGA n=477; 455	0.13	0.10	8,562.26 (64,442.06)	5,677.32 (25,710.75)	0.078	0.193
ALL UNAFFECTED n=8,522; 8,496		**0.20**	**0.20**	**12,784.10 (47,936.32)**	**14,482.61 (54,864.51**	**0.013**	**0.016**
TOTAL		**0.19**	**0.20**	**12,248.41**	**13,868.69**	**0.011**	**0.049**

N = 10,864; 10,469		**(46,390.42)**	**(52,376.10)**

Source: Author’s computation, APIS 2013-2014;

Note: Affected regions were identified as those along the path of the typhoon.

Means may not add up due to rounding. Standard deviations in parentheses. Figures for remittance participation represent proportion of subsample.

^ Reported observations n=”2013 figure”; “2014 figure”

Table 2.A.1.8. Income decile distribution and average household per capita income

Decile	APIS average household per capita income	Average monthly household per capita income	Frequency Percent of Sample
First Decile	5,815.36	969.23	2365
	(1,323.09)	(220.51)	11.09%
Second Decile	8,875.06	1,479.17	2351
	(813.01)	(135.50)	11.02%
Third Decile	11,444.81	1,907.47	2276
	(876.00)	(146.00)	10.67%
Fourth Decile	14,325.82	2,387.64	2208
	(1,053.72)	(175.62)	10.35%
Fifth Decile	17,724.27	2,954.04	2126
	(1,364.99)	(227.49)	9.97%
Sixth Decile	22,296.69	3,716.12	2075
	(1,725.10)	(287.52)	9.73%
Seventh Decile	28,192.03	4,698.67	2004
	(28,192.03)	(379.73)	9.39%
Eighth Decile	37,216.37	6,202.73	1997
	(3,475.28)	(579.21)	9.36%
Ninth Decile	53,645.15	8,940.86	1976
	(6,956.11)	(1,159.35)	9.26%
Tenth Decile	126,952.97	21,158.83	1955
	(108,402.60)	(18,067.10)	9.16%

Source: Author’s computation, APIS 2013-2014

Note: Standard deviation in parentheses. APIS typically collects information for six-month periods and assumes a family size of 5 for per capita income. Monthly household per capita income is based on total income divided by six (months) and divided by the household’s actual family size.

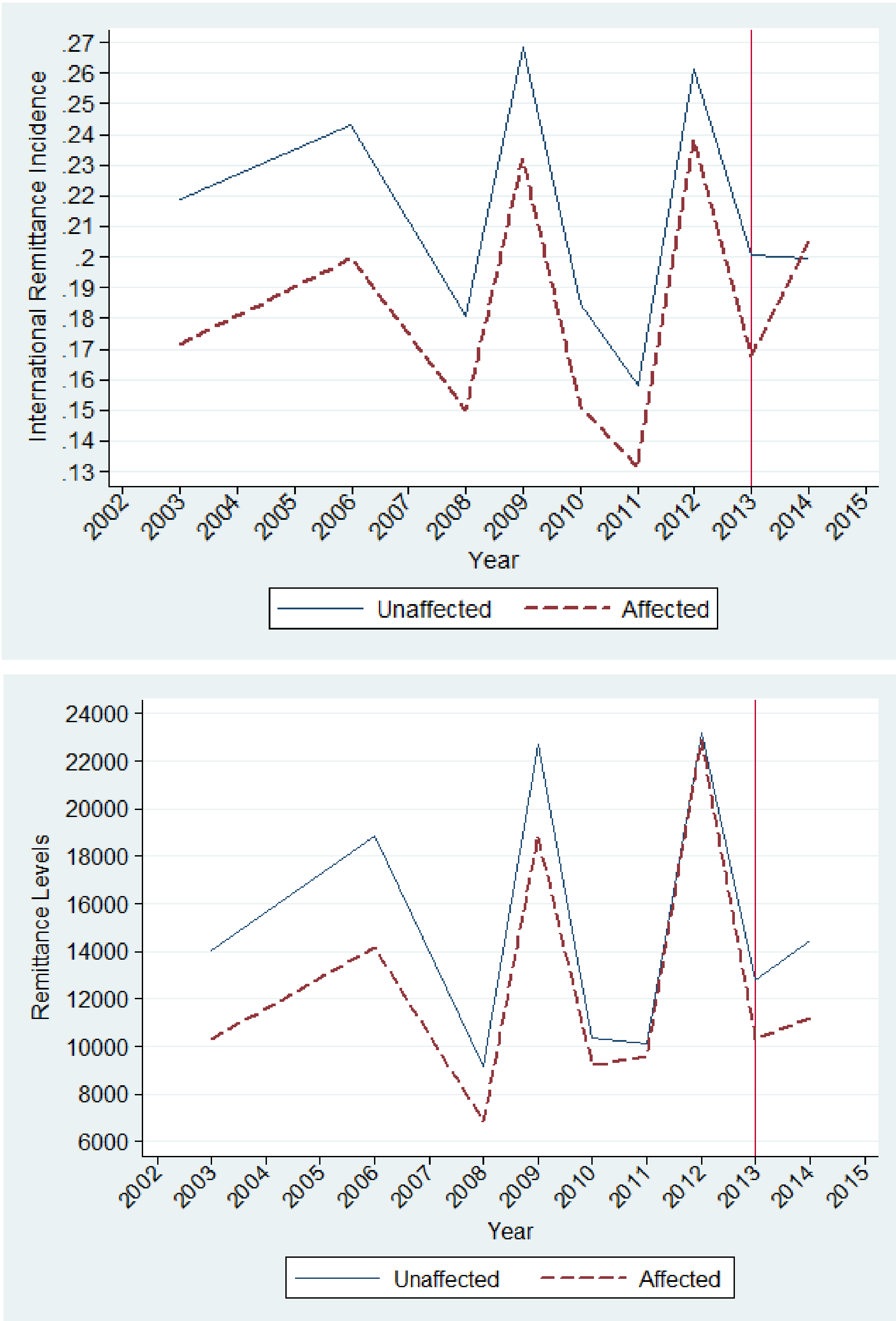


Figure 2.A.1.1. Average remittance (a) incidence and (b) levels between unaffected and affected areas over time, APIS and FIES.

Source: Author’s computation, FIES 2003, 2006, 2009, 2012, APIS 2008, 2010, 2011, 2013, 2014.

2.A.2 Notes on the 2013 and 2014 APIS

This study uses the 2013 and 2014 APIS dataset published by the PSA. The survey is a household level survey with individual-level variables, containing data on demographics (age, educational attainment), income and expenditures, as well as indicators of social protection.

The two survey rounds utilized one replicate of the 2003 master sample based on the 2000 Census of Population and Housing (CPH) of the PSA (PSA, 2015b). For each region and stratum, three-stage sampling was implemented: first, the selection of primary sampling units (consisted of a *barangay* or a group of contiguous *barangays*) with probability proportional to the number of households in the 2000 CPH and stratified according to the proportion of households living in housing with strong materials, engaged in agricultural activities, and city/municipality per capita income; second, enumeration areas (EA) (area with discernable boundaries consisted of approximately 350 contiguous households); and third, at most a sample of 30 housing units per EA selected randomly using systematic sampling. All households in the unit were interviewed except for those with more than three where three were selected at random (PSA, 2015b).

For each household, only members related to the household head by blood, marriage or adoption were interviewed. OFWs were excluded from the interview.

2.A.3 More on Typhoon Haiyan: Problems and Challenges

A series of challenges were met by victims, ranging from food and potable water shortages, displacement, and immediate health concerns such as diarrhea and influenza outbreaks, respiratory illnesses, and leptospirosis followed from water and food crop contamination and crowding in shelters (Chan, Liu, and Hung, 7 December 2013; Chiu, 23 November 2013). Health services and immunization supplies were severely impacted following the damage that hospitals and health facilities had received (Chiu, 23 November 2013; The Lancet, 23 November 2013). In Tacloban, only two hospitals (one public, on private) were operational, but the private hospital was only able to render service for a week before running out of resources due to the absence of support from the national government (Labarda, Labarda, and Lamberte, 2017). Victims, particularly younger people, faced psychological distress as well, and older people particularly due to the loss of housing (Lavenda, Hoffman, Grossman, Ben-Ezra, 2017). Within a week after the typhoon, people had begun fleeing the Tacloban City (Chiu, 23 November 2013).

Among the major challenges and key priorities identified were communication and access to information, particularly in terms of educating people on what to do in the event of a crisis (Lagmay et al, 2014; Chan, Liu, and Hung, 7 December 2013). Labarda, Labarda, and Lamberte (2017) suggest strengthening leadership and governance, including private hospitals in the support given by national governments, and building the capacity of hospital and medical staff to be more resilient to disasters. Lagmay et al (2014) recommend the use of storm surge inundation maps for better planning and response. Saban (2015) highlighted the role of multilateral agencies and the ministry of foreign affairs to broker humanitarian assistance from international sources.

2.A.4. Notes on CEM

One of the limitations of using the APIS 2013 and 2014 is that the survey excludes household members who are OFWs. This makes it impossible to control for having migrant members and may inflate coefficients since I make the comparison between households that may or may not have migrants, and therefore have structurally different probabilities of receiving remittances. To improve precision, this study performs Iacus, King and Porro's (2011) CEM to make remittance-receiving and non-remittance-receiving households more comparable based on their likelihood of having a migrant.

Several treatment studies have previously used Propensity Score Matching (PSM) to calculate treatment effects, using the likelihood of receiving treatment as the basis for matching. Thus, this approach to matching has been somewhat of a standard. PSM has been criticized, however, of having the risk of selection on unobservable characteristics (that selection was determined by factors not captured by the selected covariates for program selection), that is, the conditional independence assumption is not met. Therefore, as an additional robustness check, this study implements CEM.

CEM is a method that improves the estimation of causal effects by matching treated and control groups according to a set of covariates rather than just the probability, thus greatly reducing imbalance in covariates between groups. Blackwell, Iacus, King, and Porro (2009) lists the advantages of CEM: it is faster and can be automated and implemented more easily, has fewer binding assumptions, and better statistical properties. CEM first sorts observations into various bins (strata) based on having identical values for coarsened pre-treatment covariates, and then discards all observations in strata that do not have a unique value of treatment (Blackwell, Iacus, King and Porro, 2009). The treatment effect is then calculated by normal means (OLS) adjusted by the weighting each observation is given by the CEM procedure. Unmatched observations are given a weight of zero.

In implementing CEM, this study bases the matching on characteristics households are likely to have if they have a migrant. A handful of studies look at the determinants that most likely determine whether a household has an international migrant, regardless of permanent or temporary migration (Chakraborty and Kuri, 2017; Hatlebakk, 2016; Atamanov and Van den Berg, 2012; Gubhaju and De Jong, 2009). First, this study bases the matching on family size coarsened into bins of 0-3, 4-6, 7-8, 9-10, and 11+ for CEM, reflecting the expansion of family sizes in the Philippines (nuclear, extended, etc.). Further matching is then based on the household head's educational attainment, uncoarsened and grouped according to classifications presented in Tables 2.A.1.5 and 2.A.1.6. Age of the household head is then classified into 24 and below (youth but most likely to be employed), 25-36, 37-48, 49-54, 55-65, and 66+, to reflect the various decades of employment until they reach the retirement age of 65. The bin 49-54 is purposely created to reflect the relatively high concentration of households receiving remittances in the sample with this characteristic (about 3%). Lastly, matching is done based on whether a household owns the house and lot they are currently residing in. Equation (2.1) is then estimated using OLS while applying weights generated by the CEM algorithm.

2.A.5. Additional notes on descriptive statistics

Table 2.A.1.5 presents the summary statistics of time-varying characteristics of households such as income, wealth, family size and the receipt of domestic remittances across regions and affected areas. It may be seen that there is vast heterogeneity across regions, particularly when grouping regions according to those affected by the typhoon and those that were not. On average, the those in unaffected regions have higher total income than those in affected regions. The region with the highest average total income is Region 13, the National Capital Region (NCR), followed by Region 14, the Cordillera Administrative Region (CAR) and the Region 3, the Central Luzon region. The richest among affected regions is Region 7, Central Visayas, which is no surprise since Cebu City, which is considered the economic hub of the Visayas island group, is located here. Additionally, affected regions have slightly higher family size but the difference is too small to be considered significant. In terms of house construction, across the sample, about 86% of households have strong roofing materials and 77% for strong wall materials. Notably though, the percentage of households with strong housing materials are lower for affected regions, and these regions have higher

percentages of households with light housing materials. Affected regions have a higher incidence of domestic remittances.

Table 2.A.1.6 presents the distribution of the population in each region according to the highest grade completed of the household head. Across the board, it may be noticed that for the entire country, many household heads are high school graduates (22%), followed by elementary graduates (18%), high school undergraduates (13%) and college graduates or higher (11%). Though there is a similar trend of distribution between affected and unaffected regions, it may be noted that on average in affected regions, there are more household heads with only an elementary undergraduate attainment than elementary graduate (30% vs 18%) whereas in unaffected regions, those with only elementary undergraduate attainment constitute only 18% and elementary graduates constitute 19%. There is also a lower proportion of high school undergraduates and graduates in affected regions (12% and 17%, respectively) than in unaffected regions (14% and 23%, respectively). There are also more college graduates and college undergraduates in unaffected regions (11% and 8%, respectively) compared to affected regions (9% and 6%, respectively).

The variables presented in Tables 2.A.1.5 and 2.A.1.6 represent time-varying characteristics of households that have significant impacts on the receipt of remittances. Of note is domestic remittances, remittances sent from domestic migrants (typically rural-urban), which tend to substitute international remittances. Table 2.A.1.7 reports the incidence and level of remittances across regions and affected areas in 2013 and 2014. It is notable that there are fewer people receiving remittances in affected regions in 2013 (on average 17% vs. 20% in unaffected regions), but affected regions experience a jump in 2014, making it equal the incidence of remittances in unaffected regions (20%). The mean total remittance levels for affected regions is PHP10,299.13 (USD190.41) in 2013 and PHP 11,225.10 (USD207.52) whereas unaffected regions posted PHP12,784.10 (USD236.35) in 2013, and PHP13,382.61 (USD267.75) in 2014. I may see that both remittance outcomes have increased for affected regions.

2.A.6. Issues on foreign aid during Typhoon Haiyan

The response of the Philippine government to the onslaught of Typhoon Haiyan was riddled with breakdowns in communication, infrastructure, and limited coordination, causing it to perform quite poorly (Saban, 2015). The government was, however, able to react sufficiently to facilitate the rapid mobilization and coordination with foreign aid (e.g. international NGOs), and these international agencies filled the gaps in the government's relief effort (Saban, 2015). The relief effort from the foreign agencies were met with much appreciation and endearment from the affected communities at the beginning, but this had later turned into criticism and resentment (Ong et al, 2015). In their report on the receipt of foreign humanitarian aid of affected communities during Typhoon Haiyan, Ong et al (2015) document that the people resented being excluded from the aid distribution due to the humanitarian's beneficiary selection procedures. Field (2017) characterizes this as a "disconnect between the disaster priorities of many affected Filipinos and the programming of an externally driven response applying the disaster management formula" (p.338). Dalgas (2018) notes that the delivery of international humanitarian response is often based on equitable provisioning, that is, international aid agencies first identify a "list" of the most vulnerable or most "affected", then distribute aid according to this targeting. Though it is logically sound and efficient, the problem with this type of targeting is that they purposefully exclude untargeted people *within the same community*. The respondents in Ong et al's (2015) study often report feeling envy and resentment because of this, and that portrayed the foreign aid agencies as "disengaged" or "disconnected". Dalgas (2018) and Field (2017) criticize that foreign humanitarian agencies do not factor in the recipient's culture when administering aid. Particularly for the case of the Philippines where it is part of the Filipino's culture to prioritize "equality" rather than "equity" in times of disaster. Such is the culture of *pakikipagkapwa* or "shared identity" or simply "nobody gets left behind" (Dalgas, 2018; Ong et al, 2015).

What is arguably worse about how international humanitarian agencies target the recipients of aid, is how they treat households that receive remittances, or those with members abroad. Su and Mangada (2018) find that when evaluating vulnerability, international aid agencies deduct "points" from a household's vulnerability assessment if the household receives remittances, regardless of the size. Dalgas (2018) further notes that during the Bohol (region 7) earthquake in the same year, households with migrant members were automatically excluded from receiving aid. This implies that international humanitarian agencies assume that migrants will automatically remit during a crisis, and this places less priority on migrant households. However, Dalgas (2018) highlights the combination of Filipino solidarity and a migrant's attachment to her origin and presents diasporic (collective) and individual remittances as a form of aid that, contrary to the usual view that migrants only remit to their own households, may have a wider social reach while honoring the culture of *bayanihan* (to help each other without expectation of reciprocation) and *pakikipagkapwa*.

2.A.7 Calculating the index of remittance facilitators

To estimate the impact these institutions have on the likelihood of receiving remittances, this study merges the region-specific institutions data with the 2013-2014 APIS. Furthermore, the above-listed variables are not added straight away into the estimation as they have different measurements and may cause collinearity. At this point, what the study is interested in looking at is a collective measure of the impact of institutions. Rather than look at the impact of an additional branch, or flight, or peso dedicated for calamity, this study aims to look at how general improvements to these institutions may are correlated with households' likelihood of receiving remittances.

This study uses a weighted normalized index similar to the index of wealth used in Acosta (2010). The index is calculated based on all variables, and then according to four types of institutions. The index I_{jt} is computed for the *j*th region at time *t* as:

$$I_{jt} = \sum_{i}^{k} \frac{a_i(x_{ijt} - \overline{x_{it}})}{\sigma_{it}}$$

Where x_{ijt} is the value of indicator *i* for region *j* at time *t*, $\overline{x_{it}}$ is the mean across regions for the indicator *i* at time *t*, σ_{it} is the standard deviation of indicator *i* at time *t*, and a_i is the weight of indicator *i* in the first component of the principal components analysis. This index ranges from negative to positive real values and is quite straightforward to interpret. Having a negative score implies that outcomes tend to be lower than the sample average and hence reflects having relatively poor institutions. For simplicity, the empirical analysis is done only for regions affected by the typhoon (regions 4b, 6, 7, 8). As such, the basis of the index is relative to the affected regions only, which are expected to be observably closer. In addition, a binary indicator is generated to show whether a region has relatively "good" institutions, that is if its index is greater than or equal to zero, implying its outcomes are higher than the average. There is no problem combining each indicator into a single index as each of them is monotonic (larger values indicate better outcomes).

Appendix to Chapter 3

3.A.1. Issues in estimating immigrant assimilation

The number of immigrants grew rapidly in the US since the late 1800s, and with it the need for policies to manage these new people. The earliest work on assimilation was put forth by Chiswick (1978). He used the 1970 Census of Population, a CS dataset, and found that the earnings of foreign-born men are lower but increases with YSM. They also have lower returns to education and experience. By fixing the human capital and demographics of immigrants and natives, Chiswick further simulates their earnings profiles and concludes that immigrants start with lower earnings, but as it increases over time in the US, they eventually equal, and later on (after 10-15 years) exceed the earnings of natives. This served as the conventional wisdom for later studies.

However, Chiswick's (1978) analysis was limited by its CS nature. Many studies came forth to point out the pitfalls on the use of CS (and even repeated CS) and have recommended improvements. Among the methodological issues that may confound CS estimates are: 1.) selective return migration, 2.) changes in cohort quality, 3.) normalization of comparison groups, 4.) unobserved heterogeneity on the selection of immigrants and the endogeneity of post-migration schooling and experience decisions, and 5.) measurement error stemming form .

The paper that first tested the validity of Chiswick's findings was Borjas (1985). Borjas identified two sources of bias when using CS: *first*, is non-random (selective) return migration, wherein if immigrants do not do well then they emigrate and the estimates of YSM would be biased upwards since only the most successful is left; and *second*, are changes in cohort quality based on the skills that new arrivals bring with them, wherein estimates would be downward-biased if recent immigrants have higher skills upon arrival. Borjas (1985) then used repeated-cross sections with the 1970 and 1980 Censuses and emphasized improving matching controls for age groups across census years. He divides the analysis of the effects of YSM into within-cohort effects (same arrival year, different YSM across censuses) and across-cohort effects (different arrival years but same YSM across censuses). He finds that using CS confounds YSM estimates due to changes in arrival cohort (across) quality over time. This is echoed in Hu (2000), Lubotsky (2007), and Abramitzky, Boustan, and Eriksson (2014) that have proffered the use of longitudinal (panel) data to address the issue of selective return migration. They find that wage progress is systematically overstated since CS did not capture the negative return migration (lower earnings/skill) and declining cohort quality. Despite this, Friedberg (2000) comments that the use of CS may be sufficient if YSM and demographic effects are the same across census years, and if cohort effects do not follow any systematic pattern. In addition, cohort effects may or may not be present depending on whether controls are imposed over immigration (Miller and Neo, 2003). Lubotsky (2007) takes the issue of return migration further by distinguishing permanent *and* temporary out-migration and suggests that the temporary out-migration of low-earning migrants may decrease the wage of successive arrivals if they report only the most recent arrival. However, Picot and Piraino (2013) suggest there is no difference between estimates of longitudinal and CS data on Canada. The compare their results to that of the US and investigate who is leaving. They find that migrants are more likely to exit if they are from closer origin countries, economic migrants, and if there are social safety nets that may reduce the disincentives for non-employment.

