Temporary International Migration as a Risk Coping Tool:
Evidence from Typhoons in the Philippines*

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June 13, 2023

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Abstract

Temporary international labor migration makes up the largest share of migrant outflows from many developing countries. Given documented distortions that potentially lead to excess supply of migrants, how responsive is this form of migration to origin-shocks? How do international migrant demand conditions mediate its response? Using administrative migration data on the universe of land-based labor migrants from the Philippines, I study the migration responses to a decade of typhoons. Typhoons increase migration from affected regions for up to three years, but also lead to a drop in average migrant cohort wages. This drop is due to an increase in the share of migrants going to lower paying countries and occupations, even though educational attainment of migrant cohorts also increase. These results are consistent with typhoons incentivizing potential migrants to downgrade occupations and countries (in terms of wages) in order to increase their likelihood of securing an overseas contract. Employing a shift-share strategy to create a time-varying proxy for a region's migrant demand conditions, I show better demand conditions significantly increases the migration response, without a corresponding drop in wages. Correspondingly, remittance flows are also higher to affected regions in times of better migrant demand. This suggests policies that increase the availability of overseas contracts in the wake of shocks can lead to significant risk-coping gains.

JEL codes:
Keywords:

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1 Introduction

Millions of primarily low-skilled migrants leave their home countries in South Asia and Southeast Asia annually with temporary overseas employment contracts (Bossavie and Özden, 2023; Bossavie et al., 2021). With such migration on the rise, policy questions regarding its facilitation and regulation are central to many developing country governments(United Nations, 2019). Among many effects access to such migration can have on origin economies,[1] a key potential benefit is an improved ability to cope with negative origin shocks. This can take place either through existing migrants sending higher remittances in the wake of shocks, or additional migration taking place in response to shocks (which I will refer to as "ex-post" migration response). The ability to increase migration in response is particularly important, as vast majority of households do not have an international labor migrant present at any given time. Yet few studies explicitly examine the effectiveness of temporary international labor migration as an ex-post risk coping tool. I aim to fill this gap by studying the migration responses to a decade of typhoon shocks in the Philippines.

The focus on typhoons is particularly relevant as the frequency and intensity of extreme weather events are projected to increase due to climate change (IPCC, 2021). Heavy storms, including typhoons, are among the most destructive of such extreme weather events globally, accounting for nearly half of economic damages and 17% of deaths due to natural disasters between 1998 and 2017 (CRED, 2017). Beyond immediate damages, typhoons also have a long-term impact on the economic growth of affected countries (Hsiang and Jina, 2014). With the intensity of typhoons expected to increase, adapting to and mitigating the impacts of typhoons on affected regions is a key policy concern. International labor migration could be one such adaptation mechanism.

In a frictionless world, theory yields clear predictions for the migration response to an origin area shock. Insofar as the shock decreases origin utility, migrant supply curve should shift out, increasing migration and possibly decreasing migrant wages depending on the migrant demand elasticity the origin area faces. Yet it is well established that international migration from developing countries are highly frictional. Liquidity constraints can impede willing migrants from migrating due to the inability to pay the fixed cost of migrating (Bazzi, 2017). Further, and specific to the context at hand, legal temporary international migration requires migrants to secure a job contract in their home country. Previous work suggests that the supply of migrants can far exceed the contracts available at origin area, primarily due to destination and home country regulations (McKenzie et al., 2014; Mobarak et al., Forthcoming). In that case, increase in the supply of potential migrants may not translate

[1] For a review of the literature on the evidence of temporary international labor migration on, see **?**.

into additional migration. Dependence on contract availability also imply migrant demand conditions at the time of a shock can mediate the migration responses. Such theoretical ambiguity about the effectiveness of legal temporary international migration as an ex-post risk coping mechanism requires an empirical investigation to understand which forces dominate.

I study the temporary international labor migration responses to a decade of typhoons in the Philippines using administrative data on the universe of migrant labor contracts to destination countries. Specifically, in light of the theoretical ambiguities, I ask three questions: (1) Does migration from affected regions increase in response to typhoons? (2) Do migrant cohort wages react to typhoon shocks, possibly reflecting the need to "downgrade" to lower paying countries and occupations in the presence of frictions? (3) Does the migrant demand conditions at the time of a typhoon mediate the migration response? An understanding of all three of these questions would allow for better accounting for the benefits of access to temporary international labor markets, and can aid setting appropriate policy to reap these potential gains.

The Philippines provides an ideal context to study as international labor migration is exceedingly common (with 1 million new contracts signed in 2016) and it is one of the most typhoon exposed countries in the world. The highly institutionalized migration system also provides high quality administrative data. The use of administrative data is critical to my study, as it allows me to construct precise migration measures with both geographical and temporal granularity. Destination country censuses usually do not record the origin of migrants beyond the country, and are generally at 5 or 10 year intervals, making it harder to document responses in the short run, presumably when the negative impacts of extreme weather events are strongest. Survey data tend to not allow for precise measurement at granular scales due to issues with measurement and sample size. The administrative data also provides information about the contract wages, occupations, and destinations. This allows me to study migrant cohort wages and substitution patterns across occupations and countries. Such information tends to be unavailable in other common data sources.

I begin by providing a simple model of migration with directed search across multiple foreign labor markets with heterogeneous wages.[2] The search frictions are meant to capture that, in the presence of more searchers than contracts available, potential migrants may be unable to secure migrant contracts conditional on searching. In equilibrium, more desirable markets attract more searchers relative to available vacancies, decreasing the probability of finding a contract in these markets. A negative shock to origin utility increases migration, but also incentivizes the migrants to direct their search to lower paying markets, lowering

[2] Migration from an individual Filipino region constitutes a small part of destination labor markets, therefore I treat foreign wages as exogenous. I further abstract away from migrant heterogeneity as the empirical evidence in the following sections suggest drops in wages are not driven by negative migrant selection.

migrant cohort wages even in the absence of equilibrium wage responses or selection. I test these predictions empirically.

Typhoons increase outflows of temporary labor migrants. Using a measure of typhoon exposure created using meteorological data, I find that a one SD typhoon exposure increases the out migration rate by 1.43 and 1.35 per 10,000 capita in the short- (1-2 years after exposure) and medium-run (2-3 years after exposure) respectively, corresponding to 4.1 % and 4% of the mean migration rate. This finding rules out the case that binding (or worsening) liquidity constraints or excess supply of migrants at baseline completely impeding average migration response.

Wages of migrant cohorts that leave following typhoon exposure are lower, with a 1.1 % drop in average migrant wages in the short run after a one SD exposure. The drop in wages are primarily caused by a higher share of migrants going to lower paying countries and occupations. Available measures of migrant demographics (sex and gender) do not explain these effects, and in fact cohorts following a typhoon are more educated. All else equal, we would expect more highly educated migrants to command higher wages. These patterns are consistent with the idea that potential migrants are incentivized to direct their search or accept contracts in lower paying countries and for lower paying occupations. While the distortions in the global migrant labor market do not totally impede migration responses, the frictions they cause require workers to "downgrade" occupations and countries, even in the case of positive selection in terms of education.

A back of the envelope calculation combining the wage and migration estimates with evidence from household survey remittance data imply about 38 % of remittance increases following typhoons are driven by new international labor migration, underscoring the importance of the ability of such migration to take place.

Finally, I provide among the first evidence that ability to migrate in response to typhoons is mediated by the global migrant labor demand conditions facing a province/municipality at the time of a typhoon. I use a shift-share strategy that uses baseline migration shares from provinces/municipalities (shares) and GDP growth of destinations (shifts) to create a time varying migrant demand index. A one SD deviation increase in demand index almost doubles the migration response, without a correspondingly larger drop in the migrant wages. I show that better migrant demand leads to a higher share of contracts for higher paying occupations on average. The more muted wage response is then partially driven by a decreased pressure to downgrade occupations during better demand conditions. The importance of contemporaneous demand underlines the value of using a decade of shocks in the analysis. A study that focuses on one shock that corresponds to a period of particularly high or low migrant demand conditions may not generalize beyond that context.

A distinguishing feature of this work is the focus on contract-based temporary international labor migration, allowed by the unique administrative data from the Philippines. Such migration is the dominant form of migration out of many developing countries (especially in South and Southeast Asia) in terms of migrant flows, yet has been arguably understudied compared to other international migration pathways, such as migration from US to Mexico, where migrants face distinct set of conditions and regulations (Bossavie et al., 2021). Key features of this kind of migration is that it is legal, requires signing an overseas contract at home usually found through private recruitment agencies, and migrants are required to return home when their contracts are expired if they cannot renew their contract. The main destination countries are the wealthier nations in Southeast Asia and Persian Gulf, as opposed to North America and Europe. With temporary labor migration on the rise, and policy questions regarding its facilitation and regulation in the minds of policy makers for both origin and destination countries (United Nations, 2019), it is crucial to generate evidence on the potential risk coping gains such migration can afford origin communities.

This study primarily contributes to the literature on the effectiveness of (international) migration on coping with shocks in developing economies. The literature finds that international remittances respond positively to negative climate and disaster shocks.[3] However, the cross-country evidence on whether such shocks lead to increased out-migration is mixed, reflecting the underlying heterogeneity across origin-destination pairs and different modes of migration.[4] Micro evidence on origin countries is also not equivocal, with, for example, Halliday (2006); Yang (2008b) finding negative international migration responses to the 2001 earthquake in El Salvador while Giannelli and Canessa (2022) finding positive migration responses to flooding in Bangladesh. Further studying the ability for additional migration to take place is key to understanding effectiveness of international migration as a shock-coping tool, as many social networks may not have migrant members whose remittances can support them in baseline.

Two recent studies on ex-post migration are particularly relevant to my setting. First, using hurricane shocks analogous to this paper, Mahajan and Yang (2020) finds that international migration to the US increases in response to hurricanes.[5] Second, using a similar

[3]See Choi (2007); Blumenstock et al. (2016) for micro evidence. Yang (2008a); Mbaye and Drabo (2017) for cross-country evidence.

[4]For example, Drabo and Mbaye (2015) and Marchiori et al. (2012) finds disasters and weather anomalies on average increase international migration. (Marchiori et al. (2012) focuses only movement within sub-Saharan Africa). On the other hand, Cattaneo and Peri (2016) finds no average increase impact for natural disasters. For heterogeneity, Beine and Parsons (2017) documents a negative average effect, but points out migration to neighboring countries increase. Gröschl and Steinwachs (2017) also do not find any robust impact on the full country sample, but notes that for middle income countries natural disasters drive out-migration, likely reflecting that middle-income countries are less financially constrained than the poorest, while less insured than the richest. See Berlemann and Steinhardt (2017) and Cattaneo et al. (2019) for surveys of the literature.

[5]Focusing on Latin America, Hanson and McIntosh (2012) also finds natural disasters increase migration to United States, finding overall negative effects for all other countries in their analysis.

identification strategy, Winter, Christoph (2020) finds typhoons in the Philippines increases permenant out-migration from the affected regions. Both studies primarily focus on permanent migration, and they find increases driven by existing networks allowing family migration. I complement these studies by focusing on temporary labor migration, which is an order of magnitude higher in terms of annual flows compared to permanent migration in the Philippines. Labor migration also faces a different set of frictions and constraints compared to family-migration (McKenzie et al., 2014), making it a-priori unclear whether similar results will hold in this important context. The focus on labor migration with the aid of administrative data also allows me to document migrant wage and occupation responses beyond just flows, providing novel evidence on how home utility shocks impacts reservation wages of potential migrants.

In a highly complementary paper, Cinque and Reiners (2023) exploits an emigration ban in Indonesia (a country with similar migration institutions as the Philippines) to show that regions that were constrained by the ban have lower capacity to cope with natural disasters in terms of poverty reduction. I further bolster the results of this study by explicitly documenting that international labor migration and remittances indeed respond to natural disasters, adding plausibility to the idea that severely restricting such migration would decrease the shock coping capabilities of origin regions. I also complement this work by showing the importance of migrant demand conditions in destination countries for a strong migration response, as opposed to restrictions imposed by origin countries. Relatedly, Gröger and Zylberberg (2016) shows how internal labor migration is used to cope with flooding caused by Typhoon Ketsana in Vietnam. My results suggest international labor migration can have similar shock coping benefits, though likely for wealthier households who tend to be more able to send international migrants.

My findings regarding occupation and country substitution patterns in response to shocks also offer additional insights regarding the well documented phenomenon of migrant downgrading in the labor literature (Dustmann et al., 2021, 2016; Eckstein and Weiss, 2004). First, I provide evidence that origin shocks can be a driver of migrant downgrading, at least where occupation and destination decisions have to be made at the origin, and access to global labor markets are frictional. Second, I show that substituting to lower paying countries is another margin of downgrading for potential migrants along with occupational downgrading. Barsbai et al. (2019) presents complementary findings from shocks to migrant destinations. They find that family migrants who immigrate into high unemployment labor markets in the US have persistently lower earnings profile and lower paying occupations, compared to migrants who do not.

Finally, this study expands the empirical literature on how international migrant connections leads to propagation of shocks across countries (Chiswick and Hatton, 2003). For example, (Gröger, 2021) and (Caballero et al., 2021) study negative income shocks in destinations for Vietnamese households and Mexican regions respectively, showing how they can influence migration decisions and local economic conditions in strongly connected origins. I complement these findings by showing that an additional channel of propogation is that destination country demand conditions (as proxied by GDP) can directly influences the capacity of origin regions to absorb contemporaneous shocks through their effects on international migration.

The paper is structured as follows: Section 2 provides background information on temporary labor migration in the Philippines and more globally. Section **??** presents a simple theoretical framework tailored to the setting at hand. Section 4 provides information on data sources and measurement. Section 5 presents results on the effects of typhoons on migration, migrant wages, and remittances. The Section 6 presents the analysis of how migrant demand conditions coincident with typhoons mediate these effects.

2 Context

2.1 Temporary Labor Migration in the Philippines

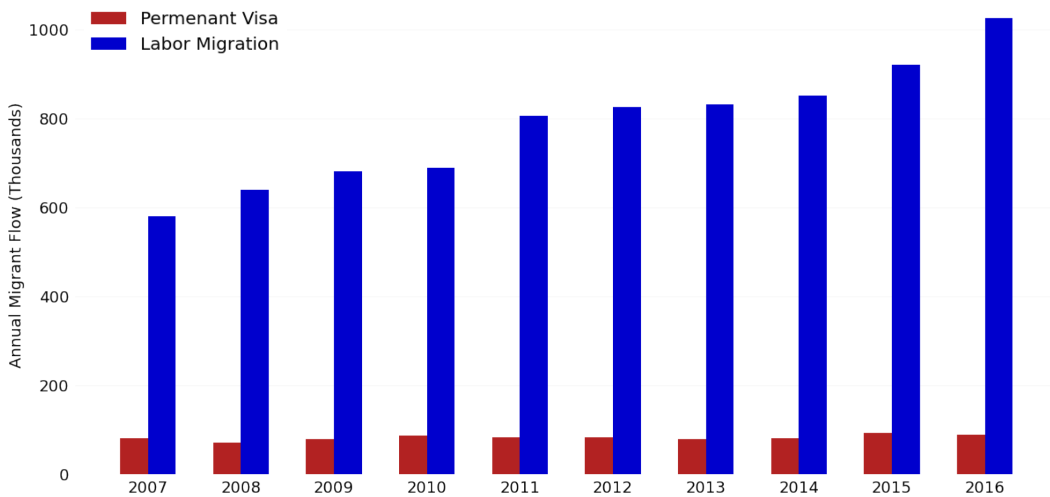
Philippines is the first country to institutionally implement temporary international labor migration at scale, going back to the 1974 Labor Code of the Philippines. Since then, international labor migration in the Philippines have increased significantly, with annual outflows increasing from 36,035 in 1975 to about one million in 2016 (IOM, 2013). According to the 2015 census, 7.5% of households Filipino households have an overseas labor migrant member and 2.2% of the population is composed of current migrants.