In Chiswick's (1978) work, immigrants are directly and indiscriminately being compared to natives. This has served as the standard for normalizing YSM estimates (Baker and Benjamin, 1994). As mentioned previously, Borjas (1985) improved upon this by distinguishing within- and across-cohort effects, that is, migrants of the same arrival cohort across time (across survey rounds) and migrants of different arrival years but same YSM across survey rounds. The within-cohort effects allows the capture of wage growth and aggregate demand changes, whereas the across-cohort effects allows the capture of changes in arrival cohort quality. Assimilation is essentially the within-cohort growth of wages. LaLonde and Topel (1992) suggest that the comparison should not be a fixed group, but rather a fixed point (the same starting wage). In a follow-up by Borjas (1995), he tests for robustness by comparing immigrants to natives with the same ethnicity, as well as immigrants of similar age at arrival. YSM estimates can be improved further by including aging effects to weed out the effect of experience, arrival cohort effects to account for changes in cohort quality, and time fixed effects to take out aggregate demand effects such as changes in wage structure or inflation (Borjas, 1995).

Immigrants are generally selected based on a set of observable characteristics, especially countries with points-systems such as Australia (Breunig, Hasan, and Salehin, 2013). Chiswick (1978) however suggested that part of the wage growth experienced by immigrants is due to favorable selection, that is, for the same education and demographics, immigrants may have greater unobservables such as ability, ambition, or motivation. These same unobservable characteristics may not only affect the immigration outcome, but also the decision to invest in post-migration schooling and experience (Skuterud and Su, 2013), which in turn, may affect assimilation estimates due to the return on origin and host human capital. Breunig et al (2013) on Australia used a Hausman-Taylor estimator to provide an instrument controlling for correlation between observables and unobservables and found that their estimates are much higher.

In Chiswick's (1978) seminal model, education and experience are typically entered as continuous variables. Friedberg (2000) raised that the wage gap between immigrants and natives is partially driven by the unequal valuation of origin and host-acquired human capital. These two are not close substitutes, and to lump them into the same variable may lead to measurement error. Skuterud and Su, 2013 find, however, that the presence of even substantial measurement error may only have negligible effects. They then comment that the value of using YSM is its exogeneity in that aging profiles are relatively exogenous.

Implicitly, assimilation occurs in two perceived stages (Cobb-Clark, Hanel and McVicar, 2012): *first* is the gap in outcomes upon arrival, and *second* is the convergence over time spent in the host country.

Chiswick (1978) attributes the initial gap to the imperfect transferability of human capital acquired externally, which may be explained by differences in home and host country labor markets and imperfect information of employers. These are consistent with the human capital theory and the screening hypothesis, respectively (Chiswick and Miller, 2009). Chapman and Iredale (1993) associate this gap with the lack of formal recognition (certification/licensing) of skills acquired from immigrants' origin countries, and national qualifications frameworks tend to influence this immensely. Chiswick and Miller (2010) link this to why many immigrants are overeducated: because very high investment in education prior to migration may not be readily transferable[28] and so these migrants often accept an occupational downgrade. This same reason may be linked to why origin-country human capital is valued much lower than human capital acquired in the host-country (Friedberg, 2000). El-Araby and Ragan (2010) suggest that the returns to pre-migration human capital are strongly driven by home-country characteristics: earnings are higher for immigrants from developed countries and countries with perceptively higher educational quality (lower pupil-teacher ratio). Generally, it may be noted that transferability tends to be better and wages mirror that of natives more when the home and host country are highly similar (Basilio et al, 2017).

[28] An example in Chapman and Iredale (1993) are lawyers. Practicing law not only requires skill but also very high knowledge of local laws. A lawyer that has learned much of the legal environment of his home country may not immediately work as a lawyer in the host country because it may have a completely different legal environment.

Convergence is the process through which immigrant outcomes gravitate toward same levels of natives. Convergence occurs when immigrants invest in acquiring host-specific human capital explicitly (e.g. formal schooling) and implicitly (e.g. learning by living) as they spend more time in the host country (Chiswick and Miller, 2011). Explicit investments in schooling and training allows for faster convergence since host-acquired human capital is valued higher than that of external source (Friedberg, 2000; Chapman and Iredale, 1993). This may be because host employers have better information on the value of host education and training, thus higher returns. Chiswick and Miller (2009) found that child immigrants that acquire host schooling have earnings profiles that mirror natives whereas adult immigrants reflect conventional wisdom. Once convergence has been achieved, immigrant earnings' may then overtake that of natives with more years spent in the host country. This is attributed to favorable selection, that is, for the same education, training and demographics, immigrants tend to have higher motivation, ability and ambition than natives (Chiswick and Miller, 2010).

The role that the transferability of human capital plays in assimilation is generally well-established. A key question remains: how does imperfect transferability cause a gap upon arrival and how do immigrant earnings converge with natives over time? Chiswick, Lee and Miller (2005) postulate that a key channel in facilitating assimilation is occupational mobility. In their study, they posit a "U-shape" pattern for occupational mobility from the last job in the origin to the first job in the destination, and to subsequent job changes as the migrant stays in the host country. The first half of the "U" is the "downgrade" in occupational status upon migration, which is due to the imperfect transferability of human capital[29]. The extent of this downgrade will depend on the extent of transferability of a person's skills (Fellini and Guetto, 2019). Less transferable skills mean a deeper downgrade in occupational status. After a few years and as the immigrant acquires host-specific human capital (be it language, recognition or accreditation), the second half of the "U" would represent his movement upward the occupation ladder. They find that mobility improves with education, host language proficiency, and pre-existing migrant networks. They also find that occupational mobility is heterogenous to the type of migrant, wherein the less transferable the skill, the "deeper" the "U". Refugees have the steepest "U", whereas economic migrants have the shallowest. This "U-shape" pattern may vary with destination country characteristics, especially the structure of labor markets. Simon, Ramos and Sanroma (2014) found that for a country with a segmented labor market such as Spain, the initial downgrade tends to be steeper and occupational mobility is hampered if not altogether blocked due the sheer size of the secondary segment[30]. This occurrence constrains assimilation and magnifies the

[29]A lawyer may have imperfect transferability due to differences in legal systems, so they may start only as a clerk in a courthouse rather than a professional. Doctors may need an additional license so they may start as an associate.
[30] Segmented labor markets are typically divided into the primary and secondary segment (Simon et al, 2014). The primary segment is composed of high-wage occupations (typically ISCO88 classifications 1-4) with better work

contribution and utmost importance of host human capital even more (Fellini and Guetto, 2019). In addition to occupational mobility, assimilation may also occur through industrial mobility (transitioning to higher-paying industries) and regional mobility (moving to other regions, potentially with higher income or larger migrant networks) (Izquierdo, Lacuesta, and Vegas, 2009).

3.A.2. Tables accompanying the wage score computation

Table 3.A.2.1. Rankings of occupations and industries by average wage score.

ISCO Code	Occupation	Wage Score	ISIC Code	Industry	Wage Score
1	Legislators, senior officials, and managers	191.22	90	Financial services and insurance	1.421
2	Professionals	158.72	20	Mining	1.405
3	Technicians and associate professionals	119.33	40	Electricity, gas and water (sanitation)	1.386
4	Clerks	87.50	100	Public administration and defense	1.211
8	Plant and machine operators and assemblers	81.61	112	Education	1.175
7	Crafts and related trades workers	80.89	113	Health and social work	1.137
5	Service workers and shop and market sales	69.98	111	Real estate and business services	1.042
6	Skilled agricultural and fishery workers	60.53	80	Transportation, storage and communications	0.991
9	Elementary occupations	56.67	30	Manufacturing	0.941
			50	Construction	0.889
			60	Wholesale and retail trade, (repair)	0.731
			114	Other services	0.713
			10	Agriculture, fishing, forestry	0.569
			70	Hotels and restaurants	0.553

conditions, prestige and promotion. The secondary segment is made up of lower paying occupations (ISCO88 classifications 5-9) that are unstable, unskilled, and with little prospect for upward mobility. Segmented labor markets are prevalent in industries with loose labor regulations, protectionist regulations (permanent employment is given to citizens, whereas new entrants get less-protected jobs), and the use of informal and irregular employment arrangements (Fellini and Guetto, 2019).

Table 3.A.2.2. Average occupation-industry wage scores across all countries, ranked by wage scores

		Ind. Score	1.42	1.41	1.39	1.21	1.18	1.14	1.04	0.99	0.94	0.89	0.73	0.71	0.57	0.55
		ISIC	90	20	40	100	112	113	111	80	30	50	60	114	10	70
Occup. Score	ISCO	**Occupation X Industry**	Financial Services	Mining	Utilities (EGW)	Public Administration	Education	Health	Real Estate	Transport and Logistics	Manufacturing	Construction	Wholesale and Retail	Other Service	Agriculture	Accommodations
191.22	1	Managers	271.71	268.82	265.13	231.47	224.72	217.49	199.29	189.4	179.84	170.06	139.89	136.34	108.77	105.83
158.73	2	Professionals	225.54	223.14	220.08	192.14	186.54	180.53	165.43	157.21	149.28	141.16	116.12	113.17	90.29	87.85
119.33	3	Technicians	169.56	167.76	165.46	144.45	140.24	135.73	124.37	118.2	112.23	106.13	87.3	85.08	67.88	66.04
87.51	4	Clerks	124.34	123.02	121.33	105.92	102.84	99.53	91.2	86.67	82.3	77.82	64.02	62.39	49.77	48.43
81.61	8	Plant and Machine Workers	115.96	114.73	113.15	98.79	95.91	92.82	85.05	80.83	76.75	72.58	59.7	58.19	46.42	45.17
80.9	7	Crafts	114.94	113.72	112.16	97.92	95.07	92.01	84.31	80.12	76.08	71.94	59.18	57.68	46.01	44.77
69.99	5	Service Workers	99.44	98.39	97.03	84.72	82.25	79.6	72.94	69.32	65.82	62.24	51.2	49.9	39.81	38.73
60.54	6	Agricultural	86.02	85.1	83.93	73.28	71.14	68.85	63.09	59.96	56.93	53.84	44.28	43.16	34.43	33.5
56.68	9	Elementary	80.53	79.67	78.58	68.6	66.6	64.46	59.07	56.14	53.3	50.4	41.46	40.41	32.24	31.37

Notes: Occupation wage scores are multiplied by 100 and rounded to one decimal point for simplicity. Industry wage scores and Industry-occupation wage scores are rounded to two decimal points.

Table 3.A.2.3. Occupation-industry wage scores, Canada, males.

		WSi,nat	0.80	1.57	0.93	1.39	1.04	0.74	0.44	0.96	1.22	1.22	1.01	1.05	0.91	0.72
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
165.7	1	Managers	132.8	260.0	153.5	230.1	171.7	122.7	73.5	158.2	202.9	202.7	166.8	173.8	150.4	120.1
137.5	2	Professionals	110.2	215.7	127.4	190.9	142.5	101.8	61.0	131.3	168.3	168.2	138.4	144.2	124.8	99.6
110.4	3	Technicians	88.5	173.3	102.3	153.4	114.4	81.8	49.0	105.5	135.2	135.1	111.2	115.8	100.2	80.0
73.0	4	Clerks	58.5	114.6	67.7	101.4	75.7	54.1	32.4	69.7	89.4	89.4	73.5	76.6	66.3	52.9
65.3	5	Plant and Machine Workers	52.3	102.4	60.5	90.7	67.7	48.4	29.0	62.4	79.9	79.9	65.7	68.5	59.3	47.3
76.0	6	Crafts	61.0	119.3	70.5	105.6	78.8	56.3	33.8	72.6	93.1	93.1	76.6	79.8	69.0	55.1
105.7	7	Service Workers	84.8	165.9	98.0	146.9	109.6	78.3	46.9	101.0	129.5	129.4	106.5	110.9	96.0	76.6
101.0	8	Agricultural	81.0	158.6	93.6	140.3	104.7	74.9	44.9	96.5	123.7	123.7	101.8	106.0	91.7	73.2
65.4	9	Elementary	52.4	102.6	60.6	90.8	67.7	48.4	29.0	62.4	80.0	80.0	65.8	68.6	59.3	47.4

Source: ILOSTAT, authors' computation.

Table 3.A.2.4. Occupation-industry wage scores, Canada, females.

		WSi,nat	0.68	1.64	0.93	1.50	0.97	0.64	0.46	0.94	1.13	1.33	0.99	1.12	0.98	0.72
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
180.7	1	Managers	122.7	295.5	167.4	270.9	174.7	114.7	84.0	169.8	203.3	240.2	178.0	201.7	176.2	130.4
155.9	2	Professionals	105.9	254.9	144.5	233.8	150.7	99.0	72.5	146.5	175.4	207.3	153.6	174.0	152.0	112.6
111.4	3	Technicians	75.7	182.2	103.2	167.0	107.7	70.7	51.8	104.7	125.3	148.1	109.8	124.3	108.6	80.4
82.9	4	Clerks	56.3	135.5	76.8	124.3	80.1	52.6	38.5	77.9	93.3	110.2	81.7	92.5	80.8	59.8
62.1	5	Plant and Machine Workers	42.1	101.5	57.5	93.0	60.0	39.4	28.8	58.3	69.8	82.5	61.1	69.3	60.5	44.8
69.4	6	Crafts	47.2	113.5	64.3	104.1	67.1	44.1	32.3	65.2	78.1	92.3	68.4	77.5	67.7	50.1
84.0	7	Service Workers	57.1	137.4	77.8	125.9	81.2	53.3	39.0	78.9	94.5	111.7	82.8	93.8	81.9	60.6
89.9	8	Agricultural	61.1	147.0	83.3	134.8	86.9	57.1	41.8	84.5	101.2	119.5	88.6	100.4	87.7	64.9
63.8	9	Elementary	43.3	104.2	59.1	95.6	61.6	40.5	29.6	59.9	71.7	84.8	62.8	71.2	62.2	46.0

Source: ILOSTAT, authors' computation.

Table 3.A.2.5. Occupation-industry wage scores, Greece, males.

		WSi,nat	0.69	1.23	0.93	1.26	0.80	0.87	0.77	1.15	1.25	1.12	0.72	1.13	1.14	0.95
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
156.2	1	Managers	107.5	191.6	144.9	196.4	125.0	135.7	120.0	179.8	194.7	175.5	112.1	176.1	178.4	149.1
120.5	2	Professionals	82.9	147.8	111.7	151.5	96.4	104.7	92.6	138.6	150.2	135.4	86.5	135.8	137.6	115.0
116.8	3	Technicians	80.4	143.3	108.3	146.8	93.4	101.5	89.8	134.4	145.6	131.2	83.8	131.7	133.4	111.5
98.1	4	Clerks	67.5	120.4	91.0	123.4	78.5	85.3	75.4	112.9	122.3	110.3	70.5	110.7	112.1	93.7
86.4	5	Plant and Machine Workers	59.5	106.0	80.1	108.6	69.1	75.1	66.4	99.4	107.7	97.1	62.0	97.4	98.7	82.5
71.9	6	Crafts	49.5	88.2	66.7	90.4	57.5	62.4	55.2	82.7	89.6	80.8	51.6	81.0	82.1	68.6
83.6	7	Service Workers	57.5	102.5	77.5	105.1	66.9	72.6	64.2	96.2	104.2	93.9	60.0	94.2	95.5	79.8
94.8	8	Agricultural	65.2	116.3	87.9	119.1	75.8	82.3	72.8	109.1	118.1	106.5	68.0	106.9	108.2	90.4
71.8	9	Elementary	49.4	88.1	66.6	90.2	57.4	62.4	55.2	82.6	89.5	80.6	51.5	80.9	82.0	68.5

Source: ILOSTAT, authors' computation.

Table 3.A.2.6. Occupation-industry wage scores, Greece, females.

		WSi,nat	0.69	1.10	0.91	1.33	0.99	0.82	0.76	1.13	1.27	1.24	0.84	1.11	1.06	0.75
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
162.1	1	Managers	112.6	177.9	148.3	215.1	160.3	132.6	123.9	182.6	205.4	200.6	136.2	179.4	172.4	121.4
124.0	2	Professionals	86.2	136.2	113.5	164.7	122.7	101.5	94.9	139.7	157.2	153.5	104.3	137.3	132.0	92.9
113.1	3	Technicians	78.6	124.2	103.5	150.1	111.9	92.5	86.5	127.4	143.4	140.0	95.1	125.2	120.3	84.7
103.9	4	Clerks	72.2	114.0	95.0	137.9	102.7	85.0	79.4	117.0	131.7	128.5	87.3	115.0	110.5	77.8
79.3	5	Plant and Machine Workers	55.1	87.1	72.6	105.3	78.5	64.9	60.7	89.4	100.6	98.2	66.7	87.8	84.4	59.4
77.7	6	Crafts	54.0	85.3	71.1	103.1	76.9	63.6	59.4	87.5	98.5	96.2	65.3	86.0	82.7	58.2
84.2	7	Service Workers	58.5	92.4	77.0	111.8	83.3	68.9	64.4	94.9	106.7	104.2	70.8	93.2	89.6	63.1
89.5	8	Agricultural	62.2	98.3	81.9	118.8	88.6	73.3	68.5	100.8	113.5	110.8	75.3	99.1	95.2	67.1
66.2	9	Elementary	46.0	72.7	60.6	87.9	65.5	54.2	50.6	74.6	83.9	81.9	55.7	73.3	70.4	49.6

Source: ILOSTAT, authors' computation.

Table 3.A.2.7. Occupation-industry wage scores, Malaysia, males.

		WSi,nat	0.44	1.53	0.76	1.09	0.66	0.66	0.55	0.83	1.50	1.13	1.52	1.51	1.19	0.64
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
245.7	1	Managers	107.4	375.9	187.3	266.6	162.4	161.0	134.8	203.3	367.7	277.4	373.0	371.5	292.9	158.5
186.5	2	Professionals	81.6	285.3	142.2	202.4	123.3	122.2	102.3	154.3	279.2	210.6	283.1	282.0	222.3	120.3
109.7	3	Technicians	48.0	167.8	83.6	119.0	72.5	71.9	60.2	90.8	164.2	123.8	166.5	165.8	130.7	70.7
80.8	4	Clerks	35.4	123.7	61.6	87.7	53.4	53.0	44.4	66.9	121.0	91.3	122.7	122.2	96.4	52.1
65.9	5	Plant and Machine Workers	28.8	100.9	50.3	71.6	43.6	43.2	36.2	54.6	98.7	74.4	100.1	99.7	78.6	42.5
49.8	6	Crafts	21.8	76.2	38.0	54.1	32.9	32.7	27.3	41.2	74.6	56.3	75.6	75.3	59.4	32.1
58.7	7	Service Workers	25.7	89.7	44.7	63.7	38.8	38.4	32.2	48.5	87.8	66.2	89.0	88.7	69.9	37.8
58.3	8	Agricultural	25.5	89.1	44.4	63.2	38.5	38.2	32.0	48.2	87.2	65.8	88.4	88.1	69.4	37.6
44.6	9	Elementary	19.5	68.2	34.0	48.4	29.5	29.2	24.5	36.9	66.8	50.4	67.7	67.4	53.2	28.8

Source: ILOSTAT, authors' computation.

Table 3.A.2.8. Occupation-industry wage scores, Malaysia, females.

		WSi,nat	0.37	1.77	0.65	1.30	0.91	0.62	0.47	0.92	1.35	1.22	1.24	1.43	1.13	0.63
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
248.0	1	Managers	91.0	439.1	162.3	321.7	226.6	153.2	115.8	227.4	335.6	301.4	307.2	354.4	280.9	156.0
185.3	2	Professionals	68.0	328.0	121.2	240.3	169.3	114.5	86.5	169.9	250.7	225.2	229.5	264.8	209.8	116.6
130.4	3	Technicians	47.8	230.8	85.3	169.1	119.1	80.6	60.9	119.6	176.4	158.4	161.5	186.3	147.6	82.0
89.6	4	Clerks	32.9	158.6	58.6	116.2	81.8	55.3	41.8	82.1	121.2	108.8	110.9	128.0	101.4	56.3
57.3	5	Plant and Machine Workers	21.0	101.4	37.5	74.3	52.3	35.4	26.8	52.5	77.5	69.6	70.9	81.8	64.9	36.0
43.4	6	Crafts	15.9	76.8	28.4	56.2	39.6	26.8	20.3	39.8	58.7	52.7	53.7	62.0	49.1	27.3
48.2	7	Service Workers	17.7	85.3	31.5	62.5	44.0	29.8	22.5	44.2	65.2	58.5	59.7	68.8	54.6	30.3
56.9	8	Agricultural	20.9	100.7	37.2	73.8	52.0	35.1	26.6	52.2	77.0	69.1	70.4	81.3	64.4	35.8
41.0	9	Elementary	15.0	72.5	26.8	53.1	37.4	25.3	19.1	37.6	55.4	49.8	50.7	58.5	46.4	25.8

Source: ILOSTAT, authors' computation.

Table 3.A.2.9. Occupation-industry wage scores, Spain, females.