Vast majority of migrant outflows from the Philippines are for temporary labor migration. The other legal alternative is to emigrate with a permanent visa, over 90% of which is through family, as opposed to employment, visas. Figure 1 plots the annual migrant outflows from 2007 to 2016 for temporary labor migration and permanent migration as recorded by Commission on Overseas Filipinos (CFO).[6] Throughout 2007-2016, less than 10 percent of out migration is through permanent visas. In 2016, about 1 million Filipinos has migrated as temporary labor migrant, while permanent emigration stands at 90,000. The dominance of labor migration in terms of flows, and greater attachment of temporary migrants to their communities and families back home, make it a particularly important migration channel to study as a shock-coping mechanism for origin regions.[7]

[6]Filipinos who hold a permanent immigrant visas must legally register with the CFO before departing.

[7]Of course, given the permenancy of "permenant migration", the stock of Filipino's abroad are not as lop-sided as suggested by the flows. According to estimates by the CFO, the 2013 stock of overseas Filipinos is composed of 48 % permanent migrants,

Figure 1: Annual Migration Flows from the Philippines



Notes: Data from POEA and CFO reports.

There are two broad categories of temporary labor migration: land-based, where migrants go to destination countries, and seafarers, where migrants work on ships and cruises. Land-based migrants have migrated to over 150 countries between 2007 to 2016, with vast majority migrating to either gulf countries (i.e. UAE, Saudi Arabia) or more developed East Asian countries (i.e. Japan, Taiwan). Occupations are also varied, where most common occupations include domestic helpers, production laborers, nurses, and entertainers.

Temporary labor migration out of the Philippines is primarily facilitated by licensed private intermediaries. Potential migrants find overseas contracts at home through these intermediaries to secure their exit visa. Recruitment agencies provide many services that includes matching with employers, filling information gaps potential migrants may have, and logistical support to navigate the legal requirements of the recruitment and migration process. Potential migrants can connect with intermediaries directly via office visits in cities/online. It is also common practice for recruitment agencies to work with informal brokers who have access to more remote areas or organize job fairs in different parts of the country.

Migration Costs. Financial costs of international migration can be substantial. Such costs can include, but are not limited to, (legal or illegal) recruitment agency fees, transportation, skills testing, and administrative costs associated with processing documents. The Filipino government has regulations in place to keep recruitment costs down and curtail predatory practices. Generally, licensed recruitment agencies are not allowed to collect placement fees higher than one month's migrant salary abroad, though regulations do vary for different

41 % temporary labor migrants, and 11 % irregular migrants.

occupations and countries. There are reports of recruitment agencies charging unauthorized fees. Agency provided loans to cover costs, where they are usually paid through a salary-deduction scheme, is also common. While such practices can relax liquidity constraints, giving up remittances for a month (or more) can still impose prohibitive costs on the house especially in the wake of disasters when the need for funds may be urgent and when the household is presumably losing a domestically productive member to migration (Bazzi, 2017).

Comprehensive data on total migration and recruitment costs is rare. Data from a survey of 822 Filipino migrants in Qatar and Saudi Arabia in 2015-2016 reports the average costs around \$ 400, with a 90-10 percentile range from \$965 to \$50.[8] The higher end of this distribution can be substantial relative to the average and median annual household income per capita of \$1185 and \$770.[9] Half the migrants in the survey borrowed money to cover the costs of migration and recruitment, suggesting the costs are beyond the immediately available financial resources of many. Given recruitment costs tend to increase with the contract wages, it is likely that countries with higher migrant wages such as Taiwan, Japan, or Canada impose larger financial burdens on potential migrants.

Wage Regulation. The wages of Filipino labor migrants are regulated through a host of regulations by the Philippines government, bilateral agreements between the Philippines and destination countries, and labor market regulations of destination countries. Work contracts that do not conform by the relevant regulations are not approved by the Filipino government. Chief among such regulations are minimum wages, such as the \$400 minimum wage for all Filipino migrants leaving for the domestic service occupations, enacted in 2006. Philippine Overseas Labor Offices is tasked with ensuring any verified contract is in accordance with both domestic and overseas regulations, along with making sure the contract wages are in line with prevailing market wages of the host country for the occupation at hand (McKenzie et al., 2014). Therefore, even for higher paying occupations and countries, where domestic or host minimum wages may not bind, there are strict limits on how low contract wages can be. Overall, the regulatory setting makes it unlikely that overseas wages of Filipino's can downward adjust easily in the short run in response to domestic migrant supply shocks, a point I return to Section 5.4.3.

2.2 Temporary Labor Migration Outside the Philippines

While the Philippines is the first country to adopt a strategy of large scale temporary international labor migration, the practice is now common, especially for developing countries in

[8]The survey is undertaken by International Labor Organization (ILO) and The Global Knowledge Partnership on Migration and Development (KNOMAD), with the specific aim of better understanding costs associated with labor migration.

[9]Author's calculation from the Family Income and Expenditure Survey. Values in 2015 US Dollars.

South and Southeast Asia. The annual outflows of temporary labor migrants have reached 463,000 for Nepal, 678,000 for India, 597,000 for Bangladesh, 713,000 for Pakistan, and 200,000 for Sri Lanka.[10] For Indonesia, nearly 9 million workers were employed abroad in 2016, corresponding to 7 % of the countries workforce (Cinque and Reiners, 2023; World Bank, 2017). The paths to migration for all listed countries are similar to the Philippines in that migrants typically leave with an overseas contract obtained at home through recruitment agencies, competing in similar international labor markets (Ahmed and Bossavie, 2022; Bazzi, 2017). Therefore, evidence from the Philippines on the migration responses to natural disasters is likely to have broader applicability to many countries that currently partake in similar markets. It is also worth noting that my analysis spans a period (2007-2016) where there were considerable competition in the international labor markets, increasing the relevance of the results for the future where such cross-country competition across potential migrants is likely to persist.

It is worth noting that recruitment and migration costs out of Philippines is lower than many other countries with comparable temporary international migration practices. Figure 2 documents this with a box plot of individual total migration costs across six countries using the ILO and KNOMAD 2015-2016 migrant cost surveys. The distribution of costs is markedly lower for the Philippines compared to the other five, with particularly extreme values for Pakistan. Appendix Figure A1 shows analogous results for total migration cost as a share of one month's overseas salary. These lower costs likely reflect the longer regulatory history of the Filipino government with this type of migration and a more competitive recruitment agency ecosystem prevailing in the country. In interpreting the results of the paper, it is therefore worth noting that liquidity constraints can be more binding in other contexts, though as contract migration becomes increasingly normalized, such costs may fall for other countries over time as well as regulatory frameworks and intermediary markets further develop.

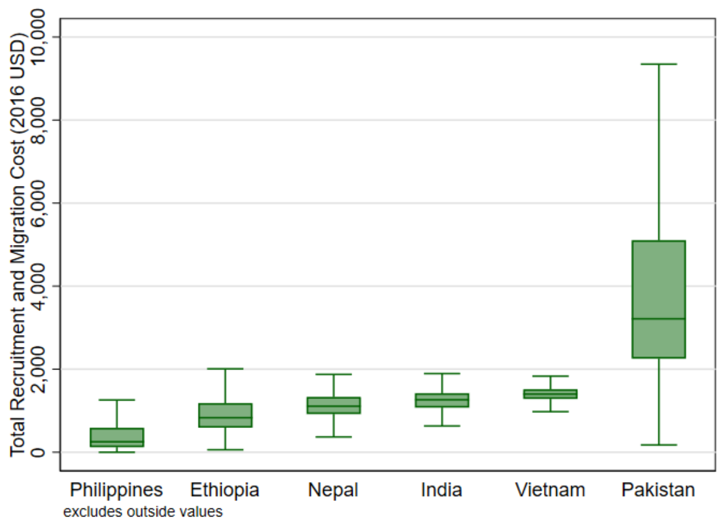
3 Theoretical Framework

Let the per capita total income from abroad for a Filipino province be given by the remittance rate times the total foreign earnings of migrants: $r \times y_F$. The total log change in income from abroad due to a local shock would be given by $d \ln r + d \ln y_F$, where the first term captures the change in remittance rates and the second term change in total income of migrants. The focus of this paper is the ex-post migration response to shocks, i.e. $d \ln y_F$.[11] Given the

[10] Values for Nepal, Bangladesh, India, and Pakistan are for 2012-2017, see Ahmed and Bossavie (2022). For Sri Lanka see (Fernando and Singh, 2021).

[11] In Section 5.6, I do show remittance results using household survey data. I than back out what average change in migration rates can be, combining the total remittance results with changes in migration.

Figure 2: Total Migration Costs Across Countries



Notes: Box plot summarizing the distribution of total recruitment and migration costs across origin countries. Limited to countries where over 80 % of migration took place through recruitment agencies or manpower agencies. Only includes migrants who applied to their jobs through private recruitment agencies or manpower agencies. Outside values are dropped. Source: KNOMAD/ILO 2015, 2016 Migrant Cost Survey

total per capita migrant income is simply the mean foreign income times the migration rate $\bar{w} \times M$, log change in total per capita migrant earnings can be written as:

$$d \ln y_F = (\epsilon + 1) d \ln M \tag{1}$$

where $\epsilon = \frac{dln\bar{w}_F}{dlnM}$ is the percent change in mean wage per additional percent of migration. This can theoretically be driven by change in equilibrium wages (determined by the slope of the migrant demand curve), changes in composition of migrants, or the changes in countries and occupations migrants leave for due to changes in home utility.

Consider two extreme cases. If additional migration neither changes foreign wages nor the composition of jobs taken by the migrants, $\epsilon = 0$ and the percent change in total migrant earnings is identical to the percent change in migration. Alternatively, suppose a setting with extreme excess supply of migrants due to frictions in international labor markets, where a local shock can't increase migration, then $d \ln M = d \ln y_F = 0$. The migration and wage response results in the empirical section rules out these two extreme cases.

The next section develops a simple model of migration choice with homogeneous workers and exogenous foreign wages[12], where workers sort across foreign labor markets based on

[12]In the Filipino context, it is highly unlikely that additional migration from a typhoon affected region will change the equilibrium wages in destination countries as Filipino migrants tend to make up a small fraction of the labor force in destination

the wage levels and the likelihood that they will be able to secure a job in the given foreign market given limited availability of contracts locally. The model demonstrates how, even in the absence of equilibrium wage changes nor selection, an origin area shock can lead to drop in migrant wages along with increased migration. I end the section by briefly embedding the model in a canonical discrete choice migration model with preference heterogeneity to underline the importance of the search frictions due to limited availability of contracts.

3.1 Model of International Labor Migration with Contract Search Frictions

3.1.1 Setup

Basics. The model is static. Homogeneous and risk-neutral individuals with home utility y_h choose between staying at origin or searching for a foreign work contract (incurring uniform search cost c_S). For simplicity, individuals can search at one foreign labor market. Suppose there are N foreign labor markets, indexed $i, j = 1, .., N$. Each market has an exogenous wage rate net of migration costs w_i. Throughout the analysis, it will be convenient to work with $\Delta_i \equiv w_i - y_h$ which denotes the additional income above home utility associated with a foreign labor market. Without loss of generality, locations are ordered such that $\Delta_1 \geq \Delta_2 \geq ... \geq \Delta_N$.

Searching for Contracts. Acquiring a contract for a foreign labor market is subject to search frictions. Each labor market has an exogenous mass of vacancies available v_i. This is meant to capture that the quantity jobs available to Filipinos in their origin country is constrained, especially in the short run.[13] Given exogenous vacancies v_i and endogenous mass of Filipinos searching in a labor market s_i, matches are realized with a Cobb-Douglas matching function: $m(v_i, s_i) = v_i^{\alpha} s_i^{1-\alpha}$.[14] The probability of an individual searcher to find a job in a given labor market (q_i) is given by matches over mass of searcher:

$$\frac{m(v_i, s_i)}{s_i} = v_i^{\alpha} s_i^{-\alpha} \equiv q_i(s_i; v_i) \tag{2}$$

countries, and there are generally binding wage regulations. Further, I do not find that the wage results are driven by selection of migrants.

[13] As I do not have data on vacancies and job availability, I do not explicitly model how the jobs become available in the home region. In the context of the Philippines, this primarily takes place through recruitment agencies. Appendix Section C extends the model to include foreign labor market specific recruitment agencies with convex costs of securing additional vacancies. This addition endogenizes v_i, but does not make a difference in the qualitative predictions discussed in this section.

[14] This functional form is assumed for simplicity, though other reasonable matching functions give qualitatively similar results. It is a work in progress to pin down the exact conditions the search function needs to satisfy for the main results to go through.

3.1.2 Equilibrium

Given workers are risk neutral, the value of searching in a foreign labor market i is given by $q_i(s_i; v_i)w_i + (1 - q_i(s_i; v_i))y_H - c_s$. The value of not searching is simply the home utility y_h. In equilibrium, individuals are indifferent between each option available to them.[15]. This implies that the value of staying home and of search in each foreign labor market is equalized. Rearranging terms, this gives us the equilibrium condition:

$$q_1(s_1; v_1)\Delta_1 = ... = q_i(s_N; v_N)\Delta_N = c \tag{3}$$

First, note that this condition implies a negative equilibrium relationship between the attractiveness of a contract in a market Δ_i and probability of securing a contract q_i. This is intuitive as possibility of high wages attract many searchers, pushing the probability any individual searcher secures a contract lower. Second, this relationship pins down the mass of searchers and migrants at each foreign labor market. Combining expression (2) with the equilibrium condition, we get that the mass of searchers for a market is $s_i = v_i\left(\frac{\Delta_i}{c_S}\right)^{\frac{1}{\alpha}}$. Mass of searchers increase in the availability (v_i) and attractiveness (Δ_i) of jobs in the labor market, and decreasing in the overall search cost (c_S). The mass of *migrants* m_i to a locations is given by the mass of searchers times the probability of securing a job:

$$m_i = v_i\left(\frac{\Delta_i}{c}\right)^{\frac{1-\alpha}{\alpha}} \tag{4}$$

Given the foreign labor market wages are exogenous and fixed, distribution of migrant wages in the model is pinned down by which labor markets individuals migrate to. Let π_i denote the share of migrants going to foreign labor market i. Using Equation (4), his share can be denoted by:

$$\pi_i = \frac{m_i}{\sum_i m_i} = \frac{v_i\Delta_i^{\frac{1-\alpha}{\alpha}}}{\sum_j v_j\Delta_j^{\frac{1-\alpha}{\alpha}}} \tag{5}$$

which indicates that the share of migrants to a location is mediated by relative abundance of contracts available to the location v and the relative attractiveness of the location Δ. The average wages of migrants $\bar{w}$ is then simply an average of foreign labor markets wages

[15] I assume that the mass of potential migrants is large enough that corner solutions where everybody searches do not emerge

weighted by the migration share :

$$\bar{w} = \sum_i \pi_i w_i \tag{6}$$

3.1.3 Response to Origin Shock

I discuss two key predictions of the model to guide the empirical analysis. The derivations of below remarks can be found in Appendix Section C. Consider the impact of a negative home shock which decreases home utility y_H. Such a shock uniformly increases the value of a contract from each foreign labor market, i.e. $\frac{\partial \Delta_1}{\partial y_H} = ... = \frac{\partial \Delta_N}{\partial y_H} = -1$.