		WSi,nat	0.55	1.05	0.99	1.51	0.80	0.78	0.59	0.86	1.60	1.13	1.02	1.13	1.25	0.73
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
187.3	1	Managers	102.3	197.2	186.3	283.1	149.9	146.0	111.0	160.2	300.0	212.1	190.6	212.1	234.3	137.5
148.2	2	Professionals	80.9	156.0	147.4	223.9	118.5	115.5	87.8	126.7	237.2	167.8	150.8	167.8	185.3	108.7
107.4	3	Technicians	58.7	113.1	106.9	162.3	86.0	83.7	63.7	91.9	172.0	121.6	109.3	121.6	134.4	78.8
91.9	4	Clerks	50.2	96.7	91.4	138.8	73.5	71.6	54.5	78.6	147.1	104.0	93.5	104.0	114.9	67.4
78.1	5	Plant and Machine Workers	42.7	82.2	77.7	118.0	62.5	60.9	46.3	66.8	125.1	88.4	79.5	88.4	97.7	57.3
62.6	6	Crafts	34.2	65.9	62.3	94.6	50.1	48.8	37.1	53.5	100.2	70.9	63.7	70.9	78.3	45.9
78.9	7	Service Workers	43.1	83.1	78.5	119.2	63.1	61.5	46.8	67.5	126.3	89.3	80.3	89.3	98.7	57.9
83.8	8	Agricultural	45.8	88.2	83.3	126.6	67.0	65.3	49.6	71.6	134.1	94.9	85.2	94.8	104.8	61.5
61.8	9	Elementary	33.8	65.1	61.5	93.4	49.5	48.2	36.7	52.9	99.0	70.0	62.9	70.0	77.3	45.4

Source: ILOSTAT, authors' computation.

Table 3.A.2.10. Occupation-industry wage scores, Spain, females.

		WSi,nat IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
187.9	1	Managers	109.8	232.4	188.0	275.6	185.6	132.0	113.4	177.8	284.2	227.3	150.0	233.4	203.6	118.2
162.0	2	Professionals	94.6	200.3	162.0	237.5	159.9	113.7	97.8	153.2	244.9	195.9	129.3	201.1	175.5	101.8
108.7	3	Technicians	63.5	134.4	108.7	159.4	107.3	76.3	65.6	102.8	164.4	131.5	86.8	135.0	117.8	68.3
89.7	4	Clerks	52.4	110.9	89.7	131.4	88.5	62.9	54.1	84.8	135.5	108.4	71.6	111.3	97.1	56.4
67.3	5	Plant and Machine Workers	39.3	83.3	67.3	98.7	66.5	47.3	40.6	63.7	101.8	81.4	53.7	83.6	73.0	42.3
70.0	6	Crafts	40.9	86.6	70.0	102.7	69.1	49.2	42.3	66.2	105.9	84.7	55.9	87.0	75.9	44.0
74.8	7	Service Workers	43.7	92.5	74.9	109.7	73.9	52.5	45.2	70.8	113.1	90.5	59.7	92.9	81.1	47.0
84.7	8	Agricultural	49.5	104.8	84.7	124.2	83.6	59.5	51.1	80.1	128.1	102.4	67.6	105.2	91.8	53.3
54.9	9	Elementary	32.0	67.8	54.9	80.4	54.2	38.5	33.1	51.9	82.9	66.3	43.8	68.1	59.4	34.5

Source: ILOSTAT, authors' computation.

Table 3.A.2.11. Occupation-industry wage scores, United States, males.

		WSi,nat	0.40	1.27	1.09	1.32	0.70	0.77	0.40	0.96	1.84	1.09	1.15	0.91	1.43	0.66
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
183.2	1	Managers	72.9	233.0	199.9	242.2	128.0	140.9	74.1	176.7	336.8	200.3	209.8	167.2	262.5	120.2
178.9	2	Professionals	71.2	227.6	195.3	236.5	125.0	137.6	72.4	172.6	329.0	195.6	204.9	163.3	256.4	117.4
143.9	3	Technicians	57.3	183.1	157.1	190.3	100.6	110.7	58.2	138.8	264.7	157.4	164.9	131.4	206.3	94.5
70.1	4	Clerks	27.9	89.1	76.5	92.6	49.0	53.9	28.4	67.6	128.8	76.6	80.2	63.9	100.4	46.0
75.2	5	Plant and Machine Workers	29.9	95.6	82.0	99.4	52.5	57.8	30.4	72.5	138.2	82.2	86.1	68.6	107.7	49.3
37.6	6	Crafts	14.9	47.8	41.0	49.6	26.2	28.9	15.2	36.2	69.1	41.1	43.0	34.3	53.8	24.7
85.8	7	Service Workers	34.1	109.2	93.7	113.5	60.0	66.0	34.7	82.8	157.8	93.8	98.3	78.3	123.0	56.3
76.4	8	Agricultural	30.4	97.3	83.4	101.1	53.4	58.8	30.9	73.7	140.6	83.6	87.6	69.8	109.6	50.2
48.9	9	Elementary	19.5	62.2	53.4	64.7	34.2	37.6	19.8	47.2	89.9	53.5	56.0	44.6	70.1	32.1

Source: ILOSTAT, authors’ computation.

Table 3.A.2.12. Occupation-industry wage scores, United States, females.

		WSi,nat	0.42	1.52	1.09	1.54	0.92	0.65	0.40	1.11	1.36	1.27	1.06	0.98	1.06	0.61
		IND Code IPUMS	10	20	30	40	50	60	70	80	90	100	111	112	113	114
WSo,nat	OCC Code IPUMS	WSo,nat x Wsi,nat	Agriculture, fishing, forestry	Mining	Manufacturing	Electricity, gas and water (sanitation)	Construction	Wholesale and retail trade, (repair)	Hotels and restaurants	Transportation, storage and communication	Financial services and insurance	Public administration and defense	Real estate and business services	Education	Health and social work	Other services
181.9	1	Managers	77.0	276.6	197.8	279.6	167.9	117.4	73.5	202.0	248.2	230.7	192.7	177.9	193.7	111.3
176.9	2	Professionals	74.9	269.0	192.4	271.9	163.3	114.1	71.5	196.5	241.3	224.3	187.3	173.0	188.3	108.3
133.7	3	Technicians	56.6	203.3	145.4	205.5	123.4	86.3	54.0	148.5	182.4	169.5	141.6	130.7	142.3	81.8
88.7	4	Clerks	37.5	134.9	96.5	136.4	81.9	57.2	35.9	98.5	121.0	112.5	94.0	86.7	94.5	54.3
58.1	5	Plant and Machine Workers	24.6	88.4	63.2	89.3	53.6	37.5	23.5	64.6	79.3	73.7	61.6	56.8	61.9	35.6
41.9	6	Crafts	17.7	63.7	45.6	64.4	38.7	27.0	16.9	46.6	57.2	53.2	44.4	41.0	44.6	25.7
99.7	7	Service Workers	42.2	151.6	108.4	153.2	92.0	64.3	40.3	110.7	136.0	126.4	105.6	97.5	106.1	61.0
74.7	8	Agricultural	31.6	113.6	81.2	114.8	68.9	48.2	30.2	83.0	101.9	94.7	79.1	73.0	79.5	45.7
44.5	9	Elementary	18.9	67.7	48.4	68.5	41.1	28.7	18.0	49.5	60.8	56.5	47.2	43.6	47.4	27.3

Source: ILOSTAT, authors' computation.

3.A.3. Institutional index computation

I calculate indices for cultural similarity, cultural diversity, migrant networks and immigration policies using Acosta's (2010) weighted normalized index of wealth by grouping various indicators under each factor. These indices reveal a country's "ranking" in that certain area relative to the mean *among countries in the sample*. The index is computed as:

$$I_c = \sum_{j}^{k} \frac{a_j(x_{cj} - \overline{x_j})}{\sigma_j}$$

Where I_c is the index for country *c*, a_j is the weight of indicator *j* based on its first principal component, x_{cj} is the level of a country's indicator *j*; $\overline{x_j}$ is the mean across countries; and σ_j is the standard deviation across countries. The index ranges from negative to positive where negative values indicate that a country has a lower-than-average level of a factor, and positive values indicates a higher-than-average level.

3.A.4. Regression tables accompanying the main results

Table 3.A.4.1. Assimilation profile, basic pooled regression.

	Dependent Variable	
YSM	Wage	Employment
0y (within year)	-31.43***	-0.0630**
1-5	-38.68***	0.0020
6-10	-30.18***	0.0198
11-15	-30.54***	0.0300***
16-20	-22.77***	0.0393***
21-25	-21.89***	0.0432***
26-30	-17.87***	0.0426***
31+	-17.20***	0.0532***
Observations	9,563,210	8,355,758
R^2	0.2535	0.0433

Source: IPUMS-I, authors' calculations.

Notes: *, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

Table 3.A.4.2. Assimilation profiles by cultural similarity.

YSM	Dep. Var: Wage High ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m}$)	Dep. Var: Wage Low ($\boldsymbol{\beta}_{t-m}$)	Dep. Var: Employment High ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m}$)	Dep. Var: Employment Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-30.45	-37.61***	-0.0723***	0.0338**
1-5	-38.68	-41.33***	0.0020***	0.0282***
6-10	-29.75***	-40.15***	0.0210***	0.0292***
11-15	-30.70***	-45.60***	0.0317**	0.0466***
16-20	-22.69***	-43.45***	0.0408***	0.0575***
21-25	-22.58***	-43.47***	0.0455***	0.0636***
26-30	-18.97***	-41.48***	0.0452***	0.0698***
31+	-18.76***	-31.38***	0.0564	0.0726***
Observations	9,563,210		8,355,758	
R^2	0.2535		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

Table 3.A.4.3. Assimilation profiles by cultural (and linguistic) diversity.

YSM	Dep. Var: Wage High ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m}$)	Dep. Var: Wage Low ($\boldsymbol{\beta}_{t-m}$)	Dep. Var: Employment High ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m}$)	Dep. Var: Employment Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-4.91	-19.22	0.0428***	-0.0637**
1-5	-39.01***	-21.67***	0.0019	0.0050
6-10	-33.67***	-14.88***	0.0173	0.0239*
11-15	-33.50***	-14.60***	0.0292	0.0328***
16-20	-27.21***	-8.55***	0.0298**	0.0441***
21-25	-27.88***	-5.95***	0.0409	0.0461***
26-30	-22.42***	-4.01***	0.0346	0.0464***
31+	-23.59***	-2.45***	0.0434	0.0567***
Observations	9,565,133		8,355,758	
R^2	0.2479		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

Table 3.A.4.4. Assimilation profiles by migration network.

	Dep. Var: Wage		Dep. Var: Employment	
	High	Low	High	Low
YSM	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$
0y (within year)	-19.43	-21.82***	-0.0729***	0.0428**
1-5	-22.15***	-39.00***	0.0041	0.0018
6-10	-15.46***	-34.18***	0.0230	0.0180
11-15	-15.16***	-33.74***	0.0318	0.0298**
16-20	-9.18***	-27.79***	0.0436**	0.0296**
21-25	-6.50***	-28.27***	0.0452	0.0411***
26-30	-4.68***	-23.04***	0.0458	0.0344**
31+	-3.19***	-23.16***	0.0560	0.0436***
Observations	9,563,210		8,355,758	
R^2	0.2536		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Low" $(\boldsymbol{\beta}_{t-m})$ represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

Table 3.A.4.5. Assimilation profiles by migration policy.

	Dep. Var: Wage		Dep. Var: Employment	
	Selective	Liberal	Selective	Liberal
YSM	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$
0y (within year)	-30.70	-34.43***	-0.0740***	0.0418***
1-5	-38.68	-39.48***	0.0019***	0.0239**
6-10	-29.67***	-39.43***	0.0207***	0.0354***
11-15	-30.55***	-43.97***	0.0313***	0.0540***
16-20	-22.54***	-42.39***	0.0409***	0.0567***
21-25	-22.35***	-42.51***	0.0454***	0.0674***
26-30	-18.75***	-41.07***	0.0452***	0.0715***
31+	-18.51***	-30.56***	0.0564	0.0708***
Observations	9,563,210		8,355,758	
R^2	0.2535		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Liberal" $(\boldsymbol{\beta}_{t-m})$ represents the assimilation profile when $H_c = 0$, "Selective" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Robust standard errors used.

Table 3.A.4.6. Country case studies: country fixed effect regressions

Panel A. Dependent Variable: Wage

YSM	Canada ($\boldsymbol{\beta}_{t-m}$)	Greece ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$)	Malaysia ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$)	Spain ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$)	US ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$)
0y (within year)	-17.47***	19.05*	-3.89	-31.58*	
1-5	-39.03***	-9.75***	-29.03***	-23.93***	-21.03***
6-10	-33.31***	-20.22***	-27.27**	-33.18	-13.78***
11-15	-32.51***	-18.41***	-33.28	-13.75**	-13.72***
16-20	-25.50***	-11.48***	-28.99	-30.58	-7.54***
21-25	-26.74***	-21.54	-29.89	-15.31	-5.10***
26-30	-20.67***	-23.46	-27.99*	-13.68	-3.25***
31+	-22.71***	3.92*	-25.55	4.12***	-1.77***
Observations			9,563,210		
R^2			0.2536		

Panel B. Dependent Variable: Employment

YSM	Canada ($\boldsymbol{\beta}_{t-m}$)	Greece ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$)	Malaysia ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$)	Spain ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$)	US ($\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$)
0y (within year)	-0.0706	0.1435***	0.0460***	0.0330***	-0.0706
1-5	0.0017	-0.0154	0.0261***	0.0523***	0.0064
6-10	0.0178	0.1016***	0.0314	0.0444***	0.0257
11-15	0.0305***	0.1224***	0.0508**	0.0414	0.0355
16-20	0.0244	0.0402	0.0642***	0.0476**	0.0478***
21-25	0.0423***	0.1107**	0.0689**	0.0554	0.0498
26-30	0.0339***	0.1341***	0.0763***	0.0371	0.0516**
31+	0.0463***	0.0034	0.0794*	0.0750	0.0620
Observations			8,355,758		
R^2			0.0433		

Source: IPUMS-I, authors' calculations.

Notes: Canada ($\boldsymbol{\beta}_{t-m}$) is the base category. Other countries' ($\boldsymbol{\beta}_{t-m}+\ddot{\boldsymbol{\beta}}_{c,t-m}$) includes the per-country differential slope $\ddot{\boldsymbol{\beta}}_{c,t-m}$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

3.A.5. Figures and regression tables when excluding USA

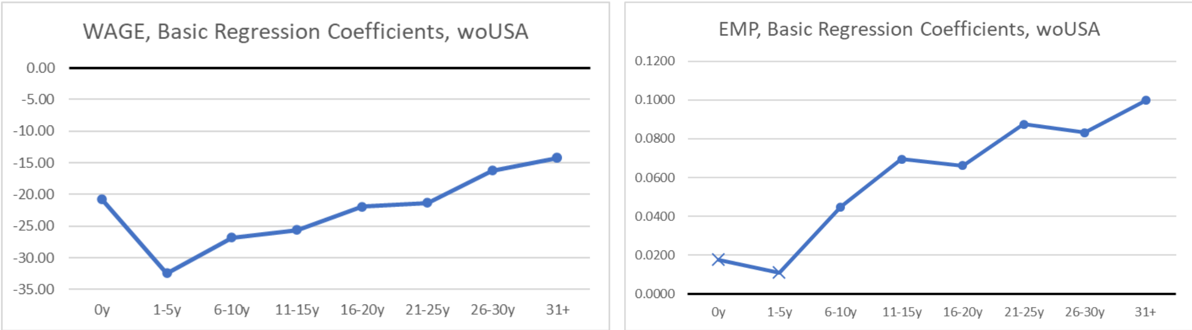


Figure 3.A.5.1. (a) Wage and (b) Employment assimilation profile, basic pooled regression, excluding US.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients.

Table 3.A.5.1. Assimilation profile, basic pooled regression, excluding US

	Dependent Variable	
YSM	Wage	Employment
0y (within year)	-20.70*	0.0176
1-5	-32.46***	0.0110
6-10	-26.82***	0.0448***
11-15	-25.62***	0.0695***
16-20	-21.94***	0.0662***
21-25	-21.30***	0.0874***
26-30	-16.25**	0.0832***
31+	-14.30**	0.0999***
Observations	2,089,157	1,990,337
R^2	0.2602	0.0577

Source: IPUMS-I, authors' calculations.

Notes: *, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

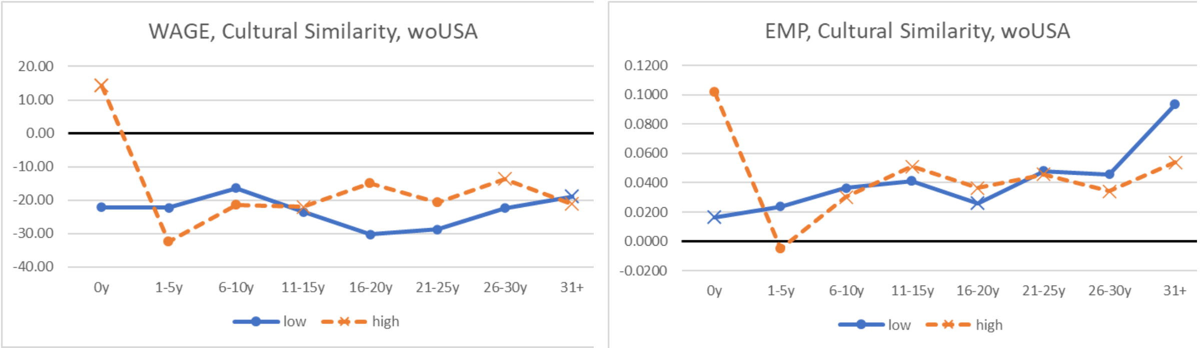


Figure 3.A.5.2. (a) Wage and (b) Employment assimilation profile by cultural similarity, excluding US.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.5.2. Assimilation profiles by cultural similarity, excluding US.

	Dep. Var: Wage		Dep. Var: Employment	
	High	Low	High	Low
YSM	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$
0y (within year)	14.14	-22.09*	0.1016***	0.0164
1-5	-32.48***	-22.23***	-0.0053***	0.0238*
6-10	-21.51*	-16.45***	0.0301	0.0365**
11-15	-22.05	-23.49***	0.0511	0.0408***
16-20	-15.03***	-30.21***	0.0366	0.0257
21-25	-20.67**	-28.78***	0.0458	0.0478**
26-30	-13.62	-22.37**	0.0341	0.0458*
31+	-21.13	-18.93	0.0539	0.0933**
Observations	2,089,156		1,995,236	
R^2	0.2602		0.0441	

Source: IPUMS-I, authors' calculations.

Notes: "Low" $(\boldsymbol{\beta}_{t-m})$ represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

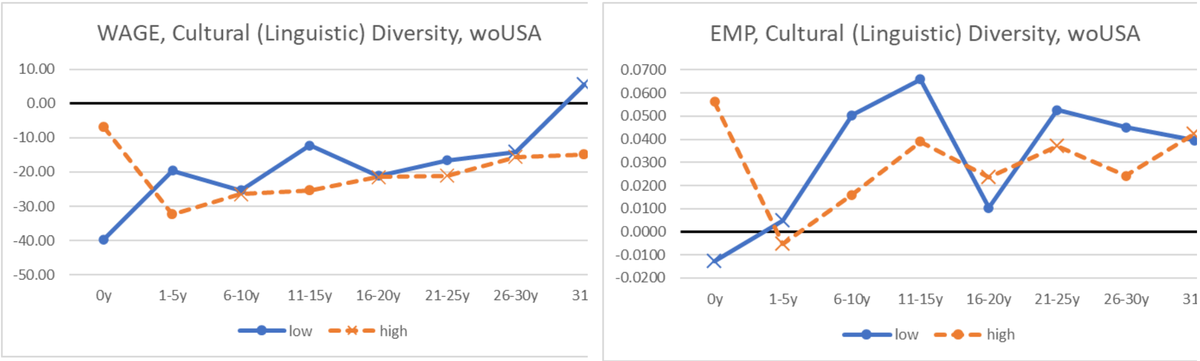


Figure 3.A.5.3. (a) Wage and (b) Employment assimilation profile by cultural and linguistic diversity, excluding US.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.5.3. Assimilation profiles by cultural (and linguistic) diversity, excluding US.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High $(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	Low $(\boldsymbol{\beta}_{t-m})$	High $(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	Low $(\boldsymbol{\beta}_{t-m})$
0y (within year)	-6.85*	-39.63***	0.0562**	-0.0126
1-5	-32.45***	-19.62***	-0.0052	0.0049
6-10	-26.41	-25.38***	0.0160***	0.0503***
11-15	-25.32***	-12.19**	0.0390***	0.0660***
16-20	-21.48	-21.05***	0.0234	0.0104
21-25	-21.07	-16.58**	0.0371	0.0527**
26-30	-15.63	-14.12	0.0242*	0.0451**
31+	-14.96***	5.65	0.0424	0.0396
Observations	2,089,156		1,995,236	
R^2	0.2602		0.0441	

Source: IPUMS-I, authors' calculations.