Result 1: Migration Response. *A negative shock to home utility increases overall migration rate $M = \sum_i m_i$.*

Result 2: Migrant Wage Response. *A negative shock to home utility increases the share of workers searching in and migrating to lower paying labor markets, therefore decreasing average migrant cohort wages.*

The intuition for these results stem from the uniform increase in value across all foreign market contracts. First, a drop in home utility increases migration overall as the returns to migrations increase. Second, given the value of contracts increases uniformly across locations, value of *search* increases most for lower paying markets with the highest likelihood of securing a contract in equilibrium. Relative increase in the value of searching in lower paying markets leads to more search (and migration) directed to lower paying markets, decreasing the average wages of migrants. This is conceptually similar to a drop in reservation wages in random search models. I document results consistent with these implications in the empirical section below.

For completeness, the model implied **migration elasticity of migrant cohort wages**, defined as $\epsilon = \frac{d \ln \bar{w}}{d \ln M}$ in the previous section, is given by:

$$\epsilon = \frac{\frac{d \ln \bar{w}}{-d \ln y_h}}{\frac{dlnM}{-dlny_h}} = 1 - \frac{\sum_i \tilde{w}_i \Delta_i^{-1}}{\sum_i \pi_i \Delta_i^{-1}} \leq 0 \tag{7}$$

where $\tilde{w}_i$ is the share of total migrant wages coming from labor market i. The expression is equal to 0 if and only if all foreign labor markets are ex ante identical. With markets differing in their average desirability in terms of wages, a prominent feature of any migration decision, origin area shocks incentivize workers to search and migrate to lower paying markets.

What if Negative Home Shocks Affect Migration Costs? The discussion so far assumed that typhoons only effect the utility of staying at origin. However, it is possible that shocks can also increase the costs of searching c_S and migrating abroad (lowering w_i, noting that w_i is defined as wages net of migration costs). This can happen through variety of unmodeled channels, such as asset/income losses making households unable to pay the fixed cost of migration, loss of necessary documents due to damages [16], increases in the price of migration services and assistance in response to increased demand, or destruction of infrastructure making it harder to access recruitment services. If these cost effects dominate the increased returns to migrating, an origin shock can decrease outmigration (Bazzi, 2017; Mahajan and Yang, 2020). In the empirical analysis, I find an increase in migration in response to typhoons, implying that increased return to migration dominates and increases in costs. I therefore continue with the assumption that typhoons are only a shock to home utility, though the two forces likely coexist in reality.

3.1.4 The Role of Search Frictions

In this section, I briefly embed the model in a canonical discrete choice migration model with heterogeneous preferences across foreign labor markets to underline the role search and matching frictions play in the wage results.

Suppose that each individual additionally draws iid preference shocks to each foreign labor market and staying at home $(\epsilon_h, \epsilon_1, ..., \epsilon_N)$, which are drawn iid from EV type 1 distribution with the variance parameter σ.[17] Through the properties of the EV1 distribution, share of migrants going to labor market i is given as:

$$\pi_i = \frac{q_i(s_i; v_i) \times e^{\frac{1}{\sigma}(q_i(s_i;v_i)\Delta_i + y_h - c_s)}}{\sum_j q_i(s_j; v_j) \times e^{\frac{1}{\sigma}(q_j(s_j;v_j)\Delta_j + y_h - c_s)}} \tag{8}$$

Intuitively, share of migrants going a market is still increasing in the job finding rate and wages of the market, though the responsiveness to these properties are now mediated by variance of the preference heterogeneity. Under a slightly stricter set of conditions, ***Result 2*** from the previous section goes through in this model as well: an origin area shock decreases the average wages of the migrants.[18] Now consider the model with search and matching

[16]See, for example, https://www.thenationalnews.com/world/filipinos-seek-middle-east-jobs-to-rebuild-lives-after-haiyan-1.260462 which reports in the context of the 2013 Typhoon Haiyan that "[m]any lost their passports, birth certificates and certificates of employment in the storm surge that followed the typhoon. At the Tacloban job fair, half of those applying for overseas jobs did not qualify because of a lack of documents."

[17]I assume the preferences are across searching for a contract in a given market (or not searching) as opposed to where a worker ultimately ends up. This simplifying assumption allows the model to admit a closed form solution for migration shares.

[18]The stricter set of conditions need to rule out the case that relative abundance of vacancies are much higher for higher

frictions turned off, i.e. probability of finding a job in each market is 1.[19] Then the share of migrants going to labor market i reduces to $\frac{e^{\frac{1}{\sigma}(w_i-c_s)}}{\sum_j e^{\frac{1}{\sigma}(w_j-c_s)}}$, which is not a function of home utility. Therefore, in a frictionless market where migrants can secure a job in each labor markets with certainty, an origin area shock increases migration without leading to any changes in the share migrants going to each location, keeping the average migrant wages the same.

4 Data Sources and Measurement

This section discusses the main data sources and measurement of variables of interest. For brevity, I primarily discuss measurement at province-year level. Variables with different spatial or temporal dimensions (i.e. municipality or bi-quarterly) are created analogously. More details are provided in Appendix Section B.

4.1 Administrative Contract Data

The key migration data is from the administrative database of the Filipino government agency POEA. Before migrating, all contract migrants are required to visit the POEA to have their contract approved and to receive exit clearance. This results in POEA maintaining a dataset of all new temporary contract hires from the Philippines.

I have access to the dataset of all land-based contracts leaving the Philippines from 1992 to 2016. The data includes information on sex, date of birth, contract occupation, destination country, and the salary of each migrant contract. For two periods in the data I also observe information about migrant's home address: 1992-1997 and 2007-2016.[20] This is critical for my research design as the unit of analysis is Filipino provinces and municipalities. I use the 1992-1997 period as the baseline period, which I use to construct measures of baseline migration intensity and baseline province/migration-country migration shares (referred to as the baseline period from now on). 2007 to 2016 is the analysis period, throughout which I observe 4 million migrant contracts, with only 8% missing province and 9% missing municipality information.

paying foreign markets. With preferences dispersed enough, this may lead to a baseline equilibrium where q_i is higher for higher paying locations, a case that was ruled out in equilibrium without preference heterogeneity involved. In such a case an origin area shock may increase wages. See Appendix Section C.

[19] Doing this without introducing preference heterogeneity would lead to degenerate solutions where all migrants would go to the same location in the absence of wages equilibriating in destination markets.

[20] Starting from 2010, the POEA data includes migrants home municipality and province. For the previous years, I rely on a matched dataset between the POEA database and the Overseas Worker Welfare Administration (OWWA) database, which was the government agency responsible for the well being of overseas workers and their families. The OWWA database includes information about migrant's home address. The matched database is created through a fuzzy matching algorithm that uses the first name, middle, name, last name, date of birth, destination country, sex, and year of departure of the migrants (Theoharides, 2018). A 95% match rate is achieved.

The main outcomes of interest are the migration rates and the wages of migrants leaving each province. I construct the migration rate by dividing the number of migrants by interpolated population calculated from the census (further discussed below). The rate is measured as per 10,000 individuals. To construct the wage measure, I first covert all salary information to one-year equivalent real 2010 Filipino Pesos. The wage measures are then constructed as the mean (along with 25th percentile, median, and 75th percentile) of the wage distribution of migrants leaving a province in a year.

Construction of Destination Country and Occupation Quartiles. Another important outcome is the share of migrants going to high versus low paying countries and occupations in a given year. I first use the baseline period data to group countries and occupations into quartiles based on their wage levels. To do so, I run a regression on log wages of contract i, to destination country d, in occupation o, in year t of the following form to jointly estimate the groupings:

$$\ln w_{idot} = \mathbf{D}_d + \mathbf{O}_o + \gamma_t + \epsilon_{iodt} \tag{9}$$

where $\mathbf{D}_d$ and $\mathbf{O}_o$ are the set of destination country and occupation fixed effects. I collect these estimated fixed effects and use the empirical bayes shrinkage estimator of Morris (1983) to account for noise in the estimation leading to possible bias. I then group countries and destinations in quartiles based on the value of the fixed effects, with an equal number of occupations and countries in each quartile. This allows me to construct variables corresponding to the share of migrants from a province in a given year that are leaving for each destination and occupation quartile. Table 1 shows the top two destinations and occupations from each quartile based on the number of contracts in the analysis period.

Table 1: Most Common Destination Countries and Occupations in Each Wage Quartile

	Countries	Count	Occupations	Count
1st Quartile	Saudi Arabia	1,404,274	Domestic Helper and Related	1,387,383
	UAE	542,319	Laborer	338,188
2nd Quartile	Libya	20,235	Plumber, Welder, and Related	200,810
	Cyprus	14,543	Bricklayer, Carpenter, and Related	116,180
3rd Quartile	Taiwan	332,949	Clerical and Related	80,498
	Israel	15,409	Material-Handling Equipment Handlers	77,663
4th Quartile	Hong Kong	264,421	Medical, Dental, and Related	192,650
	Japan	57,167	Engineers, Architects and Related	196,991

Notes: Top two destinations and occupations within each quartile grouping. Migrant counts are over 2007-2016.

Limitations. The administrative contract data has three limitations. First, while I observe the universe of new *land-based* contracts, I do not observe seafarer migration nor irregular labor migration that escapes the gaze of the administrative offices. While irregular migration is likely not a large fraction of annual migrant flows in the Philippines[21], seafarer migration corresponds to 45% of all legal temporary labor contracts in my analysis period. Therefore, generalizing my results to all temporary labor migration requires me to assume responses of other migration channels are similar to land-based migration (or that there is no substitution between these different channels). Furthermore, the stock of migrants at a point in time would also be a function of return migration decisions of migrants. If a migrant is able to renew their contract in the destination country, they do not show up in my data as a new migrant.

Second, the data only shows the legally contracted wage for each contract. There is anecdotal evidence of fraudulent practices such as recruitment agencies informing migrants that they should expect a lower wage upon arrival than the legally binding minimum that is shown in the contract (Agunias, 2010). Unfortunately, it is not possible for me to ascertain prevalence of such activity. If a natural disaster makes migrants more likely to accept such offers by increasing the returns to migration (or dropping reservation wages), the effects obtained from the administrative data would upward bias the negative wage results.

Finally, I observe the address of the migrants at time of migration. If typhoons lead to internal migration out of affected regions, I could possibly mis-classify the home province of migrants if they report their latest address. This would lead to downward bias in migration estimates. While one possible check would be to compare results using latest versus birth addresses of migrants, data on birth addresses of migrants are not available.

4.2 Typhoon Exposure Measurement

Typhoons are a potentially highly destructive form of tropical cyclone that form in the Nortwestern Pacific basin. Philippines is among the most typhoon exposed countries in the world, with approximately 20 tropical cyclones entering the region surrounding the country (named Philippine area of responsibility) every year. A subset of these cyclones reach typhoon scale winds and make landfall in the Philippines every year, causing considerable damages and welfare loss (Franklin and Labonne, 2019).

Typhoons vary considerably in their intensity (particularly wind speed), exact location, impact area, and how populated the affected areas are. The stronger the wind speeds and the more populated the areas they impact, the higher the economic (and human) damages

[21] 2013 estimates by the Commission on Overseas Filipinos suggests that irregular migrants made up of around 10 % of the stock of overseas Filipinos.

are. Accordingly, I construct a typhoon exposure index broadly following Mahajan and Yang (2020) that accounts for these features. The meteorological nature of the index ensures that it is not prone to error or bias due to misreporting.

The general strategy I employ to create the province-year typhoon exposure index is as following. For each typhoon, I first predict the maximum wind speed that prevailed in each grid cell. Then, I take a weighted average of the normalized maximum wind speed across grid cells and storms that are within a province-year, where the cells are weighted by the population residing in the cell. Finally, I normalize this average by dividing it by the province population. The resulting index can be thought of as the intensity-weighted per capita typhoon exposure in a province-year, where intensity is both driven by the number of storms that hit the province in a year, and by the wind speed of each storm. Further details are provided below.

I use the best-track data provided by the Joint Typhoon Warning Center (JTWC) from 2003 to 2020. This data contains meteorological information on the position, maximum sustained wind speed, radius of maximum winds, and radius of tropical storm speed winds (34 knots) at 6 hour intervals for every tropical cyclone's storm center.[22] I linearly interpolate the data to create 30 minute interval storm segment observations from the provided 6 hour interval observations.

For each 30 arc-second grid cell i, storm segment $\bar{s}$, in province p in year t, I calculate the predicted maximum prevailing wind speed as follows:

$$w_{i\bar{s}pt} = \mathbf{1}[mw_{\bar{s}pt} >= 34] \times \begin{cases} mw_{\bar{s}pt} & \text{if } i \text{ is within radius of max winds} \\ \left[34 + (mw_{\bar{s}pt} - 34)\left(1 - \frac{d_{i\bar{s}pt}}{rad_{\bar{s}pt}}\right)^2\right] & \text{if } i \text{ is between radius of max winds and ra} \end{cases} \tag{10}$$

where $w_{i\bar{s}pt}$ is the predicted wind speed, $mw_{\bar{s}pt}$ is the maximum sustained wind speed for the storm segment of interest, $d_{i\bar{s}pt}$ is the closest distance between grid cell i and maximum wind speed radius of storm segment $\bar{s}$, and $rad_{\bar{s}pt}$ is the radius of tropical storm level speed for storm segment $\bar{s}$. In words, if grid cell i is within the radius of maximum winds for storm segment $\bar{s}$, then the predicted maximum speed is the maximum wind speed of the segment. If i falls between the radius of maximum winds and the radius of tropical storm level winds, the predicted maximum prevailing speed is decaying quadratically between the two borders

[22]The radius of tropical storm level speed winds is provided for each 4 quadrant (northeast, southeast, southwest, and northwest) from the center of the typhoon, which the index takes into account. For a small subset of observations, information on the the radius of tropical storm level speed winds are missing. For these observations, if possible, I interpolate the radius from surrounding observations. Otherwise, I predict the radius using a model trained on the data without the radius information missing.

from the maximum wind speed to 34 knots.

Next, for each storm s, I take the maximum wind speed prevailing at each grid cell across storm segments (mw_{ispt}), subtract the threshold of 34 knots, and normalize it by the maximum wind speed observed in the data (w^{max}). The numerators and denominators are squared to account for the fact that climatologists model the impact of wind speed on structures usually with a quadratic term (Emanuel, 2011).

$$x_{ispt} = \begin{cases} \frac{(mw_{ispt}-34)^2}{(w^{max}-34)^2} & \text{if } \geq 34 \\ 0 & \text{if } mw_{ispt} < 34 \end{cases} \tag{11}$$

Finally, I aggregate this storm-grid cell level information to province-year level index. To do so, I first use the 2000 gridded population of the world data from Socioeconomc Data and Applications Center to extract grid cell level population $N_{ip,2000}$. I then take a population weighted average across storms and grid cells that are within a province-year and normalize this by the total population of the province:

$$T_{pt} = \frac{\sum_i N_{ip,2000} \sum_s x_{ispt}}{\sum_i N_{ip,2000}} \tag{12}$$

which leaves me with the province-year level typhoon exposure index T_{pt} which can be viewed as an intensity-weighted typhoon exposure per capita measure. For ease of interpretation, I standardize the index to be mean 0 and SD 1 throughout the paper. I validate the index by how well it predicts government damage estimates and drops in nighttime light intensity in Section 5.1.

I drop the September 2016 Typhoon Meranti from my analysis. This highly destructive typhoon missed the main island groups of the Philippines entirely, and primarily made landfall in Taiwan and Mainland China. However, the northernmost municipality Itbayat of the northenmost province of Batanes was struck by Meranti at its peak strength. This leads to 2016 Batanes typhoon index to be an extreme and influential outlier with Meranti included. The affected regions are also outliers in terms of population (Batanes is the least populated province of the Philippines, with very few migrants) and remoteness, with Itbayat closer to Taiwan than the northern tip of the island of Luzon in the Philippines. I discuss the consequences of this decision in the robustness discussion of Section **??**.