Notes: "Low" $(\boldsymbol{\beta}_{t-m})$ represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

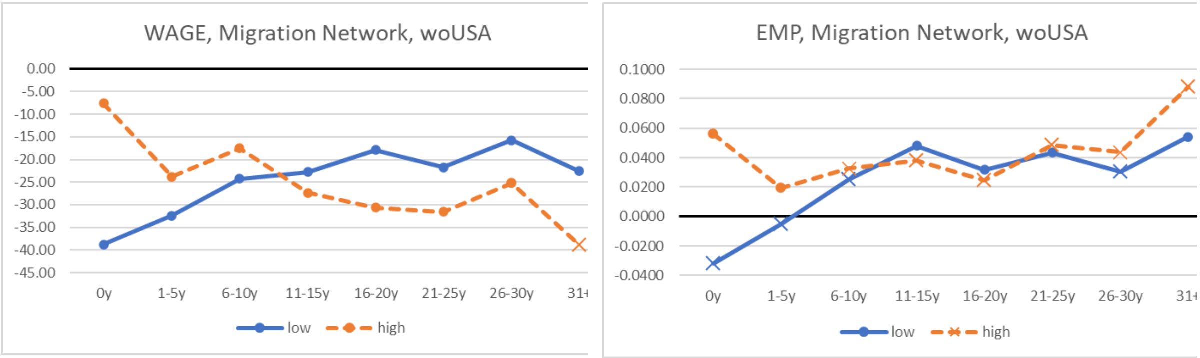


Figure 3.A.5.4. (a) Wage and (b) Employment assimilation profile by migration network, excluding US.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.5.4. Assimilation profiles by migration network, excluding US.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-7.55*	-38.72***	0.0559***	-0.0319
1-5	-23.78***	-32.45***	0.0196**	-0.0052
6-10	-17.54*	-24.24***	0.0325	0.0254
11-15	-27.36**	-22.74***	0.0378	0.0479**
16-20	-30.65***	-17.89***	0.0248	0.0317*
21-25	-31.57***	-21.74***	0.0487	0.0433**
26-30	-25.26*	-15.72***	0.0436	0.0305
31+	-38.98	-22.60***	0.0879	0.0540**
Observations	2,089,156		1,995,236	
R^2	0.2602		0.0441	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

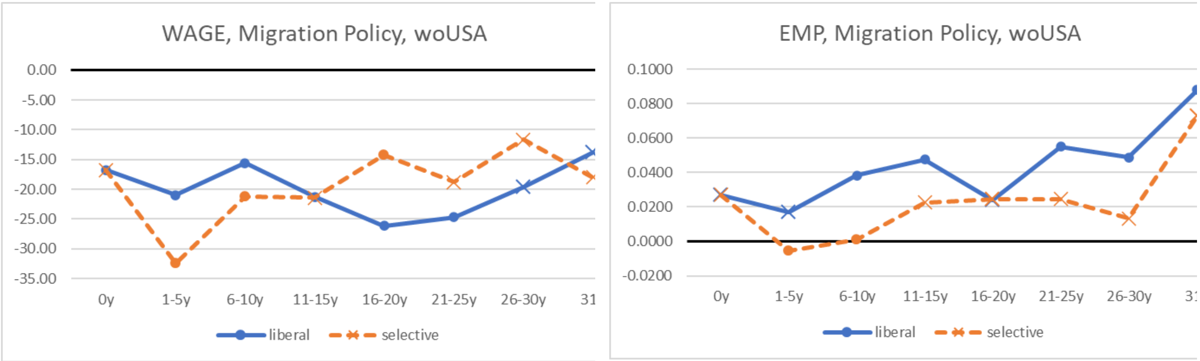


Figure 3.A.5.5. (a) Wage and (b) Employment assimilation profile by migration policy, excluding US.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "Selective" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Liberal" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.5.5. Assimilation profiles by migration policy, excluding US.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	Selective ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Liberal ($\boldsymbol{\beta}_{t-m}$)	Selective ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Liberal ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-16.78	-16.78	0.0272	0.0272
1-5	-32.46***	-20.99***	-0.0057**	0.0168
6-10	-21.22**	-15.61***	0.0011**	0.0384**
11-15	-21.43	-21.25***	0.0225	0.0477**
16-20	-14.27***	-26.14***	0.0246	0.0241
21-25	-18.81*	-24.67***	0.0246	0.0549**
26-30	-11.64	-19.70***	0.0133	0.0488**
31+	-18.01	-13.79	0.0727	0.0880***
Observations	2,089,156		1,995,236	
R^2	0.2600		0.0441	

Source: IPUMS-I, authors' calculations.

Notes: "Liberal" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "Selective" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Robust standard errors used.

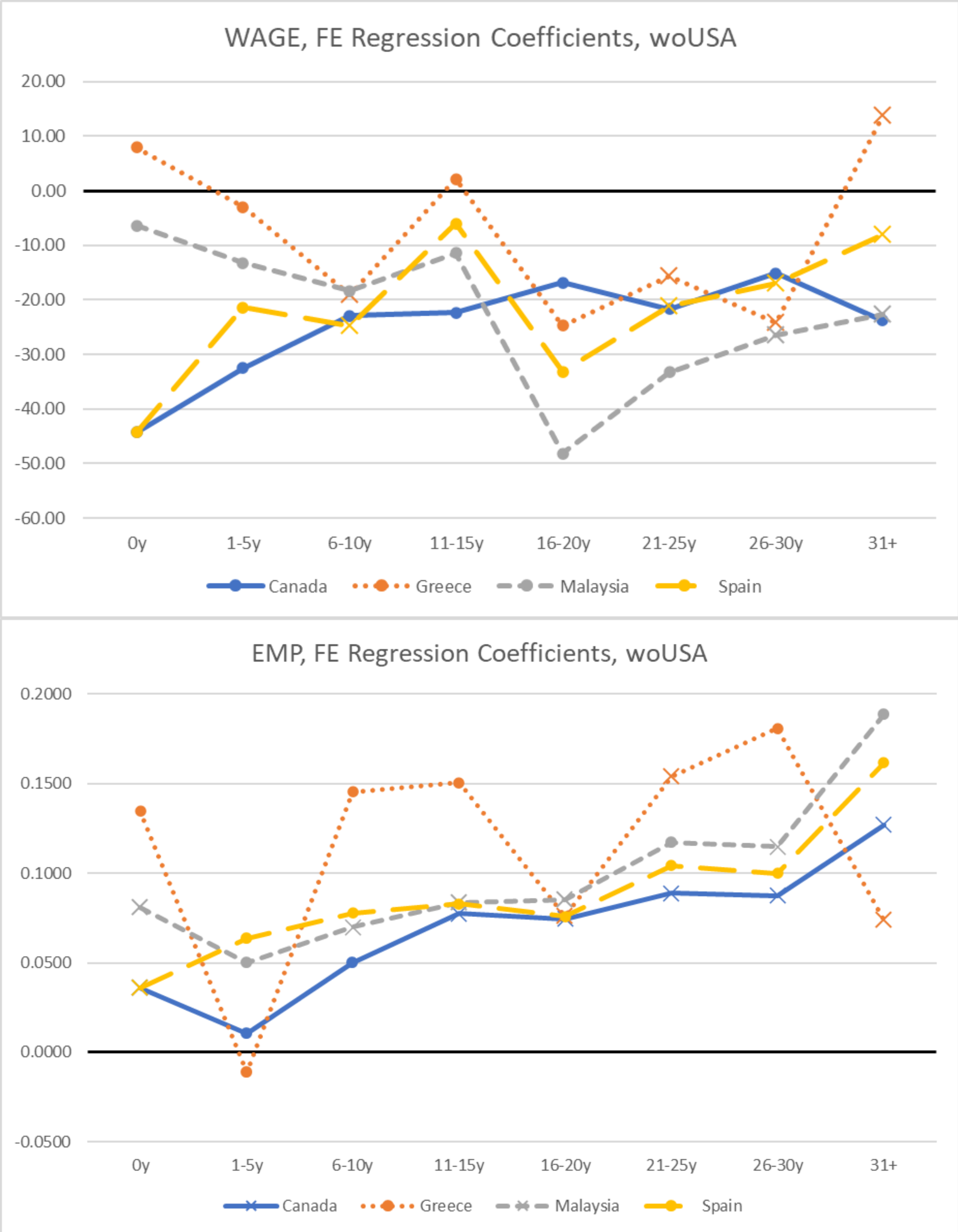


Figure 3.A.5.6. (a) Wage and (b) employment assimilation profiles using a country fixed effects regression, excluding US.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients. Note: Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. Spain is the base category. Other countries represents the $\boldsymbol{\beta}_{t-m} + \ddot{\boldsymbol{\beta}}_{c,t-m}$, which is the Canada assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the respective per-country differential slope $\ddot{\boldsymbol{\beta}}_{c,t-m}$..

Table 3.A.5.6. Country case studies: country fixed effect regressions, excluding US

Panel A. Dependent Variable: Wage				
YSM	Canada $\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$	Greece $\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$	Malaysia $\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$	Spain* $(\boldsymbol{\beta}_{t-m})$
0y (within year)	-44.26	7.93**	-6.41**	-44.26***
1-5	-32.48***	-2.94**	-13.21***	-21.41***
6-10	-22.95	-19.08	-18.39*	-24.74***
11-15	-22.30*	2.15**	-11.41**	-6.05
16-20	-16.85**	-24.71*	-48.18***	-33.21***
21-25	-21.69	-15.67	-33.29***	-21.19*
26-30	-15.10	-24.23	-26.47	-17.08
31+	-23.80	13.76	-22.68	-7.98
Observations	2,089,157			
R^2	0.2602			

Panel B. Dependent Variable: Employment				
YSM	Canada $\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$	Greece $\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$	Malaysia $\boldsymbol{\beta}_{t-m}+\widetilde{\boldsymbol{\beta}}_{t-m,c}$	Spain* $(\boldsymbol{\beta}_{t-m})$
0y (within year)	0.0359	0.1347***	0.0809	0.0359
1-5	0.0107***	-0.0111**	0.0499*	0.0638***
6-10	0.0502***	0.1455***	0.0699	0.0779***
11-15	0.0776	0.1505***	0.0836	0.0828***
16-20	0.0746	0.0760	0.0852	0.0758***
21-25	0.0888	0.1540	0.1172*	0.1043***
26-30	0.0876	0.1808***	0.1149	0.1000***
31+	0.1269	0.0738	0.1884***	0.1618***
Observations	1,990,338			
R^2	0.0577			

Source: IPUMS-I, authors' calculations.

Notes: Spain $(\boldsymbol{\beta}_{t-m})$ is the base category. Other countries' $(\boldsymbol{\beta}_{t-m}+\ddot{\boldsymbol{\beta}}_{\boldsymbol{c},\boldsymbol{t}-\boldsymbol{m}})$ includes the per-country differential slope $\ddot{\boldsymbol{\beta}}_{\boldsymbol{c},\boldsymbol{t}-\boldsymbol{m}}$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

3.A.6. Figures and regression tables of disaggregated components of institutional indices

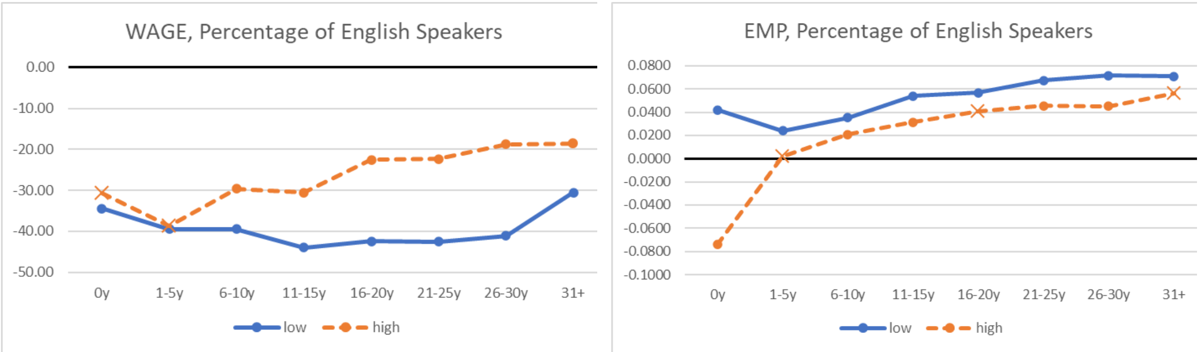


Figure 3.A.6.1. Assimilation profile by percentage of English speakers.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.6.1. Assimilation profiles by proportion of English-speakers.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-30.70	-34.43***	-0.0740***	0.0418**
1-5	-38.68	-39.48***	0.0019***	0.0239**
6-10	-29.67***	-39.43***	0.0207***	0.0354***
11-15	-30.55***	-43.97***	0.0313***	0.0540***
16-20	-22.54***	-42.39***	0.0409***	0.0567***
21-25	-22.35***	-42.51***	0.0454***	0.0674***
26-30	-18.75***	-41.07***	0.0452***	0.0715***
31+	-18.51**	-30.56***	0.0564	0.0708***
Observations	9,563,210		8,355,758	
R^2	0.2535		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

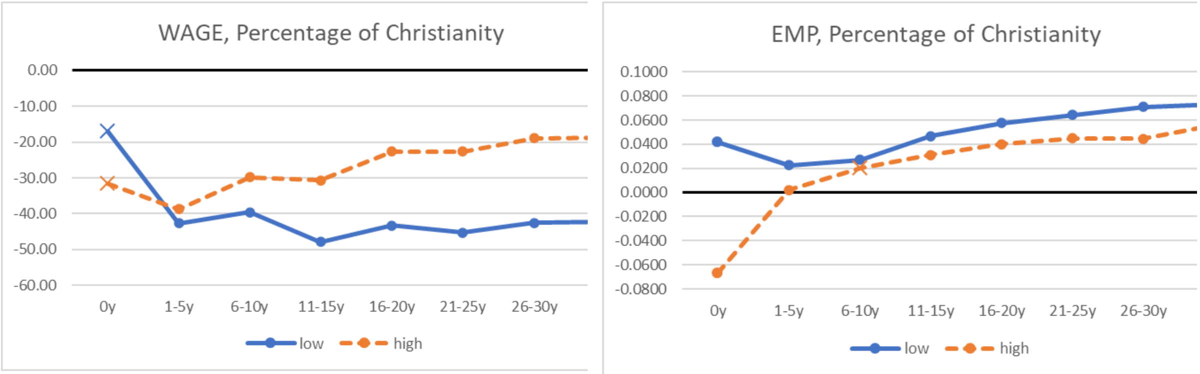


Figure 3.A.6.2. Assimilation profile by percentage of Christianity.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.6.2. Assimilation profiles by percentage of Christianity.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-31.58	-16.91	-0.0667***	0.0418*
1-5	-38.68***	-42.75***	0.0020***	0.0225**
6-10	-29.81***	-39.66***	0.0202	0.0269**
11-15	-30.73***	-47.96***	0.0310**	0.0470***
16-20	-22.69***	-43.34***	0.0399***	0.0576***
21-25	-22.62***	-45.30***	0.0448***	0.0643***
26-30	-18.91***	-42.55***	0.0444***	0.0709***
31+	-18.74***	-42.28***	0.0557	0.0731***
Observations	9,563,210		8,355,758	
R^2	0.2535		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

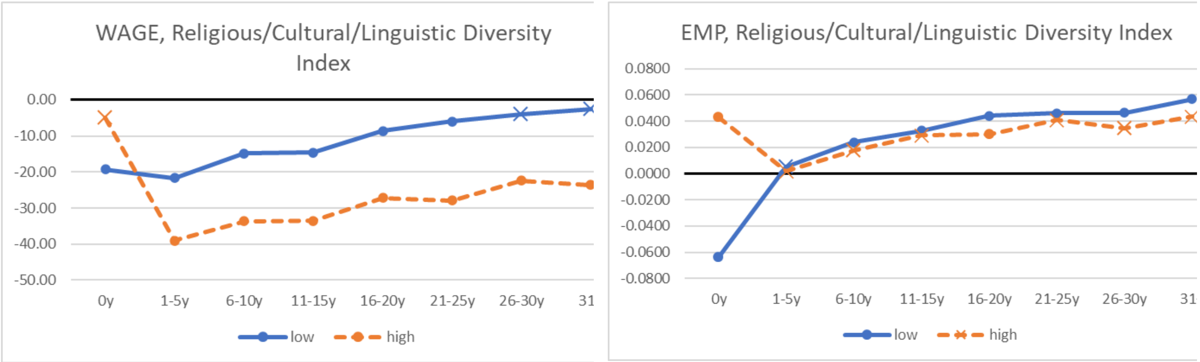


Figure 3.A.6.3. Assimilation profile by cultural (religious and linguistic) diversity index.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.6.3. Assimilation profiles by cultural (religious and linguistic) diversity index.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High $(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	Low $(\boldsymbol{\beta}_{t-m})$	High $(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	Low $(\boldsymbol{\beta}_{t-m})$
0y (within year)	-4.91	-19.22***	0.0428***	-0.0637**
1-5	-39.01***	-21.67***	0.0019	0.0050
6-10	-33.67***	-14.88***	0.0173	0.0239*
11-15	-33.50***	-14.60***	0.0292	0.0328***
16-20	-27.21***	-8.55***	0.0298**	0.0441***
21-25	-27.88***	-5.95**	0.0409	0.0461***
26-30	-22.42***	-4.01	0.0346	0.0464***
31+	-23.59***	-2.45	0.0434	0.0567***
Observations	9,563,210		8,355,758	
R^2	0.2536		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: Classification according to cultural, religious, and linguistic diversity indices (CDI, RDI, LDI, respectively) are all perfectly collinear, that is, the set of countries with comparatively high CDI, RDI and LDI are the same. "Low" $(\boldsymbol{\beta}_{t-m})$ represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

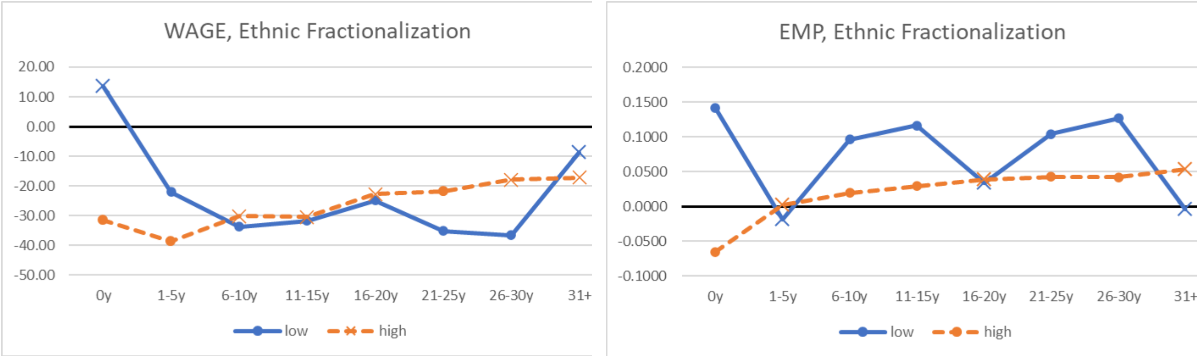


Figure 3.A.6.4. Assimilation profile by ethnic fractionalization index.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.6.4. Assimilation profiles by ethnic fractionalization index.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-31.47**	13.66	-0.0651***	0.1413***
1-5	-38.71***	-22.06***	0.0019	-0.0184
6-10	-30.17	-33.71***	0.0195***	0.0965***
11-15	-30.53	-31.74***	0.0295***	0.1165***
16-20	-22.76	-24.90***	0.0393	0.0344
21-25	-21.85**	-35.12***	0.0427*	0.1045***
26-30	-17.83	-36.61***	0.0424***	0.1270***
31+	-17.17	-8.60	0.0529	-0.0039
Observations	9,563,210		8,355,758	
R^2	0.2535		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

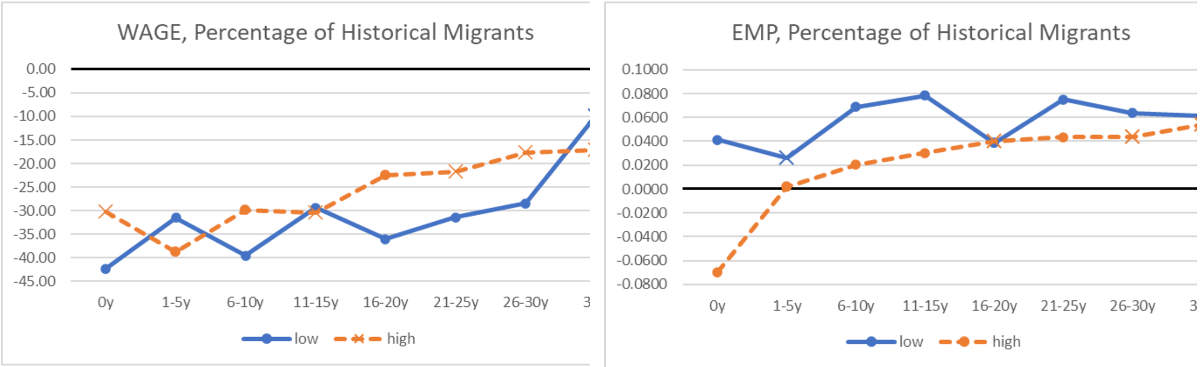


Figure 3.A.6.5. Assimilation profile by percentage of historical immigrants.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.6.5. Assimilation profiles by percentage of historical immigrants.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-30.16	-42.33***	-0.0695***	0.0414**
1-5	-38.68***	-31.47***	0.0019*	0.0259
6-10	-29.90***	-39.52***	0.0204***	0.0689***
11-15	-30.43	-29.34***	0.0301***	0.0783***
16-20	-22.52***	-36.02***	0.0402	0.0383*
21-25	-21.73	-31.41***	0.0435*	0.0750***
26-30	-17.67	-28.41***	0.0434	0.0637***
31+	-17.06	-9.99	0.0538	0.0616**
Observations	9,563,210		8,355,758	
R^2	0.2535		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

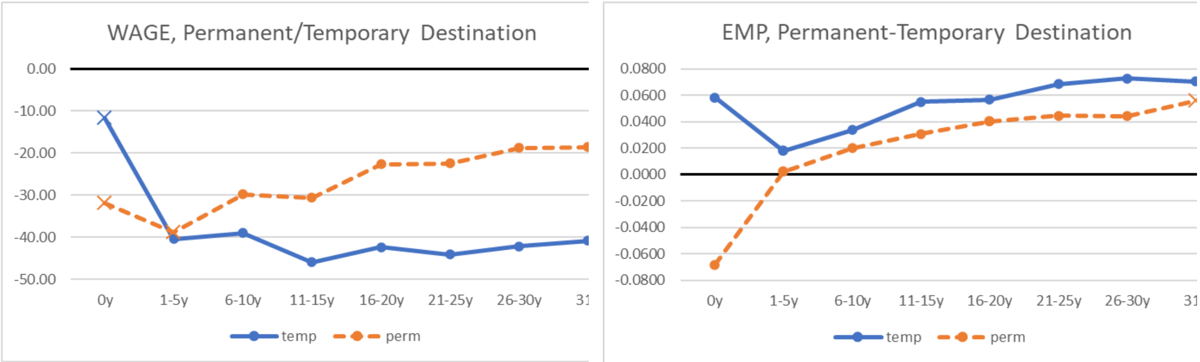


Figure 3.A.6.6. Assimilation profile by permanent/temporary destination.