Figure 3 visualizes the province-year level typhoon index for three years in the analysis period: 2011, 2012, and 2013. The left panel shows the path of all tropical depression and above level storms that passed through the Philippines in a given year, along with the maximum predicted wind speeds across the year in each pixel. The right panel shows the final typhoon exposure index T_{pt} at the province level. The figure underlines how common typhoons are in the Philippines, and also visualizes the variability in the exact location and intensity of the typhoons, which is the variation I exploit in my empirical analysis.

4.3 Other Data Sources

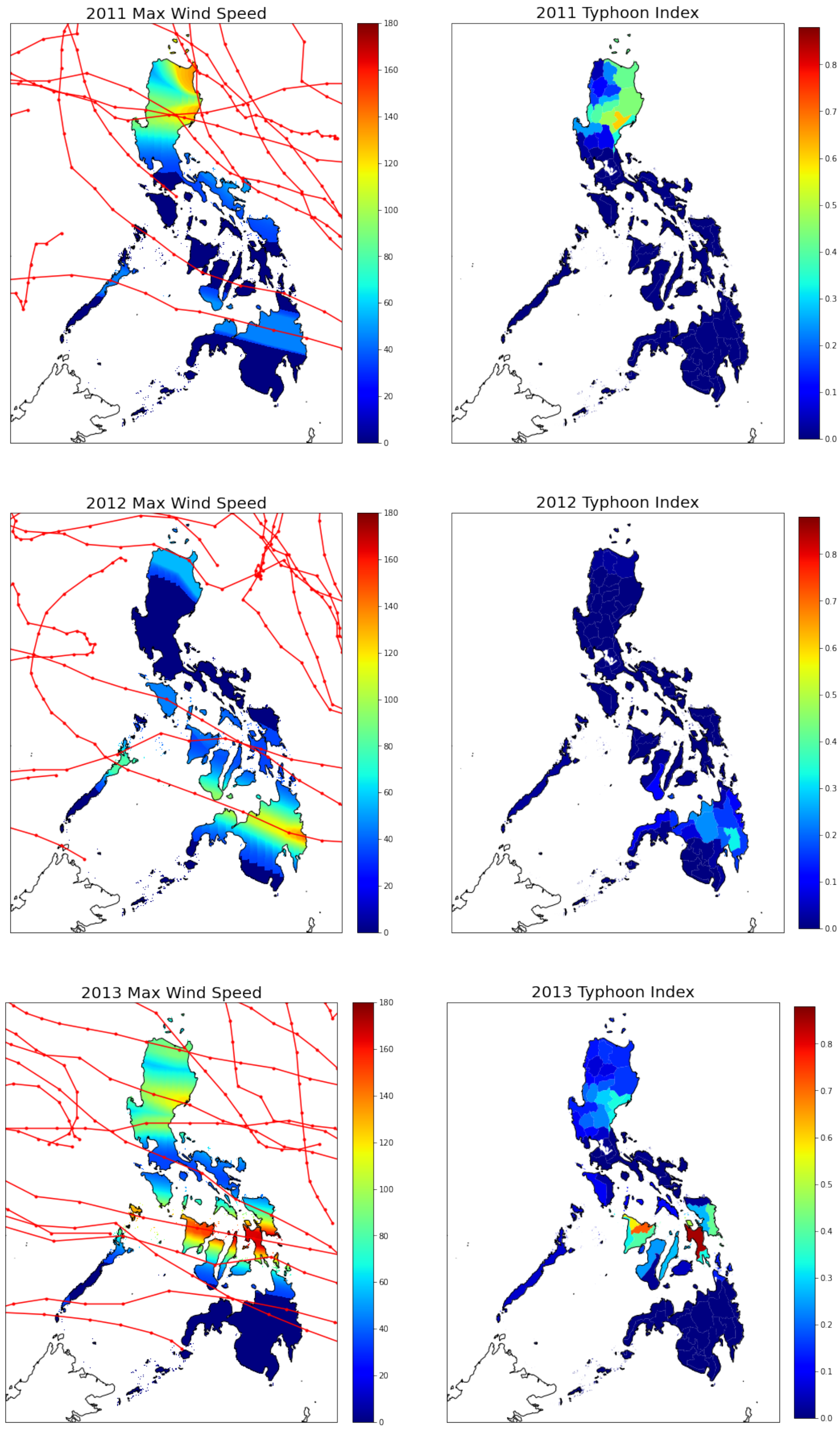
Below I briefly discuss the additional data sources used throughout the paper. Further details on data construction can be found in Appendix Section B or relevant sections I note to for each data source.

Census. The 100% census data is used to construct baseline province level controls, to aid in the calculation of migration rates, and to construct outcome variables for the education level of stock of migrants. I use the 2000 census to construct baseline log gdp, share of population completed primary school, secondary school, and college, and share of households that are in rural areas variables. I further use the 2007, 2010, and 2015 census to create measures of stock of labor migrants who completed secondary school, some college education, and college education. I further use interpolated population counts from the census to use as the denominator for migration rate variables.

Family Income and Expenditure Surveys (FIES). To both construct province level baseline controls and to study affects of typhoons on remittances, I use the cross-sectional FIES data conducted by the National Statistical Office of the Philippines. I use the 2006, 2009, 2012, 2015, and 2018 rounds to construct household and province level remittance measures using the "income from abroad" variable. I use the 2003 round of the FIES to construct the baseline total income per capita, variance of household income per capita, and total expenditure per capita at the province level to use as baseline controls in robustness checks. This data is not available at the municipality level.

Survey of Overseas Filipinos (SOF). To assess the shifts in educational composition of migrants in response to typhoons, I use the Survey of Overseas Filipinos data from 2007 to 2016. This is an offshoot of the naturally representative Labor Force Survey in the Philippines that collects data on migrants who have left the country up to 5 years before the survey year (including past migrants who have since returned). I limit the data to migrants who have left for overseas contract work. After 2011, the data also contains information on whether the migrant was a land-based migrant, which is the sample I mainly use for comparability with the main migration analysis. I discuss the data further in Section 5.4.2 when I discuss the education results.

Figure 3: Prevailing Maximum Wind Speeds and Typhoon Exposure Index From 2011 to 2013



Notes: Left panel shows the path of each tropical depression passing the Philippines (red lines) and presents the maximum wind speed (if $\geq$ 34 knots) that prevailed in each 30 arc-second grid cell. The right panel shows the resulting province-year level typhoon exposure measure T_{pt}

Destination Country GDP. To construct the province and municipality level migrant demand index, I obtain real GDP per capita data from World Bank World Development Indicators. I supplement this source with real per capita GDP data for Taiwan (missing from the WDI data) from the Penn World Tables version 10.0. The construction of the migrant demand index measure is discussed in Section 6.

Typhoon Damages. I obtained province level estimates of typhoon damages and casualties from the Philippines National Disaster Risk Reduction and Management Council (NDRRMC). I create a province-year level damages and casualties dataset to validate the typhoon exposure index I constructed.

Nightlight Intensity. I use the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) satellite data available from the World Bank[23] This data is available from the second quarter of 2012 to 2020. I construct a quarter-province level nighttime intensity dataset (see Appendix Section D.1 for details) to assess its response to typhoon exposure.

The results are organized as follows. I first analyze the effects of typhoons on international labor migration flows and wages. I find that migration flows increase while the contract wages of migrant cohorts decrease. I conclude this section by looking at remittance responses using household survey data. Next, in section 6, I document how international demand for migrant labor (as proxied by GDP of destination countries) mediate this effect.

5 Migration Responses to Typhoons

5.1 Validating the Typhoon Exposure Index

I start by validating my typhoon exposure index by showing that the index predicts physical and economic damages. As detailed in Appendix Section D.1, I do so by using province level casualty and damage data I obtained from the Philippines government and using nighttime lights satellite data. The typhoon index is a strong predictor of number of casualties, number of people affected, and pecuniary damages as reported by the government. Further, moving away from government reported data, a one SD typhoon exposure in a given quarter-province leads to approximately a 2 % drop in nighttime light intensity. I interpret these results as a drop in home utility in typhoon affected regions, increasing the returns to migration. The rest of the section focuses on migration-related responses to typhoons.

[23]Information about and access to the data can be found at https://registry.opendata.aws/wb-light-every-night/.

5.2 Empirical Approach

To estimate the causal effects of typhoon exposure, I use a fixed effect strategy that exploits the exogeneity of the exact location, intensity, and timing of typhoons. I mainly employ a summary specification throughout the paper that summarizes the short run (0 to 1 years) and medium run (2 to 3 years) effects of typhoons. Additionally, I show results from an event study specification that allows me to assess dynamics more granularly and check for pre-trends. In both approaches, the identifying assumption is that, conditional on time and location fixed effects, the occurrence and the intensity of a typhoon is uncorrelated with other shocks that may drive migration related outcomes.

I present results for two geographical administrative units: 79 provinces and 1588 municipalities.[24] The advantage of using municipalities is that it provides much more geographical granularity. However, not all outcomes throughout the paper can be estimated at the municipality level (mainly remittances from the FIES). Given provinces are aggregated up from municipalities, any differences in the municipality and the more aggregate province level results can also be informative about spatial spillovers, though the results tend to be similar across the two levels of analysis throughout the section. Unless otherwise noted, the analysis period is 2007-2016.

Below, I discuss the main specifications. In cases where modifications are made, they are discussed in the relevant sections of the paper.

Summary Specification. To summarize the effects of typhoons on an outcome of interest in the short- and the medium-run, I estimate the following regression as my main specification:

$$y_{pt} = \beta_{SR} T_{p,(t,t-1)} + \beta_{MR} T_{p,(t-2,t-3)} + \gamma_p + \gamma_{r(p),t} + \epsilon_{pt} \tag{13}$$

where y_{pt} is the outcome of interest for province (or municipality) p in year t. The variables $T_{p,(t,t-1)}$ and $T_{p,(t-2,t-3)}$ are averages of the typhoon exposure index T of province (or municipality) p in either the past two years or two and three years ago. γ_p is province (or municipality) fixed effects that controls for any time-invariant characteristics of the geographic unit of analysis. $\gamma_{r(p),t}$ is an island-group by year fixed effect that controls flexibly for any aggregate shocks or differential trends within Filipino island groups over time.[25] While equation (13) is the preferred specification, I also show robustness of main outcomes to using just

[24]In cases with individual or household level regression, the level of variation of the typhoon exposure is still either the province or the municipality.

[25]Island groups are the the largest administrative unit in the Philippines, dividing the country into three administrative regions: Luzon, Visayas, and Mindanao.

year fixed effects as opposed to year by island groups, and to controlling for linear trends in baseline province (and municipality) characteristics.[26] For both municipality and province level analysis, I present two sets of standard errors. First, I cluster at the province level. Second, given the spatially correlated nature of both typhoons and many of my outcomes of interest, I present spatially clustered standard errors following Conley (1999), allowing for up to 200 kilometers around the centeroid of the province/municipality and for auto correlation of order 10 years. When the outcomes are characteristics migrant cohorts (for example average wage or share of females), I weight the regressions by the number of migrants used to calculate the characteristic y_{pt}, i.e. the cell size.[27]

The coefficients of interest in this specification are β_{SR} and β_{MR}. The coefficient β_{SR} (short-run) can be interpreted as the effect of one s.d. increase in the average typhoon exposure across the current and the previous year, which I refer to as the short-run effect. Similarly, β_{MR} (medium-run) can be interpreted as the effect of one s.d. increase in the average typhoon exposure across two and three years ago, which I refer to as the medium-run effect.

Event Study Specification. I further employ an event study specification for key outcomes to document more detailed dynamics and assess pre-trends. The estimating equation is:

$$y_{pt} = \sum_{\tau=-K,\tau\neq-1}^{\tau=T} \delta_\tau T_{p,t-\tau} + \gamma_p + \gamma_{r(p),t} + \epsilon_{pt} \tag{14}$$

where $T_{p,t-\tau}$ is the typhoon exposure index of province p at τ periods before t, and o_{pt}, γ_p, $\gamma_{r(p),t}$ are the same as the summary specification above. As opposed to the summary specification, the periods in the event study specification are not standardized to be annual and vary across different outcomes. For the event studies, I focus on the province level estimates in the body of the paper and relegate the municipality level results to the appendix.

Potential Issues with the TWFE Specification. The estimating equations (13) and (14) falls under the umbrella of TWFE estimators, applied in a setting with multiple periods, variation in timing of treatment (typhoon exposure), continuously distributed treat-

[26]For the province level analysis, the baseline controls are constructed from the 2000 Census and the 2003 FIES. Census controls include baseline population, share of population with primary school, secondary school, and college education, and share of households that are rural. FIES controls include the logs of average household expenditures, average household income, and the variance of household income. Municipality controls only include the census variables, due to FIES missing municipality identifiers (and not being representative at the municipality level.)

[27]This approach is common in migration literature (Bertoli et al., 2017; Borjas, 2003; Mishra, 2007). I employ it to ensure that the results are not driven by noisy cells with low number of migrants, which particularly is a concern with the municipality level analysis. For survey outcomes, I use the sum of the individual weights in the cell.

ment, multiple treatments per unit, and with no never-treated unit. A recent and growing literature raises concerns that, with staggered treatment timing and multiple periods, the presence of treatment heterogeneity across units or over time can contaminate the difference-in-difference estimates and the leads and lags in event studies. (Roth et al., 2023) While this literature has provided robust estimands under a variety of research context (such as binary treatment, pure control group etc, see Sun and Abraham (2021) and citetcallaway-DifferenceindifferencesMultipleTime2021), to the best of my knowledge, there is no robust estimators in the literature corresponding to a case with all five of the characteristics of my setting listed above.

In Appendix Section , I follow the stacked regression approach of Cengiz et al. (2019) using a binarized version of my exposure index to see if results are consistent with the TWFE specification results I present in the body of the paper. The stacked regression ensures that the estimates are not influenced by "bad comparisons" by constructing a control group for each treatment-cohort that have not been "treated" for a window around the treatment-cohort of interest. Using a window of three years before and after a bi-quarterly period, I show that for binary typhoon measures constructed as extreme typhoon exposure ($\geq 90th$ percentile), the stacked event study results mirror the findings in the body of the paper, without worrying pre-trends.

Callaway et al. (2021) studies the TWFE estimator with continuous treatment. They point out that, for my estimates to be interpreted as a weighted average of causal responses in outcomes to an incremental change in typhoon exposure, one needs to assume that selection bias stemming from units selecting intro treatment based on treatment effects need to be ruled out. This is reasonable in my setting, as the randomness of exact location, timing, and intensity of typhoons essentially rules out the possibility of regions selecting into a particular treatment dose (deviation average typhoon exposure) in a given period.