Note: Y-axis denotes differential slopes relative to natives. Points with an “x” mark symbolize statistically insignificant coefficients/differential slopes. “High” represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the “Low” assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.6.6. Assimilation profiles by permanent/temporary destination.

	Dep. Var: Wage		Dep. Var: Employment	
	Permanent	Temporary	Permanent	Temporary
YSM	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$
0y (within year)	-31.88	-11.73	-0.0684***	0.0584**
1-5	-38.69***	-40.36***	0.0019***	0.0180*
6-10	-29.78***	-38.97***	0.0199***	0.0338***
11-15	-30.59***	-45.90***	0.0307***	0.0551***
16-20	-22.60***	-42.26***	0.0400***	0.0567***
21-25	-22.40***	-44.07***	0.0447***	0.0684***
26-30	-18.73***	-42.11***	0.0443***	0.0727***
31+	-18.51***	-40.74***	0.0557	0.0705***
Observations	9,563,210		8,355,758	
R^2	0.2535		0.0433	

Source: IPUMS-I, authors’ calculations.

Notes: “Permanent” destinations tend to have more permanent migrants rather than temporary migrants. The opposite is true for “Temporary” destinations. “Temporary” $(\boldsymbol{\beta}_{t-m})$ represents the assimilation profile when $H_c = 0$, “Permanent” represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

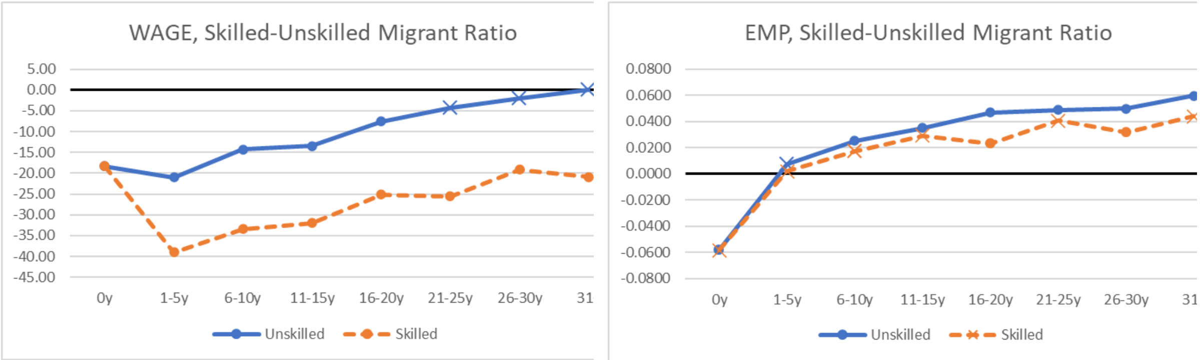


Figure 3.A.6.7. Assimilation profile by ratio of skilled-unskilled immigrants.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.6.7. Assimilation profiles by ratio of skilled-unskilled immigrants.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	Skilled ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Unskilled ($\boldsymbol{\beta}_{t-m}$)	Skilled ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Unskilled ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-18.31	-18.31***	-0.0586	-0.0586*
1-5	-39.01***	-21.03***	0.0018	0.0072
6-10	-33.37***	-14.32***	0.0169	0.0251*
11-15	-31.96***	-13.40***	0.0293	0.0350***
16-20	-25.13***	-7.54***	0.0231***	0.0467***
21-25	-25.55***	-4.23	0.0407	0.0487***
26-30	-19.15***	-2.02	0.0318**	0.0498***
31+	-20.90***	0.04	0.0440	0.0597***
Observations	9,563,210		8,355,758	
R^2	0.2536		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Skilled" implies the number of immigrants in primary occupations (ISCO88 1-4) is greater than the number of immigrants in secondary occupations (ISCO88 5-9). The opposite is true for "Unskilled". "Unskilled" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "Skilled" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.
*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

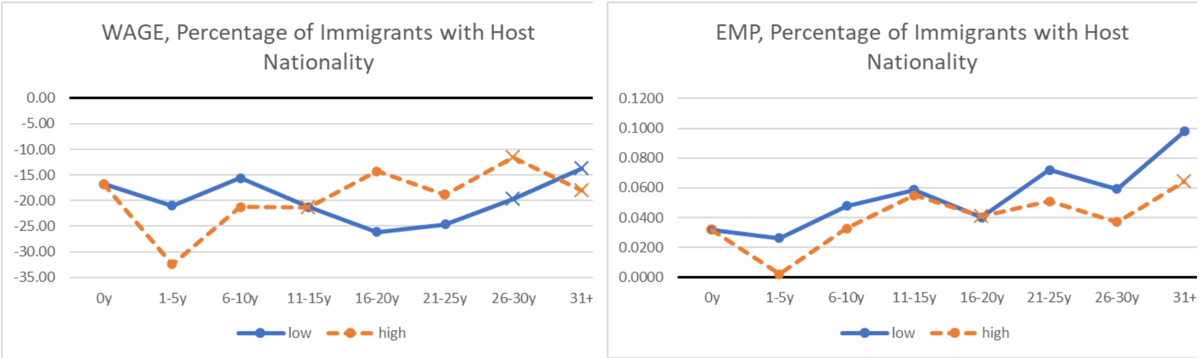


Figure 3.A.6.8. Assimilation profile by percentage of immigrants with host nationality.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.6.8. Assimilation profiles by percentage of immigrants with host nationality.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-16.78	-16.78	0.0320	0.0320
1-5	-32.46***	-20.99***	0.0021**	0.0263**
6-10	-21.22**	-15.61***	0.0327**	0.0478***
11-15	-21.43	-21.25***	0.0550	0.0587***
16-20	-14.27***	-26.14***	0.0407	0.0401**
21-25	-18.81*	-24.67***	0.0510***	0.0720***
26-30	-11.64	-19.70***	0.0371***	0.0592**
31+	-18.01	-13.79	0.0641	0.0980***
Observations	2,089,156		1,990,337	
R^2	0.2602		0.0503	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

3.A.7. Figures and regression tables for indicators with subnational variation

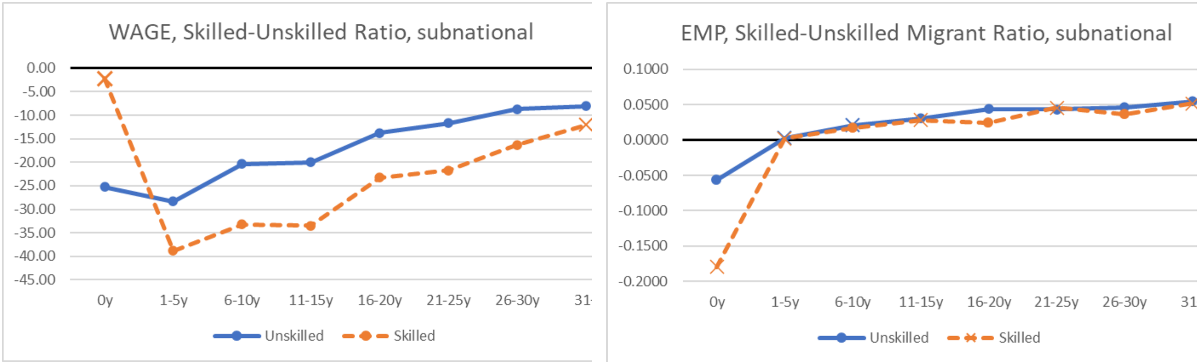


Figure 3.A.7.1. Assimilation profile by ratio of skilled-unskilled immigrants, subnational variation.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.7.1. Assimilation profiles by ratio of skilled-unskilled immigrants, subnational variation.

	Dep. Var: Wage		Dep. Var: Employment	
	Skilled	Unskilled	Skilled	Unskilled
YSM	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$	$(\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m})$	$(\boldsymbol{\beta}_{t-m})$
0y (within year)	-2.07	-25.26***	-0.1795	-0.0569*
1-5	-38.84***	-28.34***	0.0019	0.0023
6-10	-33.20***	-20.37***	0.0168	0.0212
11-15	-33.44***	-20.01***	0.0283	0.0308***
16-20	-23.23***	-13.79***	0.0247**	0.0440***
21-25	-21.71***	-11.70***	0.0457	0.0434***
26-30	-16.28***	-8.65***	0.0362	0.0462***
31+	-11.99	-8.08**	0.0514	0.0549***
Observations	9,563,210		8,355,758	
R^2	0.2535		0.0433	

Source: IPUMS-I, authors' calculations.

Notes: "Skilled" implies the number of immigrants in primary occupations (ISCO88 1-4) is greater than the number of immigrants in secondary occupations (ISCO88 5-9). The opposite is true for "Unskilled". "Unskilled" $(\boldsymbol{\beta}_{t-m})$ represents the assimilation profile when $H_c = 0$, "Skilled" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

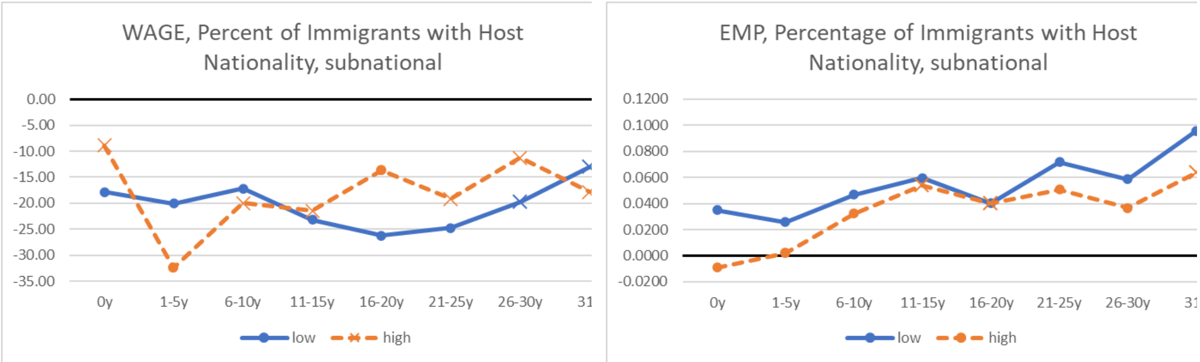


Figure 3.A.7.2. Assimilation profile by percentage of immigrants with host nationality.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients/differential slopes. "High" represents the $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$, which is the "Low" assimilation profile $\boldsymbol{\beta}_{t-m}$ plus the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ attributed to H_c.

Table 3.A.7.2. Assimilation profiles by percentage of immigrants with host nationality.

	Dep. Var: Wage		Dep. Var: Employment	
YSM	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)	High ($\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$)	Low ($\boldsymbol{\beta}_{t-m}$)
0y (within year)	-8.87	-17.84*	-0.0093**	0.0349*
1-5	-32.46***	-20.05***	0.0021**	0.0256**
6-10	-19.98	-17.16***	0.0323**	0.0466***
11-15	-21.46	-23.16***	0.0541	0.0596***
16-20	-13.69***	-26.21***	0.0401	0.0401**
21-25	-19.13	-24.73***	0.0507**	0.0716***
26-30	-11.24	-19.71***	0.0366*	0.0586**
31+	-17.85	-13.11	0.0636	0.0958***
Observations	2,089,156		1,990,337	
R^2	0.2602		0.0503	

Source: IPUMS-I, authors' calculations.

Notes: "Low" ($\boldsymbol{\beta}_{t-m}$) represents the assimilation profile when $H_c = 0$, "High" represents $\boldsymbol{\beta}_{t-m} + \widetilde{\boldsymbol{\beta}}_{t-m}$ which includes the differential slope $\widetilde{\boldsymbol{\beta}}_{t-m}$ when $H_c = 1$.

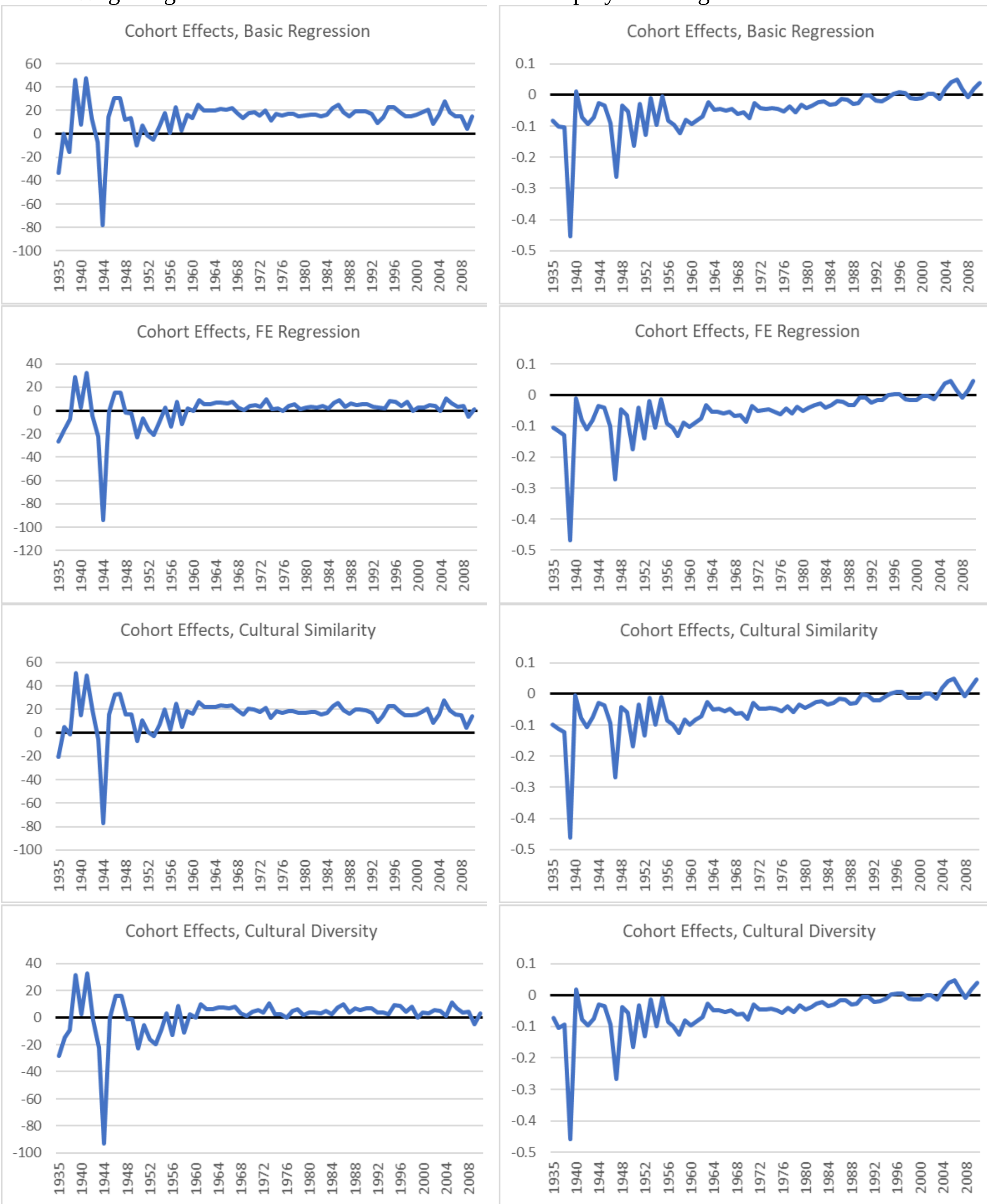
*, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

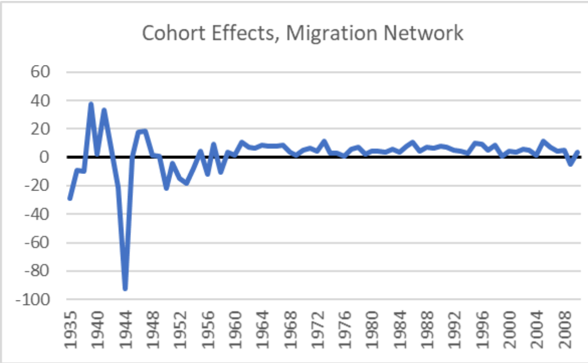
3.A.8. Figures for cohort quality effects

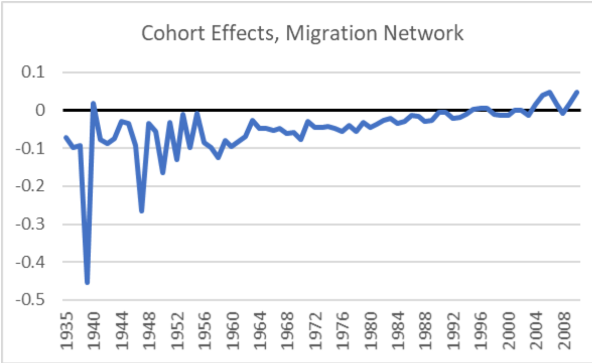
Figure 3.A.8. Cohort quality effects accompanying assimilation profile regressions.

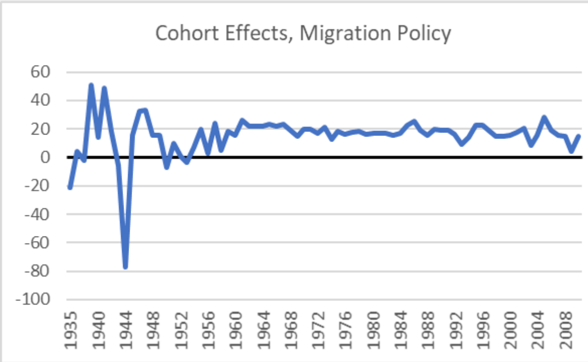
Wage Regressions Cohort Effects

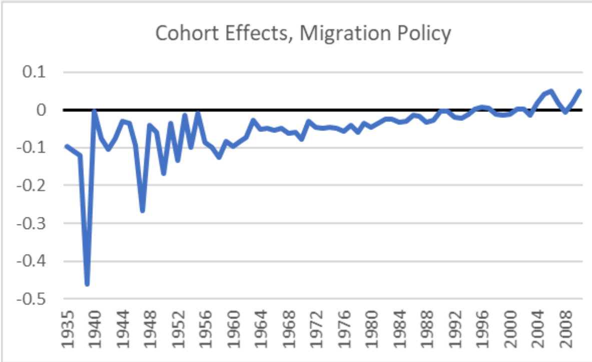
Employment Regressions Cohort Effects




Cohort Effects, Migration Network
60
40
20
0
-20
-40
-60
-80
-100
1935 1940 1944 1948 1952 1956 1960 1964 1968 1972 1976 1980 1984 1988 1992 1996 2000 2004 2008


Cohort Effects, Migration Network
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
1935 1940 1944 1948 1952 1956 1960 1964 1968 1972 1976 1980 1984 1988 1992 1996 2000 2004 2008


Cohort Effects, Migration Policy
60
40
20
0
-20
-40
-60
-80
-100
1935 1940 1944 1948 1952 1956 1960 1964 1968 1972 1976 1980 1984 1988 1992 1996 2000 2004 2008


Cohort Effects, Migration Policy
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
1935 1940 1944 1948 1952 1956 1960 1964 1968 1972 1976 1980 1984 1988 1992 1996 2000 2004 2008

3.A.9. Figures and regression tables for sectoral intensity

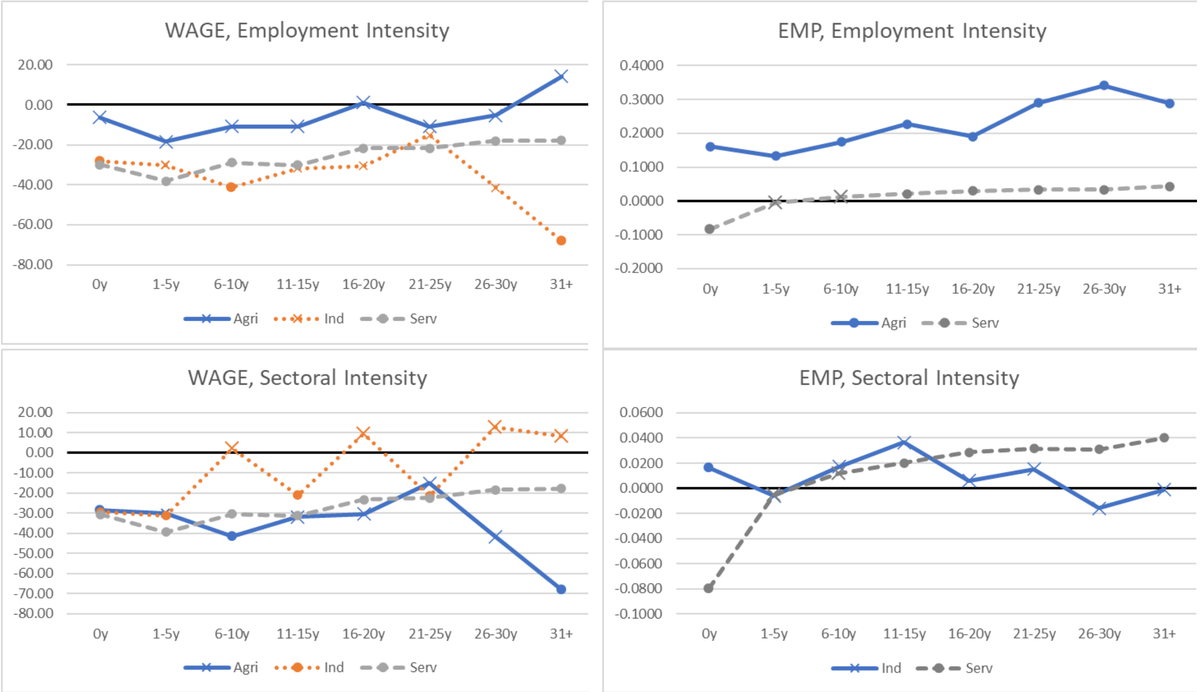


Figure 3.A.9.1. Assimilation profile of wage and employment by employment intensity and sectoral intensity (% of GDP)

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients.

Table 3.A.9.1. Assimilation profiles by sectoral intensity

Panel A. Dependent Variable: Wage

	% of Total Employment			% of GDP		
YSM	Agri.	Ind.	Serv.	Agri.	Ind.	Serv.
0y (within year)	-6.30	-28.37***	-29.85***	-28.37***	-29.35***	-30.45***
1-5	-18.43	-30.16	-38.12***	-30.16	-31.08***	-39.23***
6-10	-10.73	-41.39*	-28.91***	-41.39*	2.30	-30.44***
11-15	-10.72	-31.81	-30.03***	-31.81	-20.98***	-31.09***
16-20	1.03	-30.44	-21.72***	-30.44	9.45	-23.20***
21-25	-10.80	-15.06	-21.77***	-15.06	-21.41***	-22.43***
26-30	-5.25	-41.50	-18.04***	-41.50	12.97	-18.38***
31+	14.37	-68.13*	-17.89***	-68.13*	8.12	-17.76***
Observations	728,978	790,744	8,159,099	790,744	1,360,178	8,274,710
R^2	0.3430	0.3487	0.2467	0.3487	0.2307	0.2516

Panel B. Dependent Variable: Employment

	% of Total Employment			% of GDP		
YSM	Agri.	Ind.	Serv.	Agri.	Ind.	Serv.
0y (within year)	0.1605		-0.0840		0.0167***	-0.0800**
1-5	0.1326		-0.0051		-0.0059	-0.0053
6-10	0.1745		0.0124		0.0172	0.0118
11-15	0.2272		0.0214		0.0366	0.0202*
16-20	0.1902		0.0296		0.0060	0.0288*
21-25	0.2895		0.0332		0.0152	0.0315**
26-30	0.3415		0.0328		-0.0159	0.0310**
31+	0.2883		0.0426		-0.0010	0.0400***
Observations	728,978		7,005,293		1,261,359	7,120,904
R^2	0.0806		0.0409		0.0434	0.0419

Source: IPUMS-I, authors' calculations.

Note: Results unavailable for employment assimilation profiles for high industry employment and high agriculture % of GDP due to full employment participation. *, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

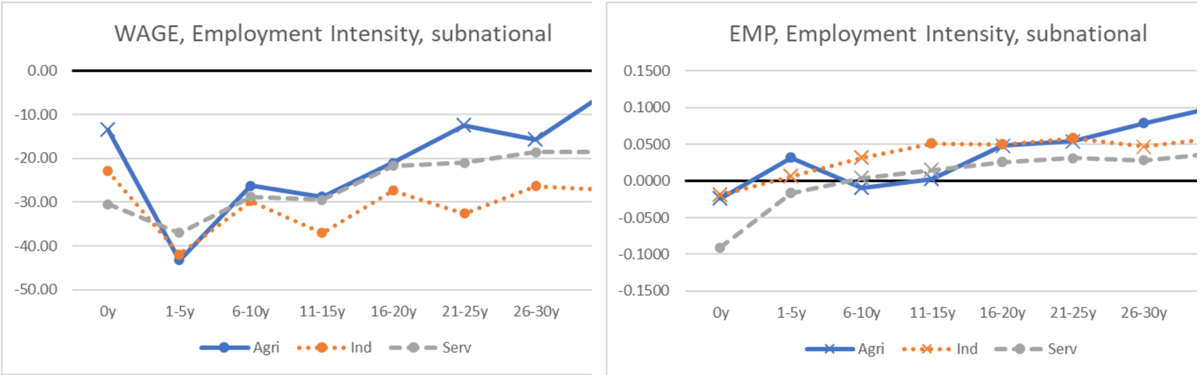


Figure 3.A.9.2. Assimilation profile of wage and employment by employment intensity and sectoral intensity (% of GDP), subnational variation.

Note: Y-axis denotes differential slopes relative to natives. Points with an "x" mark symbolize statistically insignificant coefficients.

Table 3.A.9.2. Assimilation profiles by employment intensity, subnational variation.

	Wage			Employment		
YSM	Agri.	Ind.	Serv.	Agri.	Ind.	Serv.
0y (within year)	-13.46	-22.90**	-30.46***	-0.0240	-0.0189	-0.0910**
1-5	-43.26***	-41.88***	-37.01***	0.0311**	0.0062	-0.0171**
6-10	-26.21***	-29.78***	-28.80***	-0.0091	0.0313	0.0033
11-15	-28.72***	-36.97***	-29.48***	0.0027	0.0506**	0.0144
16-20	-21.02**	-27.38***	-21.71***	0.0481	0.0497*	0.0255*
21-25	-12.50	-32.54***	-21.03***	0.0539	0.0578*	0.0309**
26-30	-15.65	-26.39***	-18.60***	0.0783*	0.0468	0.0282**
31+	-4.80	-27.22***	-18.50***	0.1001**	0.0577*	0.0379***
Observations	1,840,533	4,447,219	5,383,177	1,695,991	3,862,818	4,674,194
R^2	0.2660	0.2604	0.2432	0.0411	0.0408	0.0306

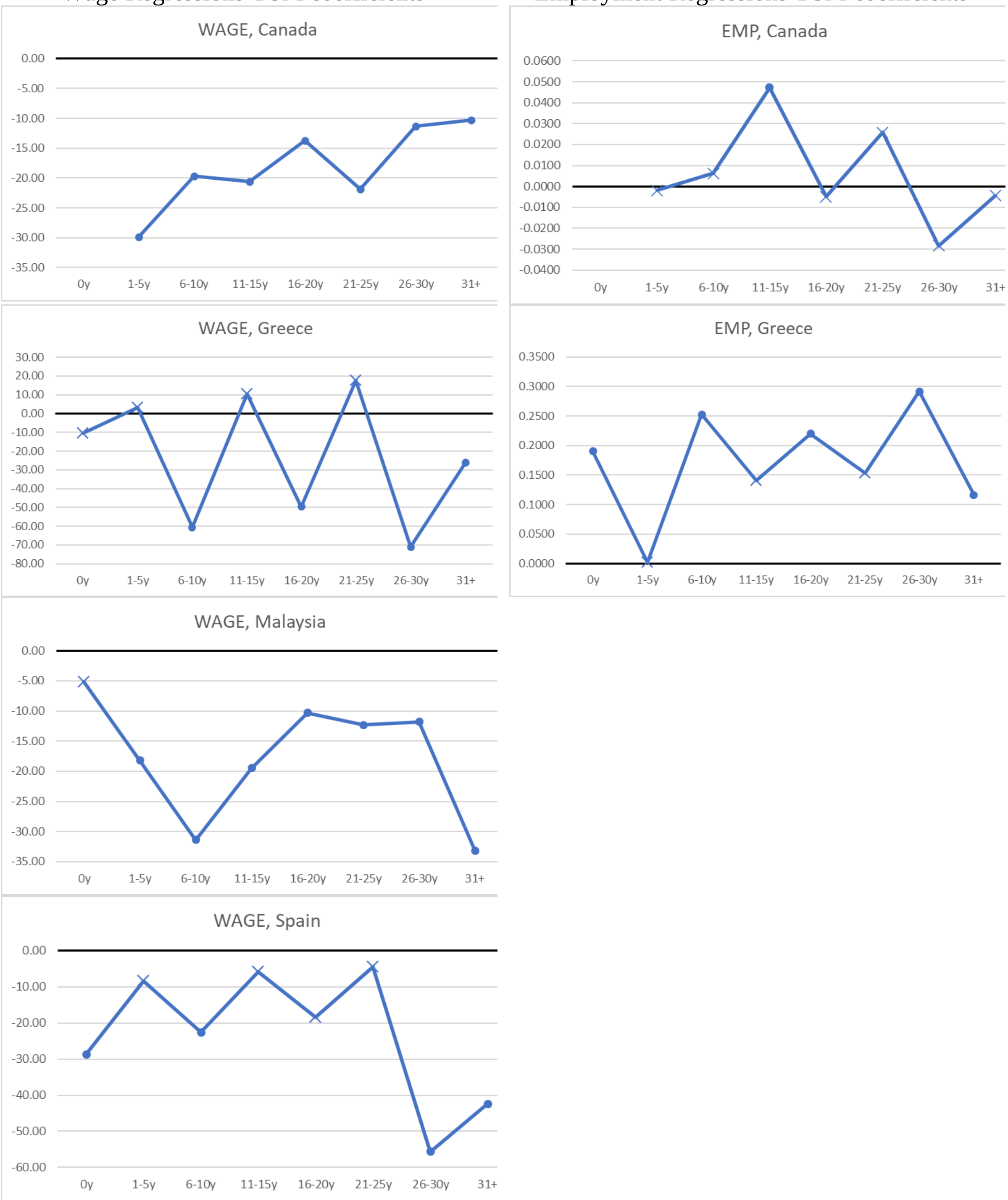
Source: IPUMS-I, authors' calculations.

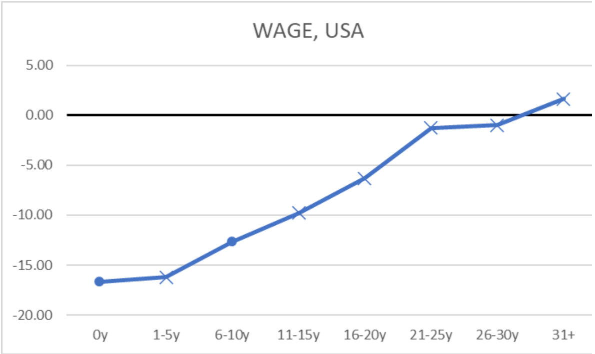
Note: *, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

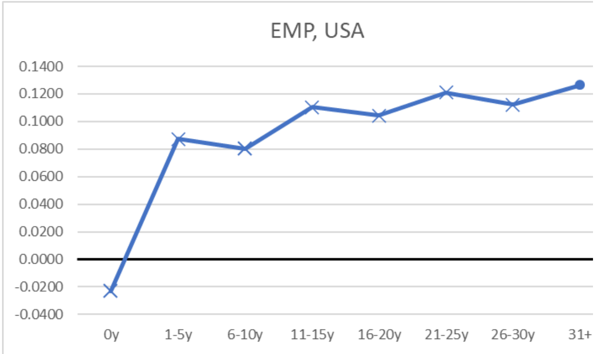
3.A.10. Figures and regression tables for each country

Figure 3.A.10.1. Individual country regressions.

Wage Regressions YSM coefficients　　Employment Regressions YSM coefficients







Note: Employment assimilation profiles not available for Malaysia and Spain due to the cross-sectional nature of the data and full employment of all Filipinos.

Table 3.A.10.1. Country case studies: individual country regressions

Panel A. Dependent Variable: Wage

YSM	Canada	Greece	Malaysia	Spain	US
0y (within year)		-10.36	-5.14	-28.62***	-16.65**
1-5	-29.91***	3.11	-18.22***	-8.32	-16.22
6-10	-19.70***	-60.58***	-31.37***	-22.53**	-12.69*
11-15	-20.59***	10.24	-19.46***	-5.78	-9.76
16-20	-13.76***	-49.68**	-10.31***	-18.40	-6.29
21-25	-21.88***	17.47	-12.30**	-4.44	-1.26
26-30	-11.32**	-71.00***	-11.79**	-55.67***	-1.00
31+	-10.29***	-26.16***	-33.16**	-42.38***	1.62
Observations	685,045	613,367	115,611	675,133	7,474,054
R^2	0.1984	0.2916	0.4047	0.3058	0.2514

Panel B. Dependent Variable: Employment

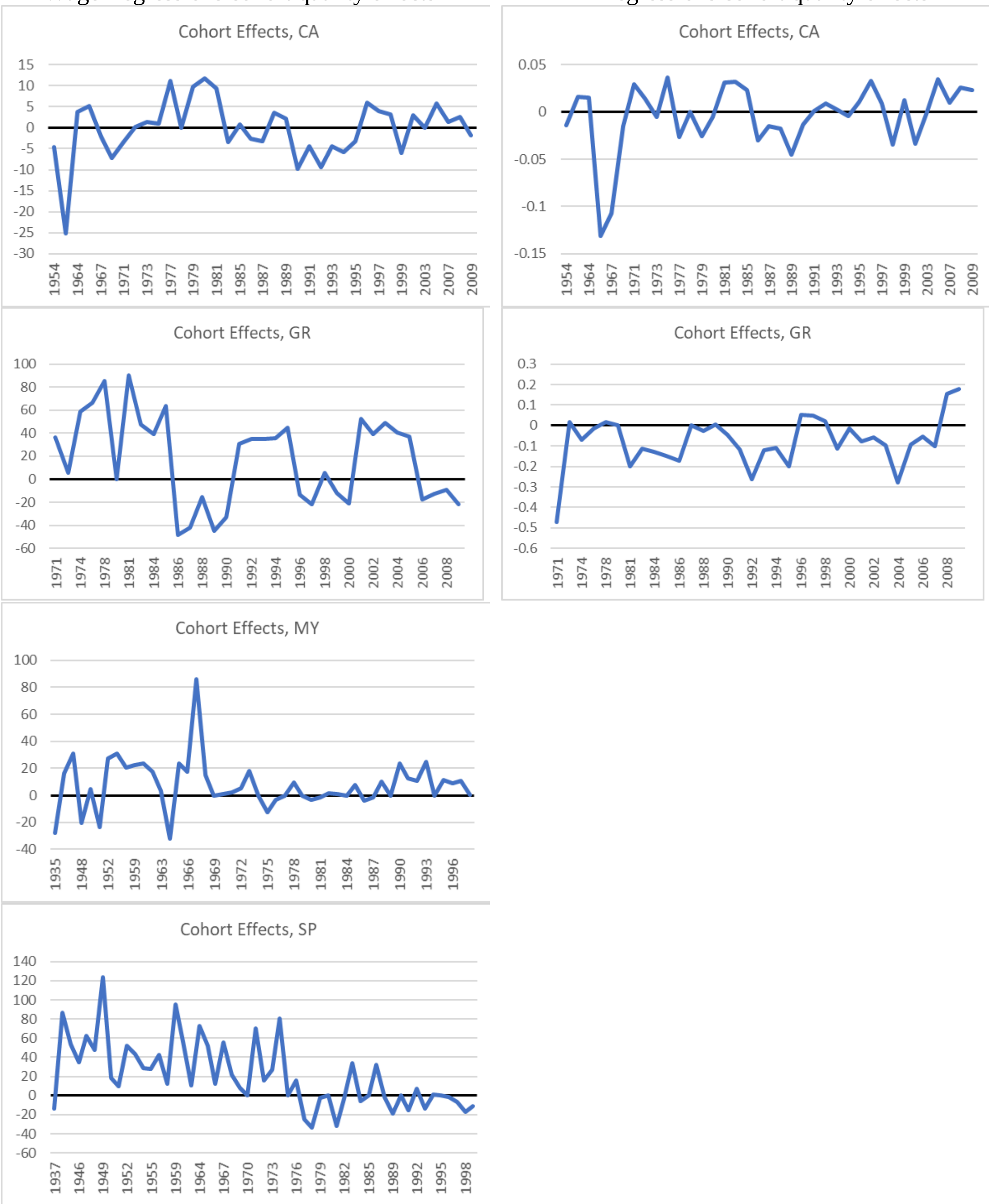
YSM	Canada	Greece	Malaysia*	Spain*	US
0y (within year)		0.1905***			-0.0234
1-5	-0.0019	0.0021			0.0874
6-10	0.0062	0.2527***			0.0803
11-15	0.0471*	0.1405			0.1104
16-20	-0.0048	0.2201***			0.1044
21-25	0.0259	0.1535			0.1211
26-30	-0.0284	0.2914***			0.1121
31+	-0.0044	0.1165***			0.1266*
Observations	639,872	613,367			6,365,421
R^2	0.0293	0.0459			0.0423

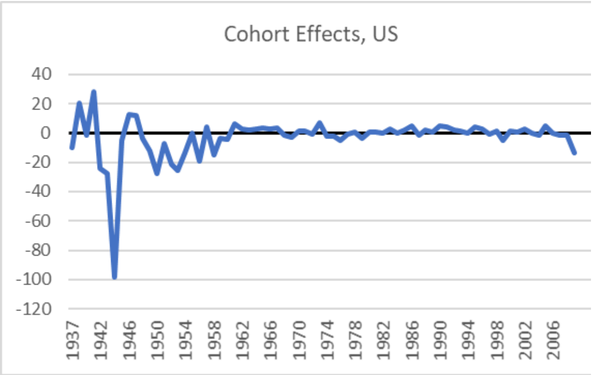
Source: IPUMS-I, authors’ calculations.

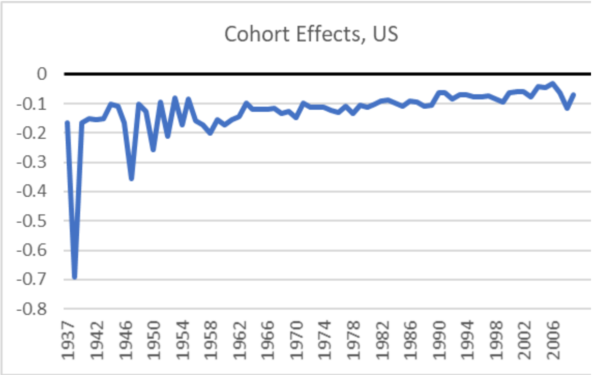
Notes: *, **, *** indicates 10%, 5%, 1% significance. Includes the following control variables: arrival cohort fixed effects, a vector of educational attainment dummies, age, year fixed effects, country fixed effects, subnational fixed effects. The employment equation includes additional occupation and industry controls. Regression weighted with person weights. Robust standard errors used.

Figure 3.A.10.2. Individual country regressions, cohort effects.

Wage Regressions cohort quality effects — EMP regressions cohort quality effects







Note: Employment cohort effects not available for Malaysia and Spain due to the cross-sectional nature of the data and full employment of all Filipinos.

3.A.11. Additional tables for occupational and industrial transition

Table 3.A.11.1. Occupational transition of Filipnos among occupations across YSM.