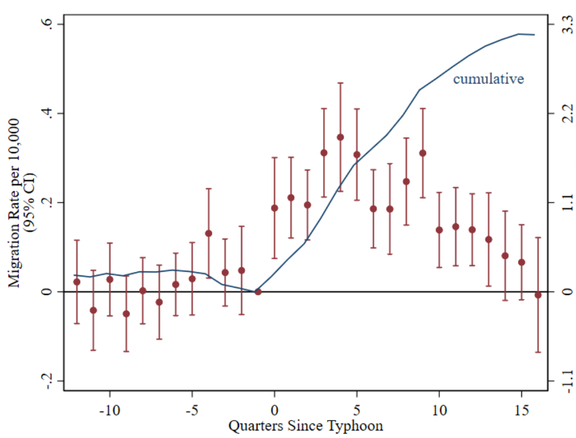
5.3 Typhoons Increase Migration and Decrease New Migrants' Wages

I begin by documenting that typhoons lead to an increase in international labor migration from affected regions. Column 1 of Table 2 presents results of the main summary specification with migration rate as the outcome, for both municipality (panel A) and province (panel B) as the unit of analysis (this structure will be used for the rest of the paper whenever appropriate). At the province level, a one SD average hurricane exposure in the past two years increases the province migration rates by 15 migrants per 10,000. This increase persists in the medium-run, with an increase of 14 migrants per 10,000. These are economically meaningful effects corresponding to 4.4 and 4.1 percent of the mean migration rates. Municipality level results yield very similar conclusions.

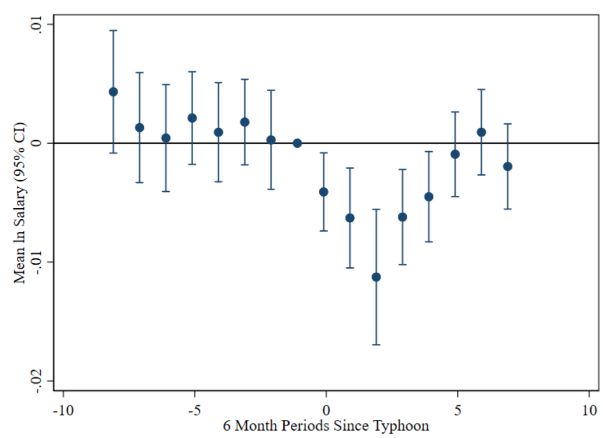
One concern with using migration rates as the outcome is that natural disasters can change the population level or growth in affected regions, creating an increase in migration rates through changing the denominator. Column 2 of Table 2 shows that the migration results hold if we use the rates per 2007 population as our outcome variable, indicating that population changes are not driving the results. Additionally, as shown in column 3, results are broadly unchanged if we use log migrants as the outcome variable as opposed to migration rate.[28]. Finally, given the contract data collects origin information at time of migration, some observations can have mis-classified origin province/municipalities if they internally migrated out of a typhoon-struck region before migrating. This would bias my results towards zero.

To further assess the dynamics of these migration effects more granularly, Figure 4a presents results from the quarterly province-level event study specification for migration rate. Migration effects of a typhoon starts manifesting immediately, peaks at around five to six quarters from the typhoon incidence, and dissipates after fifteen quarters. Therefore, while the summary specification shows persistent results three year out, the event study confirms that the response dissipates after about four years.

Figure 4: Event Study Results for Migration Rate and Mean ln(wage)



(a) Migration Rate



(b) Mean ln(Wage)

Notes: Panel (a): Dependent variable is migration rate. Unit of observation is province-quarter. The specification includes province and quarter-by-island-group FEs. Confidence intervals based on province clustered standard errors. Panel (b): Dependent variable is mean log(wage) of migrants. Unit of observation is province-biquarter. The specification includes province and biquarter-by-island-group FEs. Observations are weighted by the number of migrants in each cell. Confidence intervals based on province clustered standard errors.

While increasing migration rates, typhoons lead to a decrease in the wages of new migrant cohorts. Column 4 of Table 2 presents results on responses of average wages to typhoons.

[28]I estimate the log migration regression using the Poisson Pseudo Maximum Likelihood (PPML) estimator to account for 0s in municipality level analysis. (Silva and Tenreyro, 2006)

Table 2: Typhoons Increase Migration and Decrease New Migrant Wages

Panel A: Municipality Level (1588 Municipalities)								
	Migrants...			Migrant Wages				
	per capita	per 2007 capita	log count	mean log wage	log mean wage	log 25th pct.	log 50th pct.	log 75th pct.
$T_{m,[t,t-1]}$ ($\beta_{ShortRun}$)	1.279***	1.179***	0.041**	-0.010***	-0.015***	-0.010***	-0.013***	-0.015***
	(0.339)	(0.394)	(0.016)	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)
	[0.391]	[0.412]		[0.002]	[0.005]	[0.004]	[0.004]	[0.004]
$T_{m,[t-2,t-3]}$ ($\beta_{MediumRun}$)	1.490***	1.400***	0.029*	-0.005***	-0.006	-0.007**	-0.010***	-0.005
	(0.496)	(0.413)	(0.015)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
	[0.429]	[0.397]		[0.002]	[0.003]	[0.003]	[0.003]	[0.003]
Observations	15,970	15,970	15,900	15,788	15,788	15,768	15,768	15,768
Adjusted R2	0.877	0.892	.	0.904	0.874	0.677	0.836	0.862
Mean Dep. Var.	33.644	34.581	231.675	5.476	5.573	5.287	5.377	5.576
Panel B: Province Level (79 Provinces)								
	Migrants...			Migrant Wages				
	per capita	per 2007 capita	log count	mean log wage	log mean wage	log 25th pct.	log 50th pct.	log 75th pct.
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	1.434***	1.399***	0.041**	-0.011***	-0.016***	-0.013***	-0.015***	-0.016**
	(0.455)	(0.520)	(0.016)	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)
	[0.512]	[0.539]		[0.003]	[0.006]	[0.004]	[0.006]	[0.006]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	1.357**	1.614**	0.029**	-0.005***	-0.006*	-0.008**	-0.013**	-0.005
	(0.674)	(0.637)	(0.014)	(0.002)	(0.004)	(0.004)	(0.006)	(0.005)
	[0.614]	[0.603]		[0.002]	[0.004]	[0.004]	[0.007]	[0.005]
Observations	790	790	790	790	790	790	790	790
Adjusted R2	0.927	0.941	.	0.966	0.959	0.849	0.910	0.933
Mean Dep. Var.	34.300	35.565	4698.152	5.493	5.615	5.293	5.371	5.583

Notes: Unit of observation is municipality-year (Panel A) or province-year (Panel B). All regressions include unit and year-by-island-group fixed effects. Observation numbers for Panel A columns 4-8 are lower due to municipality-years with no migration. In columns 4-8, observations are weighted by the number of migrants making up each cell. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. *** p<0.01, ** p<0.05, * p<0.10

In the short run, a one SD average hurricane exposure in the past two years decrease the average log contract wages by 1.1 %. The wage effect falls to about half its initial magnitude two to three years after exposure, unlike the persistent effects on migration rates.[29] Columns 6-8 show that the short run drop is not constrained to the mean, with the 25th, 50th and 75th percentiles of wages falling 1.3, 1.6, and 1.8 percent respectively.

Again, to assess dynamics, 4b shows event study results for average log wages. Given the average becomes noisier when calculated over low number of observations, I calculate the wage results in bi-quarterly periods. Similar to migration rate results, the drop in cohort

[29] I focus on the mean log wages throughout the body of the paper, as opposed to log of mean wages, as it yields more precise results and is consistent with individual contract level regressions I run in section 5.4.2. Column 5 of Table 2 shows that the short-run drop in migrant wages is around 1.5 % if log of mean wages are used.

wages start in the same period as typhoon exposure, peaks about a year and a half after the typhoon (around the same peak with migration response), and dissipates slightly quicker than the migration results (3 as opposed to 4 years).

Robustness. The migration and wage results are robust to including year as opposed to year-by-island fixed effects (column 1 of Appendix Tables A1 and A2). I further check whether differential baseline trends in municipalities and provinces with different baseline characteristics could be confounding results. Controlling for linear trends in baseline characteristics of provinces and municipalities do not make qualitative differences (Column 3 of Appendix Tables A1 and A2). Results are broadly similar with linear province- or municipality-trends are included (Column 4 of Appendix Tables A1 and A2).

For the reasons discussed in Section 4.2, I drop the 2016 Typhoon Meranti from my analysis. Appendix Table A1 column 5 presents baseline migration results with Typhoon Meranti included. Especially at the province level, inclusion of Meranti decreases the short-run migration response estimates and severely inflates the standard errors.[30] Batanes is unique in that it is the smallest (in terms of population and number of migrants) and most remote Filipino province. Therefore, I also show results with Batanes excluded from the analysis entirely, which leads to larger and more precise migration rate estimates compared to my main outcomes (column 6).[31] To ensure no other province is as influential, I show the stability of the results to dropping provinces one at a time in Appendix Figure A2.

Discussion and Magnitudes. Taken together, the evidence suggests that international labor migration is indeed used as a short term ex-post risk coping mechanism for Filipino households. The positive migration results go against the hypothesis that binding (or worsening) liquidity constraints or excess supply of migrants at baseline is completely impeding any additional migration from taking place on average.

Yet the migration response is accompanied by a decrease in the wages of new migrants. The estimated migration elasticity of migrant wages is $\epsilon = -0.25$. A naive analysis that only focus on migration responses without taking wage responses into account would overestimate the effect of a SD typhoon exposure on total new migrant contract earnings by 25%. I focus on the drivers behind this wage drop in the next section.

Empirical studies that estimate the effect of origin shocks on regional temporary legal international labor migration is rare. One exception is Bazzi (2017), who finds that positive

[30]Because Typhoon Meranti struck in 2016, the last year in my analysis period, its inclusion does not change medium term response estimates significantly.

[31]The wage results are not meaningfully impacted by the inclusion Typhoon Meranti or exclusion of Batanes because I observations are weighted by the number of migrants used to calculate the cell. With Batanes overall having very low number of migrants, its influence in the wage results are greatly diminished. See A2 columns 5 and 6.

rainfall shocks increase labor migration in Indonesia on average. My results find positive effects in response to a negative shock. This likely is driven by differences in how binding liquidity constraints are across the populations of each study, given the income elasticity of migration is driven by two competing forces: easing of liquidity constraints versus lowering returns to international migration. In the context of rural Indonesia, their finding suggest that the easing of the liquidity constraints dominate. My setting on the other hand focuses on the entire population of the Philippines, as opposed to just the rural population who on average is less wealthy and likely constrained. Further, migration and recruitment costs out of Philippines is among the lowest in the world (see Section 2.2). Therefore, in my context the returns to migration channel is more likely to dominate as I am focusing on a possibly wealthier population[32] who faces lower migration costs. Upcoming results suggesting the marginal migrant is more educated in my context further bolsters this interpretation that it is primarily more educated (and likely wealthier) Filipinos that are driving my average effects.

Spillovers. My research design compares evolution of outcomes across provinces. If provinces that are not directly struck by typhoons are nevertheless indirectly affected, the estimated coefficients would not capture the true causal effect at the province level due to SUTVA violations. The details of the following spillover analysis and the results are presented in Appendix Section D.5.

There are two particular concerns in this setting. First, economic and population ties between provinces can lead to indirect negative shocks to control provinces. This would increase the returns to migration in control provinces. To assess this possibility, I borrow insights from the economic geography literature which documents that population and economic ties tend to decrease with distance. Creating an inverse distance weighted typhoon exposure measure for each province-year, I regress the migration outcomes of control provinces on the distance weighted typhoon exposure. While imprecise, I find a positive migration and negative migrant wage response, consistent with negative spillovers (in terms of home utility) to control provinces.

Second, and more specific to my context, if individuals in different provinces are competing for overseas work contracts, control provinces may see a *decrease* in migration due to increased competition from typhoon-struck provinces. Consider the extreme case that the total number of overseas work contracts in the Philippines each year is fixed. Typhoons could reallocate the contracts to typhoon-struck provinces that increase their search intensity, yet

[32]though GDP per capita of Indonesia is about 11 % higher than the Philippines a around the end of my analysis period (2015).

they would not lead to any aggregate increase in migration.[33] On the other hand, if each province is an "island" with its own supply of possible overseas contracts, such spillovers would not be operational. The reality is likely in between these extremes.

Assessing the empirical relevance of this type of spillover is challenging. One would need variation on which provinces are differentially competing with each for overseas contracts, which is not a-priori clear. I aim to make progress by leveraging the persistence in province-destination ties, a feature I further discuss in Section 6 in building the migrant demand proxy. If the propensity of a province to send migrants to certain countries are higher, it would be competing more with other provinces with similar destination ties. I leave the the specifics of how I operationalize the idea to Appendix Section D.5. Briefly, I first create a province-year level exposure measure that weights the typhoon exposure of all the other provinces by how similar their destination countries are to the province of interest (using the cosine similarity of baseline destination network vectors). I further weigh each province's contribution by the level of migrant flows in the baseline period, as provinces with more migrants would lead to higher competition in the overseas contract market. I then regress a province's migration rate on the exposure index, controlling for own typhoon exposure, along with other possible confounders such as the inverse distance weighted typhoon exposure.[34]

Puzzlingly, the (imprecise) results point to the opposite direction of my hypothesis: the exposure index increases migration and decreases migrant wages. One possible explanation for this is that there are endogenous responses by recruitment agencies. If recruitment agencies respond to typhoon driven migrant supply shifts by increasing (possibly low paying) contract availability, some of this can spillover to provinces with similar destinations. Though this raises the question of why such supply increases was not taking place earlier if there was excess supply of willing migrants in typhoon unaffected regions. Alternatively, if provinces with similar destinations also have closer economic ties, I may still be capturing the effect of economic disruptions at home as opposed to competition in the contract market, even with the included controls.

Taken together, the two analysis described above, while not conclusive, point towards the estimated effects being underestimates of the true causal effect.

[33] This can be a potential way to reconcile my findings with McKenzie et al. (2014), which conclude there is aggregate excess supply of Filipino migrants. Also note that such reallocation would still be welfare enhancing if contracts are directed towards typhoon-struck individuals who value them more.

[34] The two main concerns are that (1) typhoon realizations of other provinces are correlated with own typhoon realization and (2) similarity in terms of destination countries may be correlated other economic ties and distance. Controlling for own typhoon exposure controls for (1). I include average typhoon exposure of neighbors, inverse distance weighted typhoon exposure, and internal migration network weighted typhoon exposure as an attempt to deal with (2).

5.4 Why Are Migrant Wages Lower Following Typhoons?

Before analyzing the mechanisms behind the drop in wages, I first establish how migrant wages vary with a migrant's destination country, occupation and demographic characteristics available in the contract data (sex and age). In Appendix Section D.3, I undertake a variance decomposition exercise, finding that the destination country accounts for 39%, occupation 27%, and the demographics 3% of the variation in the wages. Around 31% of variance remains unexplained. Overall, occupation and destination choices of the migrants explain a substantial portion of the wage differentials, but reasonable variation remain even after accounting for these choices and an admittedly sparse set of demographic controls.[35]

5.4.1 Country and Occupation Downgrading Following Typhoons

I first focus on the destination country and occupation choices of the migrants following typhoon exposure. As discussed above, country and occupation of migrants explain a substantial portion of the variation in contract wages. I use the baseline country and occupation wage quartile measures discussed in section **??** to see if shares of migrants going to each of the quartiles responds to typhoon exposure.