Occ.Score	*ISCO*	*YSM*	*0*	*1-5*	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31+*
191.22	1	Managers	4.21	3.69	4.19	5.19	6.3	6.99	7.99	9.01
158.72	2	Professionals	9.37	12.22	15.36	15.34	16.51	18.66	22.69	21.45
119.33	3	Technicians	7.27	12.72	11.24	12.22	12.54	13.4	12.8	12.09
87.50	4	Clerks	11.28	13.62	16.71	19.12	19.28	18.62	18.28	15.44
Primary Occupations			32.12	42.25	47.5	51.87	54.63	57.67	61.76	57.99
81.61	5	Service Workers	17.59	21.47	20.14	18.11	15.8	14.09	12.1	12.41
80.89	6	Agricultural	0.38	0.81	0.84	0.74	0.99	0.78	0.98	0.64
69.98	7	Crafts	2.49	4.29	4.75	5.35	5.49	6.01	5.87	6.1
60.53	8	Plant and Machine Workers	4.4	8.76	8.83	8.63	7.98	7.72	6.71	5.83
56.67	9	Elementary	9.37	8.32	6.91	5.93	5.64	5.51	3.76	3.66
Secondary Occupations			34.23	43.65	41.48	38.75	35.89	34.1	29.41	28.63
# of Filipinos			523	14,182	16,216	14,424	13,928	10,653	9,000	9,986

Note: Does not add up to 100% because of missing proportion unemployed or not in labor force. As in Simon et al (2014), primary occupations are comprised of ISCO88 codes 1-4, and secondary occupations are comprised of ISCO88 codes 5-9.

Table 3.A.11.2. Tracking within-cohort occupational transition of Filipinos between primary and secondary occupations

Occ.Score	*ISCO*	*YSM*	*0*	*1-5*	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31-35*	*36-40*	*41-45*	*46-50*
191.22	1	Managers	5.97	3.7	3.96	5.17	6.74	7.05	7.62	8.33	7.44	8.12	9.33
158.72	2	Professionals	9.85	12.43	15.09	15.8	17.05	19.13	23.95	24.39	20.57	13.9	20.89
119.33	3	Technicians	8.36	9.51	9.92	10.9	11.37	12.03	12.72	11.79	9.36	12.09	9.78
87.50	4	Clerks	14.33	18.04	19.07	21.59	22.94	21.48	19.67	16.89	15.64	19.13	21.33
Primary Occupations			38.51	43.68	48.06	53.46	58.11	59.7	63.97	61.4	53.01	53.25	61.33
81.61	5	Service Workers	15.82	21.71	20.88	18.15	15.68	14.12	11.52	11.85	14.72	12.64	12.44
80.89	6	Agricultural	0.6	0.43	0.37	0.4	0.49	0.57	0.59	0.56	0.59	0.72	1.33
69.98	7	Crafts	2.69	4.03	4.84	5.46	5.46	6.41	6.05	6.15	7.02	8.66	6.22
60.53	8	Plant and Machine Workers	6.27	10.77	9.98	9.2	8.7	8.77	6.8	5.8	6.94	7.04	4.89
56.67	9	Elementary	8.66	5.76	6.01	5.15	4.07	3.44	3.35	3.95	3.34	2.89	1.78
Secondary Occupations			34.03	42.7	42.08	38.36	34.4	33.32	28.3	28.31	32.61	31.95	26.67
# of Filipinos			335	8,159	11,759	10,996	9,358	7,173	6,650	3,723	1,196	554	225
		YSM, t+10	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31-35*	*36-40*	*41-45*	*46-50*	*51-55*	*56-60*
191.22	1	Managers	5.33	5.65	6.01	7.26	9.72	9.99	10.21	11.58	14.42	6.06	17.5
158.72	2	Professionals	17.95	15.25	17.27	18.9	20.84	19.57	22.27	20.08	21.15	16.67	20
119.33	3	Technicians	16.23	18	16.73	17.2	14.21	13.76	14.65	12.36	15.38	7.58	7.5
87.50	4	Clerks	11.66	12.34	13.24	13.62	15.75	14.78	12.26	13.51	7.69	15.15	10
Primary Occupations			51.16	51.24	53.25	56.98	60.51	58.11	59.38	57.53	58.65	45.45	55
81.61	5	Service Workers	19.16	18.93	16.88	14.52	14.35	14.24	11.46	10.62	12.5	16.67	12.5
80.89	6	Agricultural	0.73	0.58	0.42	0.43	0.42	0.48	0.33	0.77	0.96	1.52	2.5
69.98	7	Crafts	4.19	5.01	5.17	4.94	5.23	5.39	5.24	4.25	5.77	9.09	7.5
60.53	8	Plant and Machine Workers	5.6	6.95	6.48	5.65	6.92	6.04	4.51	6.37	6.73	7.58	2.5
56.67	9	Elementary	8.2	7.4	7.72	9.02	4.3	3.59	2.78	2.32	2.88	3.03	7.5
Secondary Occupations			37.88	38.87	36.67	34.56	31.21	29.74	24.32	24.32	28.85	37.88	32.5
# of Filipinos			139	5,572	3,962	3,095	4,041	3,238	2,140	1,671	1,509	518	104

Note: Does not add up to 100% because of missing proportion unemployed or not in labor force. As in Simon et al (2014), primary occupations are comprised of ISCO88 codes 1-4, and secondary occupations are comprised of ISCO88 codes 5-9.

Table 3.A.11.3. Tracking within-cohort industrial transition of Filipinos across YSM, disaggregated by Industry arranged by wage score.

Score	*ISIC*	*YSM,t*	*0*	*1-5*	*6-10*	*11-15*	*16-20*	*21-25*	*26-30*	*31-35*	*36-40*	*41-45*	*46-50*
1.42	90	Financial Services	5.07	3.82	4.26	6.18	6.87	7.08	6.87	5.48	4.68	4.33	7.11
1.41	20	Mining	0	0.09	0.04	0.06	0.09	0.1	0.14	0.19	0	0	0
1.39	40	Utilities (EGW)	0.3	0.17	0.11	0.29	0.43	0.57	0.6	0.78	0.25	0.54	0.44
1.21	100	Public Administration	1.49	3.13	3.22	4.45	5.76	5.41	6.08	7.31	11.2	11.19	8.89
1.18	112	Education	5.37	3.76	3.49	4.12	4.24	3.95	4.57	5.26	5.6	7.04	9.78
1.14	113	Health	10.45	16.1	22.39	20.19	20.18	20.42	22.11	22.11	19.15	10.83	7.56
1.04	111	Real Estate	6.87	6.96	5.25	6.11	6.24	5.92	6.99	5.37	4.43	5.78	4
		Cumulative (>1)	29.55	34.03	38.76	41.4	43.81	43.45	47.36	46.5	45.31	39.71	37.78
0.99	80	Transport and Logistics	2.39	3.32	3.53	4.39	5.11	6.11	5.67	6.72	6.52	9.21	7.56
0.94	30	Manufacturing	10.45	13.97	13.46	13.32	12.97	14.68	12.66	11.58	11.29	11.91	9.33
0.89	50	Construction	0.6	1.1	1.48	1.79	1.52	2.04	2.26	2.58	2.51	2.89	1.78
0.73	60	Wholesale and Retail	10.45	13.02	12.74	12.7	12.82	10.76	10.36	8.51	7.69	9.03	11.56
0.71	114	Other Services	6.87	9.05	8.48	8.42	7.97	8.88	7.94	7.28	7.36	8.12	13.33
0.57	10	Agriculture	1.79	1.27	1.11	0.72	0.9	1.05	0.93	1.37	1.51	0.9	1.33
0.55	70	Accommodation	7.46	8.96	8.86	7.67	7.19	5.97	4.99	4.7	3.68	3.43	4.44
	120	Private Household Services	2.99	2.08	2.09	1.81	0.75	0.47	0.42	0.62	0.08	0.18	0.89
		Cumulative (<1)	43	52.77	51.75	50.82	49.23	49.96	45.23	43.36	40.64	45.67	50.22
		# of Filipinos	335	8,159	11,759	10,996	9,358	7,173	6,650	3,723	1,196	554	225

		YSM,t+10	6-10	11-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60
1.42	90	Financial Services	4.01	4.14	4.4	6.02	6.07	5.69	4.77	6.37	2.88	0	2.5
1.41	20	Mining	0.3	0.29	0.4	0.19	0.09	0.36	0.2	0	0	0	0
1.39	40	Utilities (EGW)	0.35	0.29	0.3	0.46	0.75	0.72	0.86	0.39	0.96	7.58	2.5
1.21	100	Public Administration	2.68	3.72	4.21	5.44	5.42	5.92	5.96	4.44	6.73	12.12	5
1.18	112	Education	3.69	3.62	4.43	3.98	3.79	4.31	4.24	5.41	6.73	6.06	5
1.14	113	Health	25.67	23.91	24	24.21	25.89	20.65	21.4	21.24	14.42	13.64	12.5
1.04	111	Real Estate	9.21	9.6	9.26	9.51	10	9.99	10.47	10.42	11.54	7.58	5
		Cumulative (>1)	45.91	45.57	47	49.81	52.01	47.64	47.9	48.27	43.26	46.98	32.5
0.99	80	Transport and Logistics	4.04	4.68	4.53	5.74	5.19	6.46	6.56	6.56	15.38	1.52	5
0.94	30	Manufacturing	8.53	11.24	10.22	9.02	11.73	11.19	8.81	10.04	9.62	15.15	12.5
0.89	50	Construction	2.27	1.74	1.98	2.04	2.57	2.09	1.86	1.93	2.88	9.09	5
0.73	60	Wholesale and Retail	11.81	11.92	11.66	10.56	8.69	8.92	8.75	8.3	11.54	3.03	17.5
0.71	114	Other Services	5.1	5.07	5.39	4.73	4.77	5.8	5.24	4.63	2.88	4.55	10
0.57	10	Agriculture	0.71	0.48	0.54	0.53	0.61	0.54	0.27	0	0.96	3.03	0
0.55	70	Accommodation	7.75	7.4	6.58	5.84	5.33	4.91	4.51	2.9	0.96	0	5
	120	Private Household Services	3.33	2.42	2.87	3.89	1.36	0.72	0.2	0.19	0	0	0
		Cumulative (<1)	43.54	44.95	43.77	42.35	40.25	40.63	36.2	34.55	44.22	36.37	55
		# of Filipinos	3,962	3,095	4,041	3,238	2,140	1,671	1,509	518	104	66	40

Note: Does not add up to 100% because of missing proportion unemployed or not in labor force. As in Simon et al (2014), primary occupations are comprised of ISCO88 codes 1-4, and secondary occupations are comprised of ISCO88 codes 5-9.

Appendix to Chapter 4

4.A.1 Additional Tables and Figures

Table 4.A.1.1. Participating barangays in the 2015 Community-Based Monitoring System survey.

Island Group	Region	Province	City	Barangay	Number of HHs	Number of individuals
LUZON	4A CALABARZON	Batangas (10)	Lipa	Brgy. Bulaklakin	319	1529
		Cavite (21)	Dasmarinas	Brgy. Zone I (Pob.)	330	1567
			Maragondon	Brgy. Pinagsanhan I B	261	988
	13 National Capital Region (NCR)	NCR 1st District (39)	Manila	Brgy. 746	206	416
				Brgy. 731	221	860
				Brgy. 707	226	949
				Brgy. 714	164	716
				Brgy. 717	110	543
		NCR 2nd District (74)	Marikina	Brgy. Calumpang	4831	23,224
				Brgy. San Roque	1986	9,343
				Brgy. Sto. Niño	3484	16,835
VISAYAS	6 Western Visayas	Negros Occidental (45)	Bago	Brgy. Calumangan	1,724	7,085
				Brgy. Dulao	2,047	8,806
				Brgy. Ilijan	620	2,495
				Brgy. Mailum	122	469
				Brgy. Poblacion	2,124	9,253
				Brgy. Taloc	2,792	11,189
				Brgy. Sampinit	1,394	5,720
MINDANAO	10 Northern Mindanao	Misamis Occidental (42)	Ozamiz	Brgy. Gala	173	715
				Brgy. Doña Consuelo	721	2,634
TOTAL					22826	103316

Source: CBMS 2015 Data

Table 4.A.1.2. The effect of migrant hotspot to nearest migrant on imputed rent and total expenditures and select nearest migrant characteristics before and after controlling for sorting into *purok*.

Dependent Variable	Imputed Rent			Total Expenditures			Nearest Migrant Years of Schooling			Nearest Migrant Remittances		
	No control	*Sorting controlled*		*No control*	*Sorting controlled*		*No control*	*Sorting controlled*		*No control*	*Sorting controlled*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$M_{hot,i}$	774.1	639.9	560.6	-274.3	-445.8**	-463.4**	0.443*	0.156	0.142	0.0300	0.0201	0.0122
	(597.7)	(386.7)	(331.4)	(185.5)	(199.1)	(216.3)	(0.237)	(0.151)	(0.152)	(0.0348)	(0.0175)	(0.0105)
Purok dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Controls^	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	91,000	91,000	91,000	51,898	51,898	51,898	68,160	68,160	68,160	91,000	91,000	91,000
R-squared	0.004	0.101	0.107	0.000	0.012	0.012	0.003	0.334	0.336	0.001	0.241	0.246

Source: Author's computation, CBMS 2015 Dataset

Note: $M_{hot,i}$ is a migrant hotspot variable, = 1 if the non-migrant household belongs to a cluster of households considered a statistically significant hotspot for migrant households with a fixed distance band of 50m or 100m and 0 otherwise Standard errors (in parentheses) are clustered on a *barangay* level. ***, **, * denote significance levels at 1%, 5%, and 10%. *ln (idist_nmig)* stands for the natural log of the inverse distance to the nearest migrant used to denote the incremental change in the proximity to the nearest migrant.

^ include individual characteristics (sex, age), household geographical characteristics (log of inverse distance to nearest primary road, airport, seaport, school, province capital and national capital), nearest migrant characteristics (indicators for owning their house & lot and remittances, level of remittances and wealth).

Table 4.A.1.3. Summary of Getis-Ord General G Z-scores and their levels of significance across the automatic and fixed distance bands.

Province	***Barangay* (coded)**	**Automatic distance band (m)**	**Automatic distance Z-score**	**Fixed distance band 100m**	**Fixed distance band 50m**	**Fixed distance band 25m**	**Fixed distance band 10m**
Batangas	14	163.88	**1.924***	**2.480****	**1.765***	0.798	1.456
Cavite	16	47.27	**3.436*****	**2.094****	**3.295*****	**2.409****	0.423
	25	43.87	-0.673	-1.003	-0.919	-0.731	0.219
Manila	3	47.27	1.333	1.443	1.325	1.028	X
	22	952.33	0.276	0.232	-0.643	-1.361	-0.606
	29	678.55	-1.265	-0.305	-0.727	-0.957	-0.187
	32	128.84	0.734	0.958	1.291	**1.749***	0.459
	46	51.24	-1.008	-1.124	-0.826	-0.971	0.577
Marikina	3	563.38	**3.917*****	1.352	0.100	-0.158	**2.077****
	8	2133.41	-0.771	**2.44****	0.904	0.923	1.410
	10	610.26	0.268	**3.039*****	**3.609*****	**2.526****	X
Negros Occidental	9	422.76	**2.117****	**2.681*****	**2.078****	**2.078****	**1.870***
	11	365.97	**1.908***	**2.215****	**1.795***	**2.297****	1.612
	12	515.06	1.335	0.716	0.948	**2.032****	-0.016
	16	455.91	-0.884	-0.625	-0.333	-0.201	X
	20	2329.81	0.521	0.493	0.285	-0.221	**2.055****
	23	733.31	**2.405****	**1.709***	0.504	0.262	-0.322
	24	1640.46	**2.801*****	**2.313****	**2.526****	-0.076	**1.933***
Misamis Occidental	20	459.21	**2.692*****	0.859	-0.155	-0.075	X
	52	741.76	-0.946	**2.628*****	**1.788***	1.142	1.130

Source: CBMS 2015 Data.

Note: ***, **, * denote level of significance at 1%, 5%, and 10%, respectively. 'X' denotes that the tested fixed distance band is too small for any meaningful interspatial relationships to be established.

Table 4.A.1.4. Robustness checks: Excluding remittance-receiving non-migrant households.

Specification:	Non-remittance receiving non-migrants only			Tertiary-age sub-groupings		
	Primary	Secondary	Tertiary	Full 16-24	Age 16-20 only	Age 21-24 only
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Distance Effects						
D_{ij}	0.000216	-0.00114	0.00601**	0.00675**	0.0143***	-0.00281
	(0.00197)	(0.00262)	(0.00249)	(0.00257)	(0.00467)	(0.00429)
$M^{100}_{presence,i}$	-0.00833	-0.00395	0.00373	0.000960	-0.000321	0.00846
	(0.00772)	(0.00804)	(0.0117)	(0.0124)	(0.0240)	(0.0162)
$M^{50}_{presence,i}$	0.00493	-0.000389	-0.0180	-0.0182	-0.0236	-0.0105
	(0.00530)	(0.00909)	(0.0131)	(0.0130)	(0.0145)	(0.0112)
Panel B. Neighborhood effects						
$M^{100}_{count,i}$	-0.000253	0.000268	0.00125**	0.00109**	0.00148*	0.000511
	(0.000485)	(0.000687)	(0.000493)	(0.000507)	(0.000751)	(0.000316)
$M^{50}_{count,i}$	0.000389	0.000138	0.00242**	0.00223*	0.00355	0.000645
	(0.000555)	(0.000895)	(0.00112)	(0.00127)	(0.00216)	(0.000546)
$M_{hot,i}$	-0.00843	0.00245	0.0273**	0.0264**	0.0240	0.0247***
	(0.00690)	(0.00462)	(0.0110)	(0.0115)	(0.0218)	(0.00669)
No. of obs.	11,789	6,896	15,167	15,520	8,752	6,768

Source: Author's computation, CBMS 2015 Data.

Note: Standard errors clustered at *barangay* level to account for sampling design. *, **, *** represent significance at 10%, 5%, and 1% levels, respectively. Each cell represents a separate regression equation. All regressions include *purok* dummies to account for identification strategy. All $\{M_i\}$ regressions include D_{ij} as a running variable. All regressions are full specification: proximity and neighborhood effects variables, non-migrant individual and household controls: sex, age, log of inverse distance to nearest primary road, airport, seaport, DepEd school, provincial capital, and national capital, and nearest migrant household controls: house and lot ownership, remittance indicator, remittance level, and wealth index. All equations estimated with OLS.

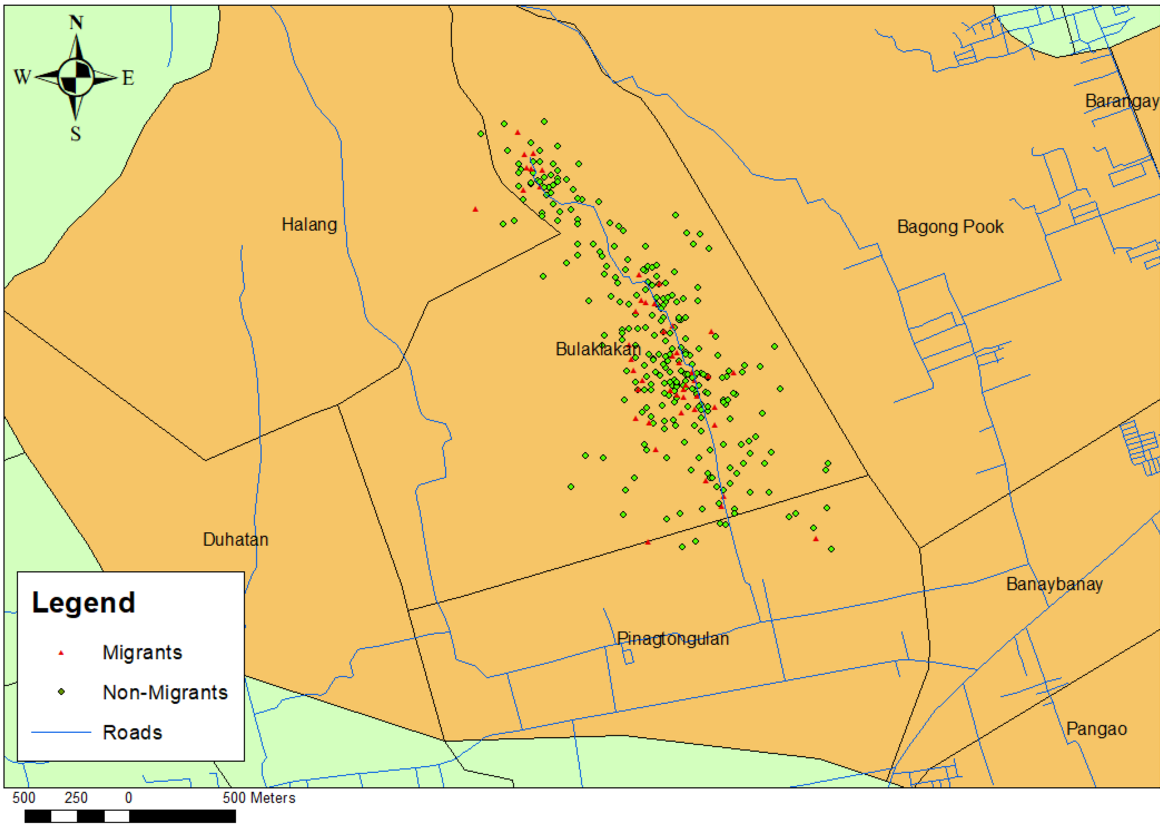
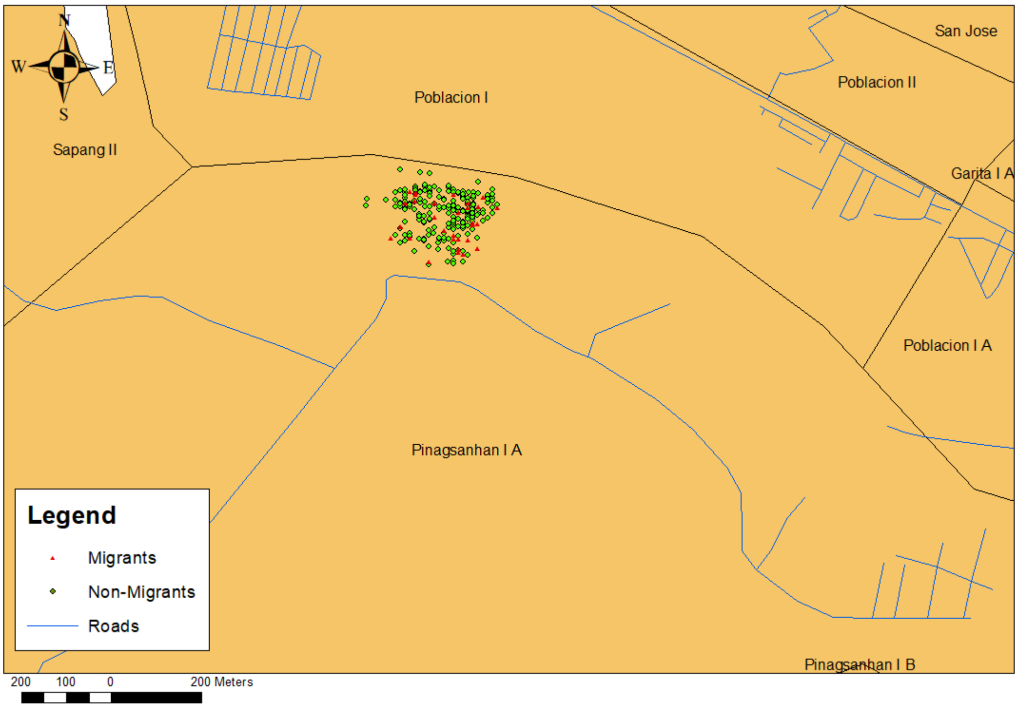


Figure 4.A.1.1. Distribution of non-migrant and migrant households in Lipa, Batangas.