Typhoons Lead to Country and Occupation Downgrading

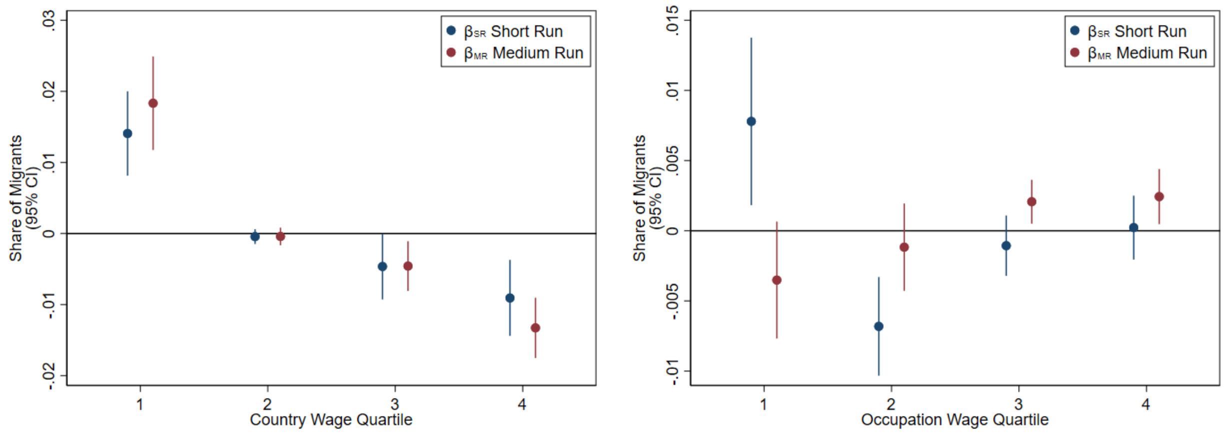
Figure 5 plots the coefficients of interest from the summary specification (13) where the share of migrants going to a given quartile of countries or occupations as the outcome.[36] The left panel shows a clear pattern for destination countries: after a typhoon, share of migrants going to the lowest paying countries persistently increase while the share going to the highest paying countries decrease. A one SD typhoon exposure leads to share of migrants going to the lowest wage quartile countries increasing by 1.4 and 1.8 percentage points in the short and medium run (1.9% and 2.4% of baseline mean), while share going to the highest quartile falls by 0.9 and 1.3 percentage points (8% and 12% of baseline mean).

A similar pattern holds for occupations in the short run. A one SD exposure increases the short run share of migrants going to lowest quartile of occupation by 0.8 percentage points (1.4%), while decreasing the second quartile by 0.8 percentage points (4.5%) with no significant changes for third and fourth quartiles. However, in the medium run the

[35]Appendix Section D.3 presents additional details and full set of results on the decomposition exercise. The decomposition values in the body of the paper refers to Panel B of Appendix Table A12 and splits the covariance terms equally across the groups of regressors. Unexplained variation falls only to 26 % if we include more granular country-by-occupation-by-year fixed effects, implying a similarly high residual variation even in occupation by country cells. It is worth highlighting that my occupation measure is an aggregation that includes multiple occupations as coded by the POEA. Therefore, some residual variation likely captures the differences between occupations within an occupation cell.

[36]Municipality results are shown in the figure. Province level results are almost identical. The regression tables for the analysis (including province level) is presented in Appendix Table A3

Figure 5: Typhoons Increase the Share of Migrants Leaving for Lowest Paying Countries and Occupations



(a) Country Quartile Shares

(b) Occupation Quartile Shares

Notes: β_{SR} and β_{MR} from summary specification (13) are plotted. Outcome variable is the share of migrants leaving for jobs in the specified country or occupation quartile (8 regressions). Unit of analysis is municipality-year. Municipality and year-by-island-group fixed effects are included. Observations are weighted by the number of migrants in each cell. Confidence intervals based on province clustered standard errors.

pattern is flattened, with a slight increase in the share of migrants going to the higher paying occupations. The flattening of the occupation results in the medium run is consistent with the finding that the drop in average wages are halved in this time frame.

These patterns are consistent with the idea that potential migrants are decreasing their reservation wages in response to a negative shock to utility of staying home. While contracts may exist abroad to accommodate the relatively few (in relation to overall labor force of the destination) Filipino migrants induced by the shock to migrate, what is relevant for migrants is that such contracts are available to them locally. Search frictions for recruitment agencies and the fact that the wages for migrant contracts tend to be heavily regulated by both the Philippines and the destination countries would constrain the ability of locally available jobs to respond proportionally to the raise in demand for migration. Further, search frictions on the migrant side for contracts would increase the relative value of searching for contracts that are relatively lower paying but are easier to get. Combined, even in the absence of selection and compositional changes due to typhoons (which I explore below), these frictions would induce migrants to search for and accept jobs in lower paying labor markets, which in this case is a destination country and occupation pair. In the absence of any frictions where the migrants can successfully find jobs in whatever labor market they have preferences for, a negative shock at home would increase migration without meaningfully changing the shares of migrants sorting into different labor markets, keeping the average wages fixed.

Downgrading Explains the Wage Decrease

How much of the drop in wages can be attributed to shifts in occupation and country shares? I explore this in two ways. I first use the individual level contract data to see if residualizing the log wages by the occupation and country of the contract decreases the observed results. I estimate:

$$\ln w_{icdpt} = \alpha + \beta_{SR} T_{p(t,t-1)} + \beta_{MR} T_{p(t-2,t-3)} + \gamma_{dp} + \gamma_{rt} + \gamma_{p} + \epsilon_{ipt} \tag{15}$$

where i is an individual migrant, p is the province/municipality of the migrant, and t is year. Results are presented in columns 1 to 3 of Table 3. Comparing the first two columns, the inclusion of occupation-destination fixed effects decreases the short and medium run wage effects by 71 % and 55 %, indicating that the bulk of the decrease in wages are due to occupation and country downgrading. Further interacting these fixed effects by year (in column 3) essentially makes the typhoon effect go to zero.

One potential worry is that using country/occupation wage information that is contemporaneous to typhoon shocks may conflate the effects of country-occupation downgrading with other changes due to typhoons. For example, the observed wages in a country may have changed due to typhoon driven migrants having different skill levels or equilibrium wage responses in the location (both of which I rule out as main mechanisms below). If our goal is to isolate the effects of downgrading absent all the changes in observed wages due to other adjustments, this may introduce bias of unclear sign. I proceed with an alternative approach where I use the predicted wages using occupation and country fixed effects estimated on the baseline period data (covering 1992 to 1997) as an outcome variable.[37] By construction these predicted values are not affected by any of the typhoons taking place in the analysis period. Column 4 of Table 3 show that in response to a SD shock, the predicted wages fall by 1.1% in the short run which is almost identical to the drop in observed wages, suggesting that the occupation and country downgrading can explain essentially all of the wage decrease we observe. The medium run effect is about twice the size of the drop in actual wages. This can partially be due to the fact that wage estimates from a decade and a half ago are not precise proxies for current wages. However, taken together, the two analyses both show that the drop in wages following a typhoon is primarily driven by migrants leaving for lower paying countries and occupations.

[37]Specifically, I use the sum of the estimated fixed effect for the occupation and destination of the contract (appropriately shrunk by the empirical bayes method) as the outcome variable.

Table 3: Occupation and Country Changes Explain the Wage Drop

Panel A: Municipality Level (1588 Municipalities)							
	Migrant Level					Municipality Level	
	ln(Wage)	ln(Wage)	ln(Wage)	ln(Pred. Wage)	ln(Wage)	Log Avg. Age	Share Male
$T_{m,[t,t-1]}$ ($\beta_{ShortRun}$)	-0.010***	-0.003***	-0.001	-0.011***	-0.009***	-0.003***	-0.007*
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
						[0.001]	[0.003]
$T_{m,[t-2,t-3]}$ ($\beta_{MediumRun}$)	-0.005**	-0.002*	0.000	-0.010***	-0.005**	-0.001	0.003
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)
						[0.001]	[0.003]
Demographic Controls	No	No	No	No	Yes	-	-
Ctry by Occ FE	No	Yes	No	No	No	-	-
Ctry by Occ by Year FE	No	No	Yes	No	No	-	-
Observations	3,573,419	3,572,522	3,568,887	3,548,480	3,573,417	15,747	15,757
Adjusted R2	0.063	0.697	0.724	0.105	0.114	0.782	0.942
Mean Dep. Var.	5.527	5.527	5.526	-0.744	5.527	3.458	0.361
SD Dep. Var.	0.470	0.470	0.468	0.424	0.470	0.053	0.184
Panel B: Province Level (79 Provinces)							
	Migrant Level					Province Level	
	ln(Wage)	ln(Wage)	ln(Wage)	ln(Pred. Wage)	ln(Wage)	Log Avg. Age	Share Male
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	-0.012***	-0.004***	-0.001	-0.012***	-0.011***	-0.003***	-0.013**
	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.004)
						[0.001]	[0.004]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	-0.005*	-0.002*	-0.000	-0.009**	-0.006*	-0.002*	0.000
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)
						[0.001]	[0.003]
Demographic Controls	No	No	No	No	Yes	-	-
Ctry by Occ FE	No	Yes	No	No	No	-	-
Ctry by Occ by Year FE	No	No	Yes	No	No	-	-
Observations	3,705,105	3,704,188	3,700,436	3,679,470	3,705,103	790	790
Adjusted R2	0.051	0.698	0.724	0.097	0.106	0.948	0.974
Mean Dep. Var.	5.525	5.525	5.524	-0.748	5.525	3.462	0.367
SD Dep. Var.	0.470	0.470	0.469	0.424	0.470	0.031	0.154

Notes: Unit of observation is individual contracts for columns 1-5 and municipality-year (Panel A) or province-year (Panel B) for columns 6-7. Typhoon exposure index is at the municipality level in Panel A and province level in Panel B. All regressions include province/municipality and year-by-island-group fixed effects. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. *** p<0.01, ** p<0.05, * p<0.10

5.4.2 Observable Migrant Characteristics

A competing explanation for the above patterns is that marginal migrants could be negatively selected, leading to a shift towards lower paying countries and occupations due to selection. To assess this possibility, I focus on whether composition of migrants in terms of age, sex, and education changes after typhoon exposure. While education is arguably the most important among the above observables as a proxy for human capital, it is missing from the administrative contract data. Therefore I first explore whether changes in sex and education composition can explain the wage drops using the contract data, and then bring in additional census and survey data to assess whether education composition of migrants change.

Typhoon Driven Migrants are Slightly Younger and More Likely to be Female...

Table 3 columns 6 and 7 presents results from the summary specification for the age and sex composition of migrants. While the average migrant following a typhoon is younger, the magnitudes are small and unlikely to be economically meaningful, with a short- and medium-run decrease of 0.3% and 0.2% for the average migrant age. More notably, there is a change in gender composition of migrants immediately after a shock. At the province (municipality) level, a one SD increase average hurricane exposure in the past two years decreases the fraction of male migrants by 1.3 (0.7) percentage points, corresponding to 3.1% (2%) of the mean. This effect is short lived, and dissipates in the medium run.

... but These Compositional Differences do not Explain the Drop in Wages

To assess whether these compositional changes can explain the drop in wages following typhoons, I use the individual level contract data to see if flexibly controlling for age and sex of the individual migrants, by creating 5 year age bins interacted with gender, dampens the negative wage effects of typhoons.[38] Columns 1 and 4 of Table 3 presents the results. Comparing the two columns, the inclusion of the demographic controls have a negligible effect on coefficients β_{SR} and β_{MR}, implying compositional changes with regards to sex and age are not a driver of the decrease in wages.

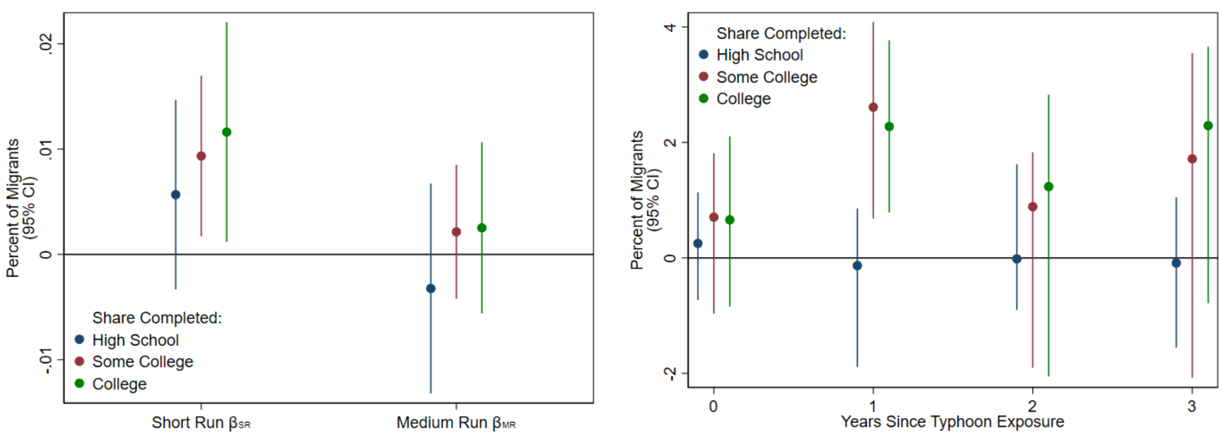
Typhoon Driven Migrants are More Educated

Educational attainment is a key proxy for the skill and earning potential of migrants. With the contract data missing educational information, I turn to two data sources: the 2007, 2010, and 2015 Population Censuses and the annual 2007-2016 Survey on Overseas Filipinos (SOF). Each of these sources have different pros and cons. With the 100% census microdata, I can construct precise municipality (and province) level estimates of the educational attainment of the stock of labor migrants. While the precision and geographical granularity are obvious strengths, the ability to only focus on the stocks mean that the population for the census analysis is not the same as the main analysis. The stock of migrants would not only be affected by land-based new migration (which is the focus of the main analysis), it would also be affected by sea-based migration and return decisions of prior migrants. Any census level

[38] While the variance decomposition analysis suggests that these demographic characteristics explain little of the variation in the presence of country and occupation fixed effects, demographics may nevertheless be important determinants of occupation and country choices, therefore meaningfully impacting the cohort wage distribution.

results would be suggestive of the education attainment of new land-based migrants, but not conclusive. On the other hand, the SOF allows me to identify new migrants and their year of migration. For 2011 to 2016, I can also identify and limit my analysis to new land-based migrants, allowing me to focus on the same population as the main analyses. However, the SOF naturally have much smaller samples compared to the census and only have region level identifiers, which is a larger administrative unit than province and municipality, partitioning the Philippines to 18 regions. This further decreases power and likely biases my estimates downward due to the measurement error introduced by the coarseness of the identifiable geography.

Figure 6: Typhoon Driven Migrants are More Educated



(a) Education of Migrant Stock

(b) Education of New Migrants

Notes: Panel (a): Unit of analysis is municipality-year. Outcome variables are the educational attainment of the stock of migrants from the 100% census (2007, 2010, and 2015). Municipality and year-by-island-group fixed effects are included. Confidence intervals based on standard errors robust to spatial (200 km) and serial (10 year) correlation. Observations are weighted by number of migrants making up each cell. Panel (b): Unit of analysis is region-year. Outcome variables are the educational attainment of the new migrants, constructed from the 2011-2016 SOF. Region and year-by-island-group fixed effects are included. Confidence intervals calculated by wild-cluster bootstrap due to low number of clusters (18). Observations are weighted by number of migrants making up each cell.

I present two analyses that focus on the effects of typhoons on the education levels of (1) municipality level migrant stocks using census data and (2) only land-based new migrants using 2011-2016 SOF data. For the SOF analysis, I calculate standard errors using a wild-cluster bootstrap procedure due to the low number of regions and therefore clusters. Figure 6 presents the results for share of migrants completed high school, some post secondary education, and completing college. Both sets of results points towards a short run increase in the educational attainment of migrants following a typhoon, especially for completing some college and college. At the municipality level, a one SD typhoon exposure increases college completion rate of the stock of migrants by 1.2 percentage points (3.1 % of the mean). Similarly, new land-based migrants from a region are 1.7 percentage points (4.2 % of the mean) more likely to have completely college a year after one SD typhoon exposure.

This finding is consistent with the well established competing forces of high returns to migration versus liquidity constraints in the context of international migration from low income countries (Mckenzie and Rapoport, 2007; Bazzi, 2017). If a typhoon increases the return to migration by decreasing home utility or increasing the marginal value of an additional dollar, but also makes the liquidity constraints more binding for lower wealth households, we would expect to see that share of new migrants with higher wealth/income would increase. As wealth is associated with educational attainment, the marginal migrant in response to a typhoon would have higher educational attainment than the average.

Overall, it is unlikely that the negative selection explains the drop in wages in response to typhoons. Composition effects in terms of age and sex are relatively small and controlling for these characteristics do not make a meaningful difference in the wage effects of typhoons. Further, available evidence suggests migrant cohorts following typhoons have higher educational attainment, which should, all else equal, push migrant wages up. Of course, in the absence of individual panel data, this analysis cannot rule out differences in unobservables that may make typhoon induced migrants have a preference or ability towards lower paying occupations and destination countries.

5.4.3 Can Equilibrium Wage Changes in Destinations Explain the Estimated Wage Drop

An obvious alternative is that destination wages fall due to increased migrant supply from the Philippines. This is an unlikely mechanism for three reasons. First, migration from affected regions of the Philippines is a very small part of the labor force of destination countries. Appendix Table

Second, wages are highly regulated, with much of migration taking place in labor markets with binding effective minimum wages (see Section 2.1). For example, focusing on domestic helpers in the lowest paying quartile of countries, less than 2% of migrants had wages below 1.05 times the Philippines imposed minimum wage of $400. This is indicative that wages in countries that are seeing the highest migration response is generally bounded below.

Finally, the estimating equation includes year-by-island-group fixed effects. Therefore any unlikely decrease in the overall wages of Filipino migrants from an island group in a year are absorbed. Given any possible typhoon driven wage effects would not only be constrained to the Filipinos from typhoon-stricken regions but would affect Filipino new migrant wages more generally, the coefficient of interest would not be capturing these aggregate wage drops. Note that this implies the wage drops estimated from my research design would underestimate the aggregate wage drops if typhoons lead to an unlikely change in equilibrium wages.

Overall, given the points above and that the occupation and destination country composition of migrants explain the majority of the negative wage results, it is unlikely that the negative wage estimates I find are driven by decreases in equilibrium wages in destinations labor markets.

5.5 Response Heterogeneity by Historical Migration

Established migrant networks can help facilitate future migration in variety ways. Previous migrants tend to be important sources of information about migration and possible job availability. For example, the 2015 and 2016 KNOMAD/ILO surveys suggest that about half the Filipino labor migrants in the sample learned about their current overseas job from relatives or friends. In the context of temporary labor migration, more past migration can also indicate more recruitment agency activity in a given area, making it easier for potential migrants to search for and apply for jobs. Overall, migration costs broadly defined tend to decrease in past migration (Munshi, 2003).

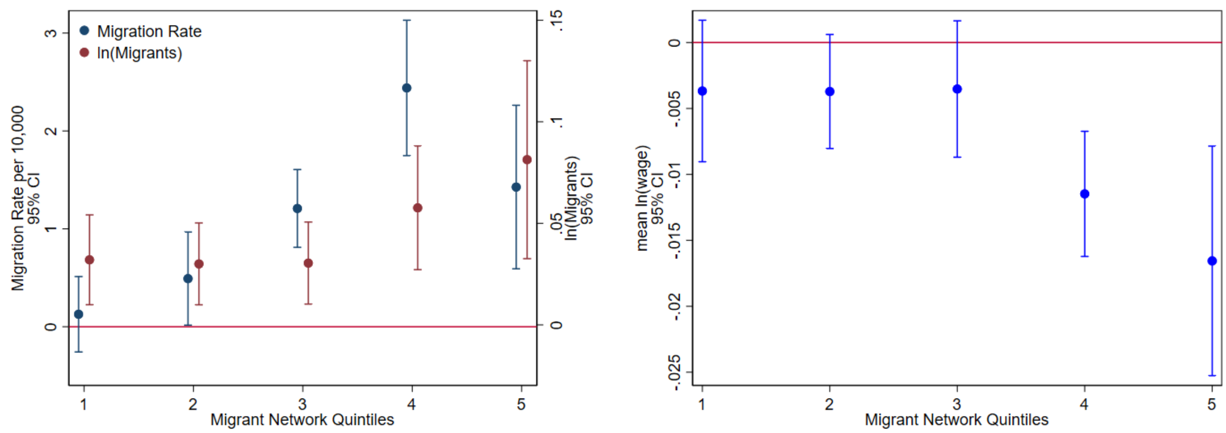
The intensity of past migration can therefore allow for a larger migration response through lower migration costs. However, a bigger existing migrant network can also decrease the incentives to additional migration by allowing for more robust insurance through remittances. Further, how would higher migrant network size mediate the wage effects? Does a bigger network allow for better searching and decrease the need to downgrade occupations and countries? Or does it allow for a bigger migration response, but only at the cost of further decreasing average wages due to aggregate limitations on job availability.

To analyze these questions, I use the baseline period data to create a municipality level network size variable measured as total migrant flows from 1992-1997 per 1995 population. Figure 7 presents migration and migrant wage results for each quintile of network size.[39]

Migration responses (in both levels and logs) are increasing in past migration. This is consistent with the findings of Mahajan and Yang (2020) and Winter, Christoph (2020), though in a context where the specific mechanisms they document (family migration enabled through existing family members) can't be operational. However, the drop in migrant cohort wages are also concentrated in the high baseline network municipalities. Any improved search conditions at home due to past networks does not seem to allow the municipality to increase migration without a proportional drop in wages. This is in contrast with the seminal results of Munshi (2003) who shows bigger migrant network in US destinations lead to better employment and wage outcomes for Mexican migrants.

[39] Appendix Figure A3 shows robustness to an alternative migrant network measure using 1995 census data.

Figure 7: Migration and Wage Response to Typhoons are Increasing in Baseline Migrant Network Size



(a) Migration

(b) Migrant Wages

Notes: Coefficients estimates for the interaction between short run typhoon exposure $T_{m,(t,t-1)}$ and dummies for baseline network size quintiles are plotted. Unit of analysis is municipality-year for both panels. Municipality and year-by-island-group fixed effects are included. Confidence intervals based on province clustered standard errors. Log migrant regression is estimated using PPML in panel (a). Observations are weighted by number of migrants making up each cell in panel (b).

5.6 Remittances Following Typhoons

I conclude this section by focusing on remittances using the Family Income and Expenditure data from 2006 to 2018 (triannually).[40] I estimate the following analogous summary specification at the household level:

$$rem_{hpt} = \alpha + \beta_1 T_{p(t,t-1)} + \beta_2 T_{p(t-2,t-3)} + \delta' \mathbf{x_{hpt}} + \gamma_{rt} + \gamma_p + \epsilon_{ipt} \tag{16}$$

where the outcome is household level for remittance outcome rem_{hpt} of h, in province p, in year t. A possible concern is that the composition of households included in the FIES may respond to Typhoon exposure. While I do not find imbalances in select household level covariates in response to typhoons (see Appendix Table A4) I nevertheless include a vector household controls $\mathbf{x_{hpt}}$ which includes household size and the demographics of the household head such as sex, age, and age squared, and the education level of the household head. Households are weighted by the provided sampling weights.

Table 4 presents household level results on the average effects of typhoons on household remittance receipts, with odd columns not including and even columns including household level controls. Household remittance receipts increase in typhoon exposed provinces. Focus-

[40] Much of temporary international migration is motivated by supporting family members back home, and temporary migrants tend to save and remit more of their foreign earnings (Dustmann and Mestres, 2010).

ing on column 2, a one SD exposure increases per capita remittance receipts by 330 PhPs in the short run, corresponding to 6.4 % of the mean. Column 4 shows that the results are similar when using the cubic root of remittance per capita as the outcome variable to deal with the right skewness of remittance per capita data.[41] Column 6 instead focuses on the extensive margin, with whether a household receives any remittances as the outcome variable. A SD typhoon exposure increases the share of households receiving remittances by 0.8 percentage points (3 % of the mean). The medium run remittance results are positive as well, with magnitudes 70 to 80% of short run results when household controls are included, yet they are imprecisely estimated and statistically insignificant. Using a back of the envelope calculation, I estimate that the aggregate remittance responses to typhoons in my analysis period is about 70% of the damages estimates of the Filipino government, suggesting remittance receipts are substantial in aggregate.[42]

Table 4: Typhoons Increase Remittances

	Abroad Inc Per Cap.		(Abroad Inc Per Cap.)$^{\frac{1}{3}}$		$\mathbf{1}$[Any Abroad Inc.]	
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	329.686**	380.646***	0.247***	0.290***	0.006	0.008**
	(127.538)	(109.670)	(0.092)	(0.084)	(0.004)	(0.003)
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	237.281	252.732*	0.188	0.203	0.007	0.007
	(164.306)	(140.932)	(0.145)	(0.128)	(0.006)	(0.006)
Household Controls	No	Yes	No	Yes	No	Yes
Observations	306,315	306,315	306,315	306,315	306,315	306,315
Clusters	79	79	79	79	79	79
Mean Dep. Var.	5134.808	5134.808	6.004	6.004	0.268	0.268
SD Dep. Var.	15340.428	15340.428	11.285	11.285	0.443	0.443

Notes: Household level regression using 2006, 2009, 2012, 2015, and 2018 FIES data. Unit of observation is a household. Typhoon exposure is at province-year level. All regressions include province and year-by-island-group fixed effects. Observations are weighted by the provided sampling weights. Household controls are household size, gender of HH head, age (and age squared) of HH head, and whether the HH head completed primary school, secondary school, some college, or college. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. *** p<0.01, ** p<0.05, * p<0.10

I now turn to how much of the increase in remittances can be attributed to new migration versus increased remittances from already existing migrant networks. Given FIES data does not provide information on the source of remittances or whether migrants sending remittances are new migrants, I take a back of the envelop calculation approach using the previous migration results. Let total remittances R be equal to to remittance rate r times

[41] Due to high incidence of 0s (74 % of households in the sample report no remittances), I do not show results for log-transformed remittances and use the cubic root transformation instead.

[42] I calculate the aggregate remittance response by taking the estimated coefficients as true causal estimates, and predicting the overall per capita response for each province-year pair using the typhoon exposure measure. I then calculate the aggregate remittance receipts using province populations. Note that the damage estimates by the government likely underestimates the true economic damage of the typhoons significantly, making the 70% figure an over-estimate.

the total foreign earnings w_F. To a first order, percent change in total remittances is the sum of percent change in remittance rate and percent change in total migrant earnings: $d \ln R = d \ln r + d \ln w_F$. Previous results show that, in response to a one SD typhoon exposure, migration rate increases by 4.2% and 4% mean wages fall by 1.1 % and 0.6 % in the short- and the medium-run. This leaves me with an estimate of $d \ln w_F$ 3.1 % and 3.4% in the short- and medium- run.

To facilitate comparison of remittance results with the province level migration results, I first run province level regressions with the log province level remittance receipt per capita as the outcome variable. This specification is different from the household level results in three ways: (1) the outcome in terms of province per capita, as opposed to household per capita, (2) each province is weighted equally, and (3) I do not include household level controls. Results are presented in Appendix Table A5. A one SD typhoon exposure leads to 7.1 % increase in remittance receipts in the short run and 11 % increase in the medium run. These provide estimates for $d \ln R$ in the short and medium run.

The estimates of $d \ln w_F$ and $d \ln R$ imply that about about 44 % of the increase in province level remittances are explained by the increase in new migration in the short-run, and 31 % in the medium run. A significant share of the remittance response therefore seems to be driven by new migration. Policies that would affect migration frictions, especially in wakes of disasters, therefore can have significant effects on the insurance value of migration.

6 Effects of Destination Country Demand During Typhoon Shocks

A constraint in the ability to respond to natural disasters through migration is that supply of jobs available in the Philippines is not perfectly elastic, even though Filipino migrants in typhoon affected regions arguably make up a very small fraction of the labor supply in destination locations. With a constrained supply of jobs, potential migrants need to accept lower paying contracts in response to a drop in home utility. This pattern suggests the ability to respond to shocks through labor migration is mediated by the migrant demand conditions of potential destination countries, which would then change the availability of contracts at home. If a typhoon hits when migrant demand is high and foreign jobs are abundant, the pressure to substitute away from higher paying countries and occupations could be less acute and therefore the drop in the average wages of cohorts would be lower.

6.1 Measurement of Migrant Demand Conditions

To assess the effects of the migrant demand conditions a Filipino province faces in time of typhoons, I create a time variant province-level migrant demand proxy. The proxy follows a shift share structure. It combines information about baseline migrant shares to each destination country (shares) with plausibly-exogenous labor demand conditions at destination countries in the form of lagged GDP level (shifts). Note that my interest is not in the direct effects of the proxy itself. I instead focus on the interaction between the exogenous typhoon shocks and the migrant demand proxy to analyze differential responses to typhoons with regards to concurrent migrant labor demand conditions.

To build the proxy, I first define $\pi^0_{p\to d}$ as the share of baseline period migrants from province p going to destination d. I then focus on the lagged GDP of destination countries $GDP_{d,t-1}$ as a proxy for the migrant demand conditions at the destination country. With these ingredients, the province level proxy is defined as the share weighted average GDP of destination countries:

$$D_{p,t} = \sum_d \pi^0_{p\to d}\, GDP_{d,t-1} \tag{17}$$

The two main requirements for the relevance of the proxy demand measure for migration response is that (1) baseline destination shares are persistent enough to be operational in the analysis period and (2) destination GDP is a meaningful measure of migrant demand conditions in each destination. Failing these requirements would bias any upcoming estimated coefficients towards zero. I assess these requirements next.

Migrants Shares Exhibit Partial but Substantial Persistence

To assess persistence of baseline shares, I simply the baseline migrant shares of each province/municipality-destination to the analysis period migrant shares. The coefficient is 0.8 for province level and 0.7 for municipality level analysis. Further conditioning on destination fixed effects approximately halves these estimates, still retaining precision. I conclude that there is partial but substantial persistence in the migrant shares. Such persistence is consistent with prior evidence showing migration flows are channelled between local areas and destination countries, due to network facilitation of migration and information frictions. (Cortes, 2015; Munshi, 2003; Khanna et al., 2022; Shrestha and Yang, 2019). For example, the 2015/2016 KNOMAD/ILO surveys suggest about how half the migrants learned about their current overseas job from relatives or friends. Similarly, in a 2004 survey, 67 % of Filipino migrants migrating for the first time reports knowing a member of their social network in their destination

Aggregate Migration to a Destination is Increasing in Destination GDP

To assess the relevance of GDP, Appendix Section D.4 presents evidence that total migration from Philippines to a destination country is increasing in the GDP of the destination using panel regressions, confirming the results from McKenzie et al. (2014) for my analysis period. I find that the destination GDP elasticity of migrant flows from Philippines to a destination is ranging from 1.7 to 2.8 across specifications. Beyond availability of contracts, there is a positive relationship between destination GDP and average contract wages, with an elasticity of 0.4 during the analysis period. This increase reflects a change in composition of jobs as opposed to equilibrium wage changes, as GDP shocks increase the share of contracts in higher paying occupations. Indeed, the mean wage response disappears when share of contracts within each occupation quartile is controlled for. The median wage response is much smaller in magnitude and insignificant. An overall shift in the wages of all occupations would have moved the median wages as well, again suggesting that equilibrium contract wages do not meaningfully respond to destination GDP shocks.

I interpret these results as the quantity of jobs available to Filipinos increasing in the destination country's GDP and slackening the migrant labor market. Beyond just the number of available contracts, composition of jobs shift as well, with relatively more contracts for higher paying occupations available.