Source: Household locations taken from CBMS (2015). Administrative boundaries and roads taken from PhilGIS.



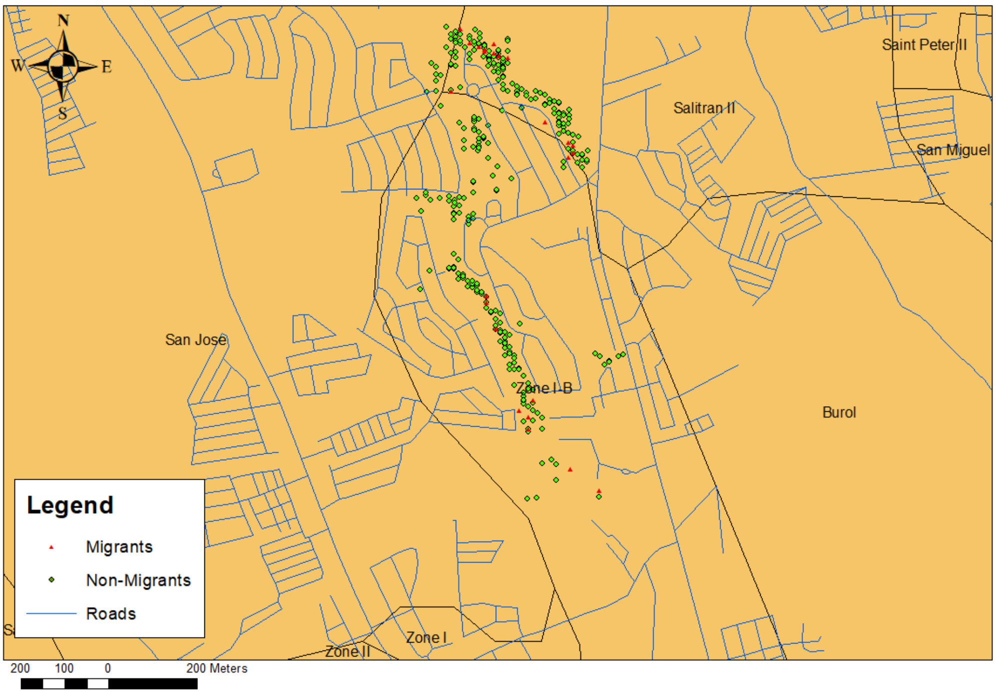


Figure 4.A.1.2. Distribution of non-migrant and migrant households in Maragondon and Dasmarinas, Cavite.

Source: Household locations taken from CBMS (2015). Administrative boundaries and roads taken from PhilGIS.

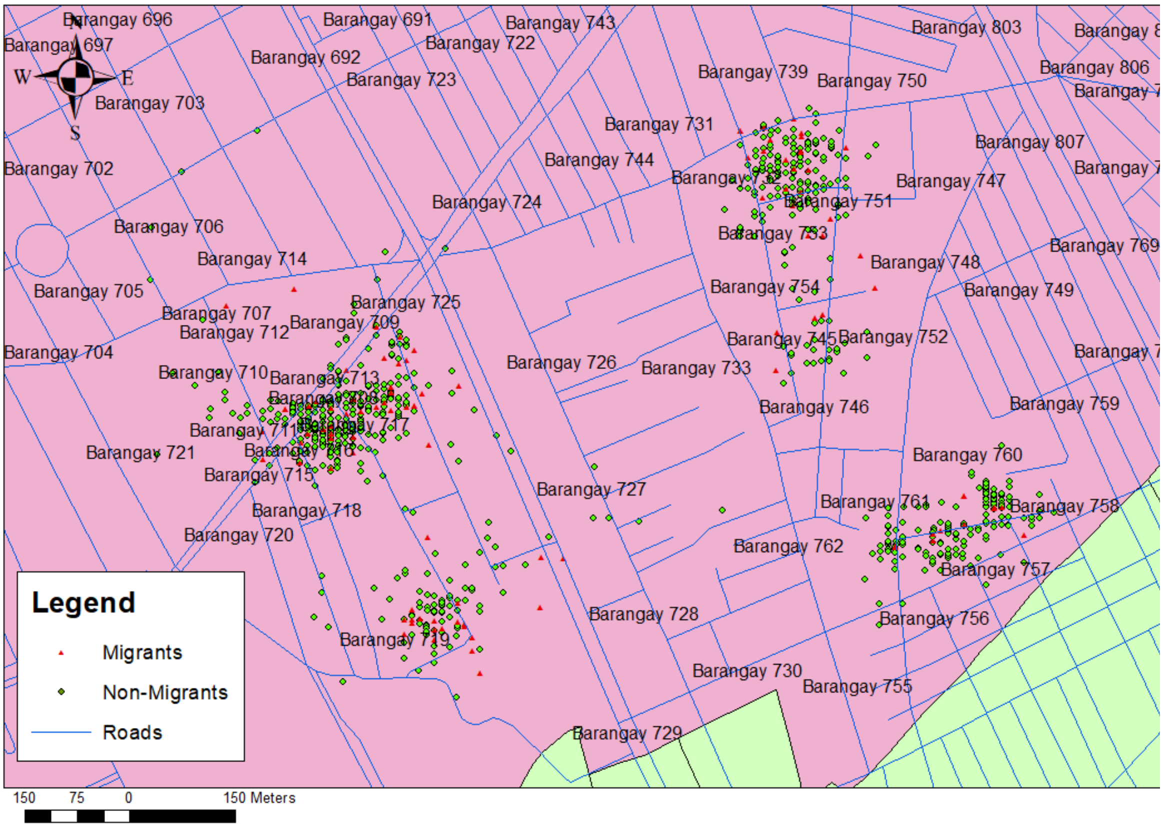


Figure 4.A.1.3. Distribution of non-migrant and migrant households in Manila.

Source: Household locations taken from CBMS (2015). Administrative boundaries and roads taken from PhilGIS.

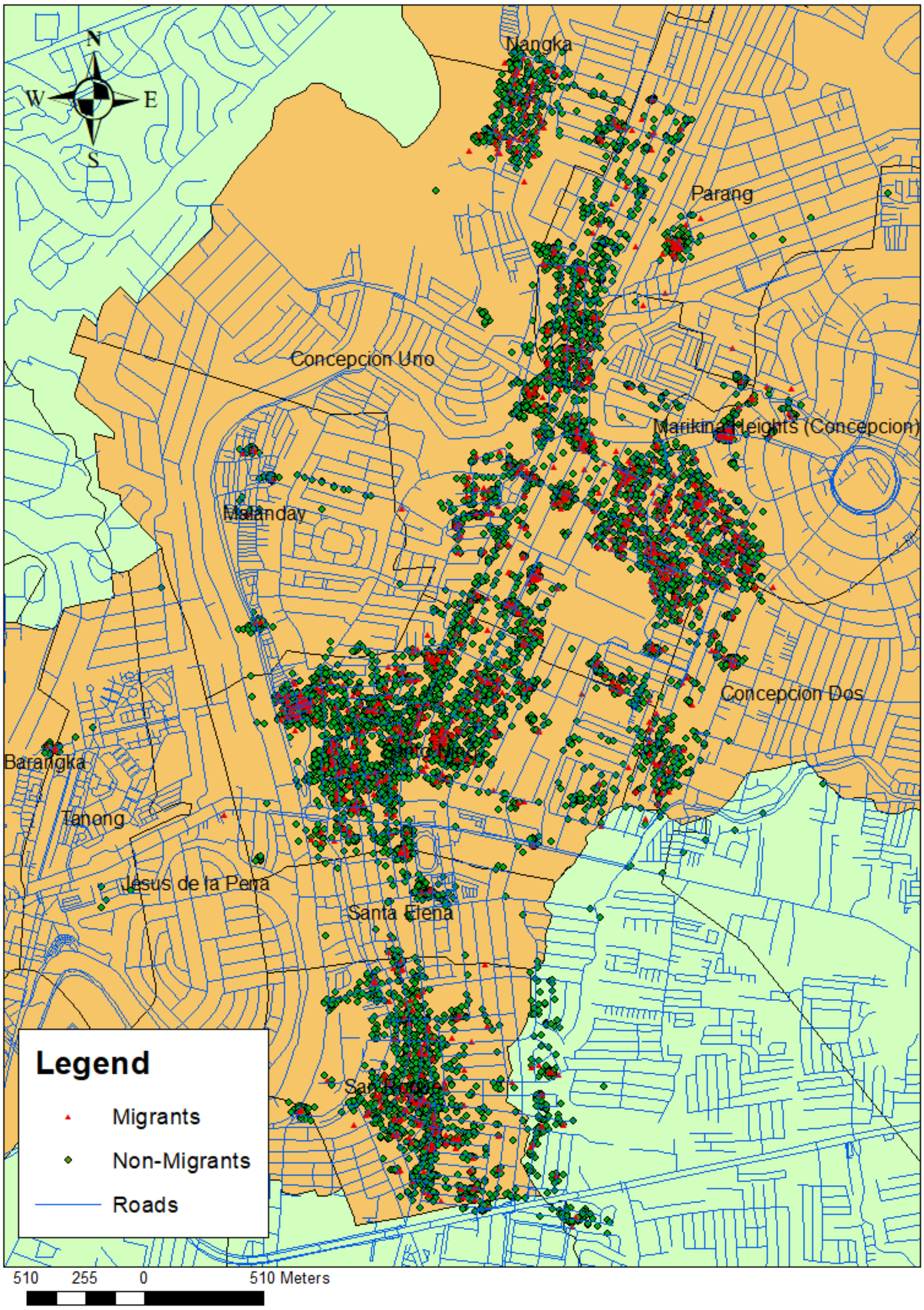


Figure 4.A.1.4. Distribution of non-migrant and migrant households in Marikina.

Source: Household locations taken from CBMS (2015). Administrative boundaries and roads taken from PhilGIS.

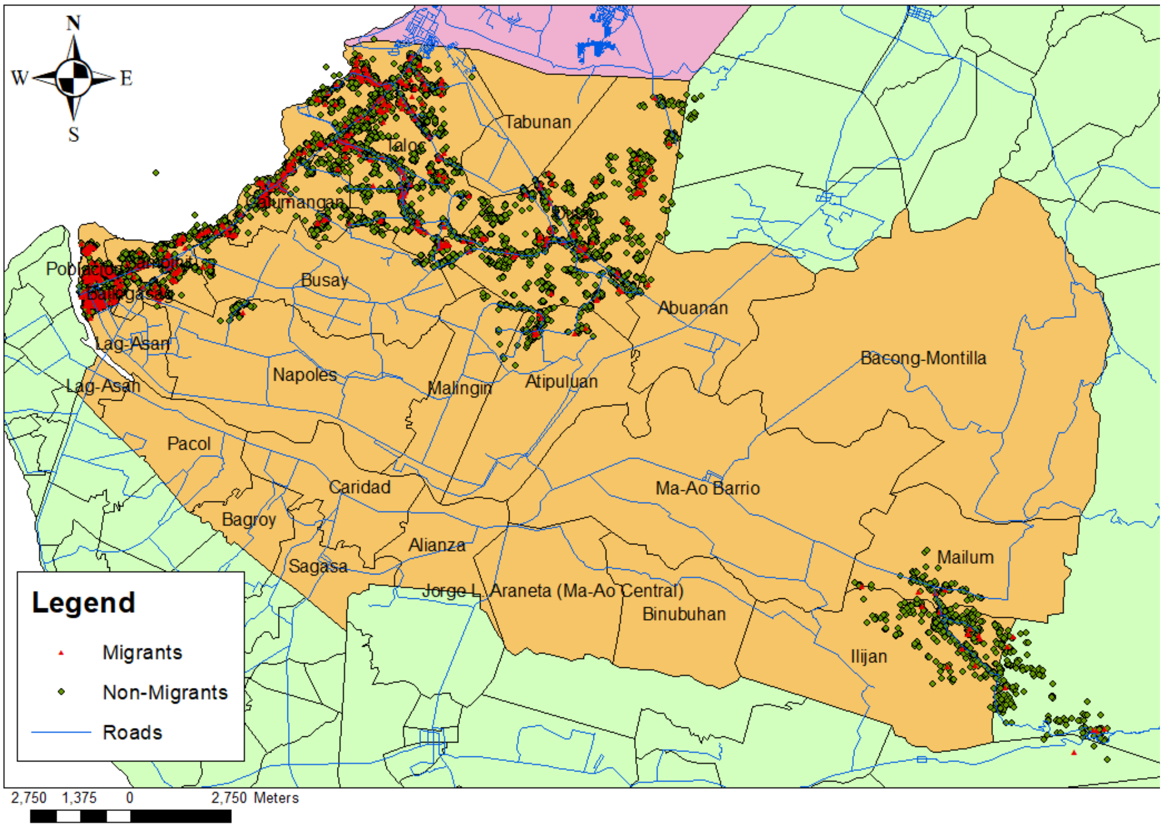


Figure 4.A.1.5. Distribution of non-migrant and migrant households in Bago, Negros Occidental.

Source: Household locations taken from CBMS (2015). Administrative boundaries and roads taken from PhilGIS.

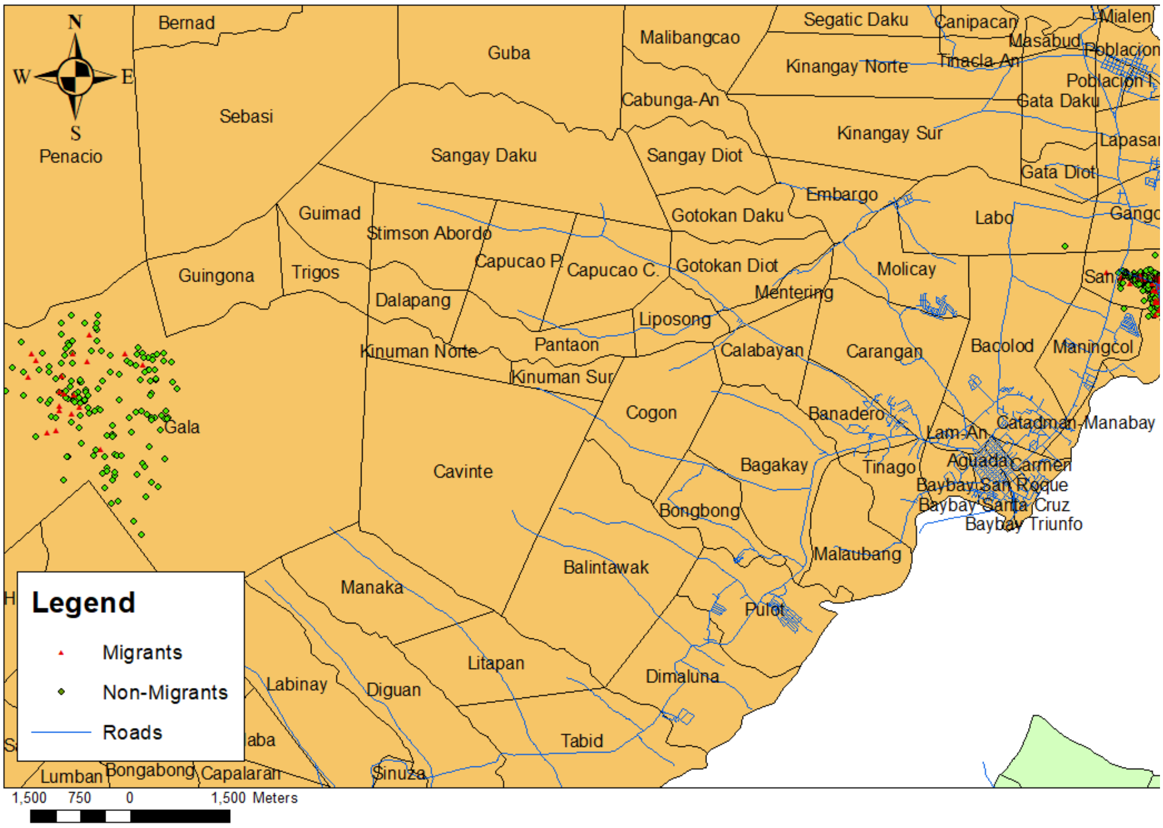


Figure 4.A.1.6. Distribution of non-migrant and migrant households in Ozamis City, Misamis Occidental.

Source: Household locations taken from CBMS (2015). Administrative boundaries and roads taken from PhilGIS.

4.A.2 Getis-Ord General G

As discussed in the ArcGIS tool help (Mitchell, 2005), the GOGG (Getis and Ord, 1992) measures the degree of clustering for high or low values. The GOGG statistic is given as follows:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} x_i x_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j}, \qquad \forall\ i\ \neq j$$

Where x_i and x_j are attribute values of features (households) *i* and *j* and $w_{i,j}$ is the spatial weight between the two. *n* is the number of features (households) in the dataset. The z-score associated with the GOGG is computed as:

$$Z_G = \frac{G - E[G]}{\sqrt{V[G]}}$$

Where $E[G] = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}}{n(n-1)},\ \forall\ i\ \neq j$ and $V[G] = E[G^2] - E[G]^2$.

The z-score is then used test the following hypothesis:

***H*₀:** values associated with features are randomly distributed (no patterns or clustering, complete spatial randomness)

***H*₁ (if the Z-score is positive)**: high and low values across features are spatially *clustered/concentrated.*

***H*₁ (if the Z-score is negative)**: high and low values across features are spatially dispersed. This implies there is a competitive process occurring where high repels high and low repels low.

4.A.3 Getis-Ord Gi*

As discussed in the ArcGIS tool help (Mitchell, 2005), given a set of weighted features, the Hot Spot Analysis tool identifies statistically significant hot and cold spots (spatial clusters) using the Getis-Ord Gi* [GOGi*] (Getis and Ord, 1992). The process produces z-scores, p-values and confidence level bins. Given a significant p-value, a high, positive z-score indicates a clustering of high values, whereas a negative z-score indicates a clustering of low values. Bins take the values {-3, -2, -1, 0, +1, +2, +3} where positive values indicate hot spots and negative values indicate cold spots. Being classified into a '0' bin implies complete spatial randomness. Values of 1, 2, 3 indicate significance at the 10%, 5%, and 1% levels, respectively.

The GOGi* is calculated as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{s \sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}{n-1}}}$$

Where x_j is the attribute value of the *j*th feature. $w_{i,j}$ is the spatial weight between feature *i* and *j*, and *n* is the total number of features. $\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$ and $s = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - [\bar{X}]^2}$. The Gi* is already a z-score and is readily used for inference.

The GOGi* looks at clustering for each feature in the context of its neighboring features. Having a high z-score may be interesting, but for it to be statistically significant, it must be surrounded by other features with the same values as well. The statistic is a local sum for a feature and its neighbors and is compared proportionally to the sum of all features. The larger the statistically significant positive z-score is, the more intense the clustering of high values. The same may be said about negative z-scores for low values.