Bilateral Migration Responses to Typhoons are Larger for Growing Destinations

I further assess whether bilateral migration flows in response to shocks are increasing in GDP using the the following province by destination country by year regression:

$$\begin{aligned} m_{pdt} =& \beta \left(T_{p(t,t-1)} \times \ln GDP_{d(t-1)}\right) + \\ & \delta \left(T_{p(t,t-1)} \times \gamma_d\right) + \gamma_{pt} + \gamma_{dt} + \gamma_{pd} + \epsilon_{pdt} \end{aligned} \tag{18}$$

where m_{pdt} migration flow from province p to destination country d. Due to the very high prevalence of 0s for migrant flows ($\sim$ 75% with all countries included), I deal with right-skewness by additionally presenting results for cubic-root of the migrant flows. $GDP_{d(t-1)}$ is the log GDP level of country d, which I lag to assuage concerns about reverse causality. $T_{p,(t,t-1)}$ is the typhoon exposure as before. The included fixed effects control for the direct effects of all time-invariant province-destination characteristics (such as distance or cultural proximity), time varying province shocks (such as natural disasters), and time varying destination shocks (such as any labor demand shocks or the direct effect of GDP). Finally, I control for the interaction between province typhoon exposure and destination fixed effects. This stringent control ensures that the results are not driven by migration responses differing due to any time-invariant destination characteristic. Without its inclusion a positive β could be explained, for example, by larger migration responses to higher GDP countries overall. Inclusion of this control ensures that identifying variation for β comes from how GDP fluctuates over time within countries, as opposed to comparing across countries.

Table 5: Bilateral Regression Results Between Destination Country

	All Destination Countries			Top 30 Destination Countries		
	Migrants	(Migrants)$^{\frac{1}{2}}$	(Migrants)$^{\frac{1}{3}}$	Migrants	(Migrants)$^{\frac{1}{2}}$	(Migrants)$^{\frac{1}{3}}$
$T_{p[t,t-1]}$ ×GDP$_{d,t-1}$	14.284**	0.366***	0.134**	50.414**	1.000**	0.268**
	(6.452)	(0.135)	(0.062)	(20.972)	(0.389)	(0.118)
Observations	94,721	94,721	94,721	23,700	23,700	23,700
Adjusted R2	0.948	0.968	0.950	0.947	0.968	0.965
Mean Dep. Var.	40.411	1.920	0.926	158.413	6.589	2.848
SD Dep. Var.	386.951	6.060	1.952	761.423	10.724	3.016

Notes: Unit of observation is a province-destination-year. Typhoon exposure is at province-year level. All regressions include province-year, destination-year, and destination-province fixed effects. Province and country (two-way) clustered standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Results are presented in Table 5. I show results for both all the destination countries in the data, and for the top 30 countries which account for 99 % of total migration to reduce noise. Across all columns, coefficient on the interaction of interest is positive and significant, implying that migration responses to typhoons are differentially larger towards countries with high recent GDP growth. The size of the effect ranges from 10 % - 30 % of the mean. Therefore, GDP of destination countries are a relevant determinant of migration responses to typhoons, bolstering the relevance of the migrant demand index. However, these results should not be interpreted as direct evidence of increases in the province level migration response, as migrants may just be reallocating across destinations based on relative abundance of jobs. The main analysis below focuses on the province/municipality level migration responses.

6.2 Empirical Approach

To examine the impact of changing migrant labor demand conditions on short term regional migration responses to typhoons, I estimate the following specification:

$$y_{pt} = \beta_1 \left(T_{p,(t,t-1)} \times \ln D_{p,t}\right) + \beta_2 \ln D_{p,t} + \beta_3 T_{p,(t,t-1)} + \delta X_{pt} + \gamma_p + \gamma_{r(p),t} + \epsilon_{pt} \qquad (19)$$

where y_{pt} is the outcome of interest for province (or municipality) p in year t. As before, $T_{p,(t,t-1)}$ is the typhoon exposure index T of province (or municipality) p in the past two years ,γ_p is province (or municipality) fixed effects that controls for any time-invariant characteristics of the geographic unit of analysis, and $\gamma_{r(p),t}$ is an island-group by year fixed effect that controls flexibly for differential trends in the outcome within Filipino island groups over time. X_{pt} includes additional controls, including past typhoon exposure. Additional variables to be included is discussed in the identification section below. The key coefficient of interest is β_1, which is informative about whether responses to typhoons are differential in migrant demand conditions.

Identification. The identifying variation for the interaction term stems from the year to year variation in $\ln D_{pt}$. The key identifying assumption is the year-to-year variation in destination country GDP levels, i.e. the yearly GDP growth, are as-good-as-random from the perspective of individual Filipino province/municipality migration decisions (Adao et al., 2019; Borusyak et al., 2022). This exogeneity condition is reasonable as destination country GDPs are driven by a myriad of factors independent of province/municipality level Filipino migration such as global economic conditions, local consumer spending and business decisions, and international oil prices for gulf countries. With the Filipino migration from typhoon affected regions constituting a small fraction of destination labor supply and my focus on new contracts, any concerns about reverse causality due to typhoons are highly diminished. To further ensure that any reverse causality between regional Filipino migration and contemporaneous economic activity in destination countries is not driving results, I lag the destination demand index by one year.

While the main effect of the demand index is identified from the year-to-year variation due to the inclusion of province/municipality fixed effects, the interaction term of interest would still pick up variation from the mean differences in the GDP of the destination networks of Filipino regions, which is not assumed to be exogenous (i.e. baseline shares $\pi^0_{p\to d}$ can be endogenous). To deal with this, I create the demeaned index measure $\ln \tilde{D}_{pt} = \ln D_{pt} - \frac{1}{T}\sum_{t'} \ln D_{pt'}$ which demeans the original demand index within each province/municipality, partialing out the mean differences stemming from possibly endogenous baseline shares. Additionally, my setup is analogous to the non-random exposure (baseline migration shares) to exogenous shocks (destination GDP growth) setting described in Borusyak and Hull (2020). Therefore, I follow Borusyak and Hull (2020) and control for the mean counterfactual demand index $\ln \hat{D}_{pt}$ to additionally control for the time-variant nature of average GDP, as GDP levels tend to rise over time (I discuss the construction counterfactual indices in the inference section below). This is a time varying control, so I include both its main effect and its interaction with the typhoon index in the specification.

Exclusion Restriction. My goal is to isolate the effects of migrant demand conditions a region faces on the migration responses to shocks. The relevant "excludability" criteria for is that the baseline migration shares are not correlated with other economic ties between countries and Filipino regions. For example, if the export share or the FDI share of a province-country pair are heavily correlated with migration shares, $\ln D_{pt}$ could presumably effect migration outcomes through possible income effects. Due to a lack of province/municipality level trade or FDI data, I am unable to check for the correlation between the shares directly. Appendix Table A8 reports aggregate statistics on the top export destinations and top sources of FDI for the Philippines for the analysis period. Top 20 export and FDI destinations, accounting for 94 % and 95% of exports and FDI flows, only accounts for 16 % and 25 % of temporary labor migration out of the Philippines in this period. Therefore, the scope for positive income gains through export market expansion or increased FDI seems limited from GDP growth in migration destination countries.[43]

As a more direct test of whether the migrant demand index is changing income independent from migration outcomes, Appendix Table A7 shows results from a household level panel regression of (1) non-remittance income and (2) remittances on the province level demand index $\ln D_{pt}$. At the mean, the domestic demand index increases remittances by about 10 % while it does not have a statistically significant relationship with non-remittance income. This is further evidence that the migrant demand index primarily acts through the channel of migration and not shifting domestic income through other channels such as export market growth or FDI promotion.

Inference. Conventional standard errors in shift-share designs can over-reject due to possibly positive unobserved correlation between regions with similar exposure shares (Adao et al., 2019; Borusyak et al., 2022). The exposure-robust standard error procedure of Borusyak et al. (2022) is not suited to my setting for two reasons. First, I am interested in the coefficient estimated on the interaction between the demand index measure and the typhoon shock, which is not supported by the method. Second, the high concentration of migration in a relatively low number of destination countries violates a key "law of large numbers" assumption for the Borusyak et al. (2022) procedure to be asymptotically valid. Given that my setting can be construed as a non-random exposure to exogenous shock, I turn to the randomization inference procedure introduced by Borusyak and Hull (2020), which remains valid even in the presence of concentrated exposure.

The procedure requires me to generate counterfactual $\ln D_{pt}$ series. Given I assume it is the yearly GDP change of a country that is as good as random, I need to create counterfactual annual GDP growth for each destination country. To construct the counterfactual GDP

[43] Though for imports, the share is up to 82 %, which makes sense as MENA countries are both common destination countries and large exporters of oil. A priori, it is unclear what process would lead to oil imports from these countries to be particularly impactful for Filipino regions sending relatively more migrants to MENA destinations.

growth, within each year, I randomly redraw without replacement destination level GDP growth from the empirical distribution. The procedure is within year to conserve the within-year correlation between country performances that are induced by global shocks such as the 2008 crisis.[44] I then use the counterfactual growth rates to generate country level counterfactual GDP levels using GDP in the year 2000 as the baseline. I finally create counterfactual $\ln \hat{D}_{pt}$ by combining the counterfactual destination GDP levels with baseline shares. I run the estimating equation (19) with the counterfactual $\ln \hat{D}_{pt}$ and check if the estimated $\tilde{\beta}_1$ and $\tilde{\beta}_2$ have larger magnitudes than $\hat{\beta}_1$ and $\hat{\beta}_2$. I repeat this procedure 1000 times and display the fraction of simulations where counterfactual estimates are higher in magnitude than main estimates. For $\hat{\beta}_1$ and $\hat{\beta}_2$, I present these p-values alongside province-clustered and Conley standard errors.

6.3 Main Results

Table presents the results. All the right hand side variables are normalized to have zero mean and unit standard deviation. Columns (3) and (6) present the preferred specification with demeaned province demand index and the mean counterfactual demand index included as a control. There is a clear relationship between migration response to typhoons and migrant demand in destination countries: better demand conditions lead to substantially higher migration response without a correspondingly higher drop in migrant wages. Looking at the more precise municipality level results, a standard deviation increase in the demand index from the mean approximately doubles the short run migration response to typhoon exposure (column 3), while dampening the wage drop by about 35 % (column 6, results are imprecise).

Figure 8a visualizes the migration rate results by using the estimated model to trace out the average short run migration response to a one SD typhoon exposure across 10th to 90th percentile of migrant demand index (with a grid of 5 percentiles). The migration response increases steeply with the migrant demand index, from small and statistically insignificant results below the 35th percentile, to an 8% migration response (at the mean) at the 90th percentile.

Next I turn to the log wage response to typhoons per additional (percent) migration. Figure 8 presents the results for the average log wage, along with other moments of the municipality wage distribution. Results are shown for 35th to 90th percentile of the migrant

[44] In Appendix Section D.6, I relax the assumption that the empirical distribution is the correct distribution, and instead draw log(1 + gdp growth) rates from a normal distribution that matches the empirical distribution's mean and variance. I further show results when the within-year correlation is relaxed and instead I construct the counterfactual growth rates using the full distribution of destination GDP growth in the analysis period, or redrawing the error terms from an AR1 process for GDP growth with country specific intercepts. The coefficients of interest are always significant at 10 % and are significant at 5 % for most cases.

Table 6: Migration Response to Typhoons are Mediated by Demand Conditions

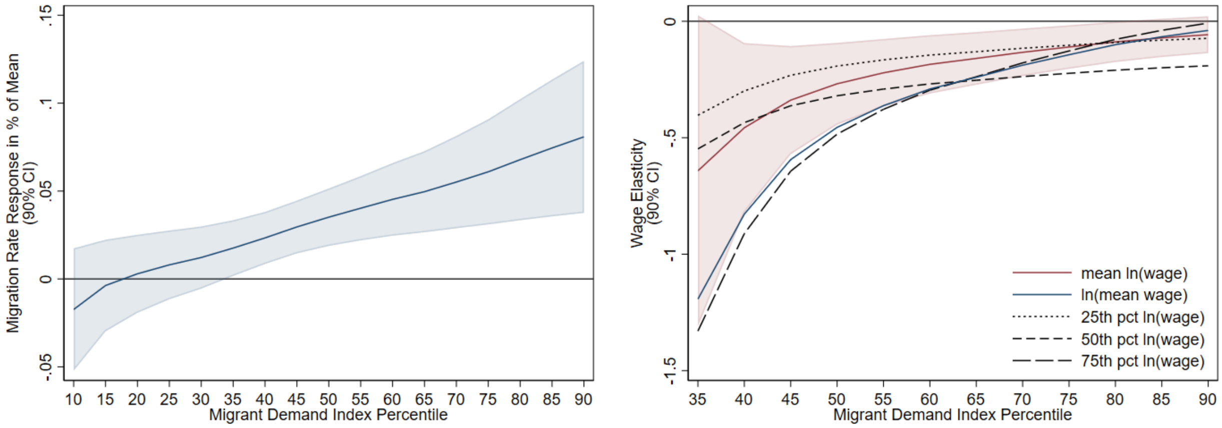
Panel A: Municipality Level (1550 Municipalities)						
	Migration Rate per 10,000			Mean ln(Wage)		
$T_{m,[t,t-1]}$	0.115***	0.120***	0.115***	-0.982***	-0.903***	-0.895***
	(0.033)	(0.034)	(0.033)	(0.249)	(0.214)	(0.203)
	[0.041]	[0.041]	[0.040]	[0.258]	[0.217]	[0.215]
$D_{m,t}$	0.607***	0.222***	0.277***	-0.703	-0.759*	-0.933**
	(0.194)	(0.068)	(0.074)	(0.436)	(0.429)	(0.424)
	[0.066]	[0.065]	[0.068]	[0.432]	[0.435]	[0.417]
	{0.335}	{0.332}	{0.205}	{0.668}	{0.651}	{0.583}
$T_{m,[t,t-1]} \times D_{m,t}$	0.072***	0.130**	0.128**	0.661*	0.430**	0.316
	(0.021)	(0.056)	(0.053)	(0.335)	(0.196)	(0.197)
	[0.032]	[0.066]	[0.063]	[0.416]	[0.183]	[0.194]
	{0.001}	{0.018}	{0.031}	{0.345}	{0.314}	{0.234}
Demeanded D	No	Yes	Yes	No	Yes	Yes
Counterfactual D	No	No	Yes	No	No	Yes
Observations	13,550	13,550	13,550	13,516	13,516	13,516
Mean Dep. Var.	3.682	3.682	3.682	548.514	548.514	548.514
Panel B: Province Level (79 Provinces)						
	Migration Rate per 10,000			Mean ln(Wage)		
$T_{p,[t,t-1]}$	1.055**	1.270**	0.992**	-0.988***	-0.866***	-0.865***
	(0.457)	(0.495)	(0.400)	(0.275)	(0.241)	(0.247)
	[0.495]	[0.529]	[0.442]	[0.275]	[0.236]	[0.237]
$D_{p,t}$	7.242**	3.083**	4.570***	-1.205*	-1.303*	-1.427**
	(3.006)	(1.281)	(1.243)	(0.693)	(0.673)	(0.712)
	[1.209]	[1.206]	[1.198]	[0.606]	[0.606]	[0.590]
	{0.383}	{0.386}	{0.149}	{0.400}	{0.372}	{0.429}
$T_{p,[t,t-1]} \times D_{p,t}$	1.614***	1.432**	1.441*	0.806*	0.536***	0.334
	(0.573)	(0.671)	(0.731)	(0.423)	(0.196)	(0.285)
	[0.744]	[0.753]	[0.790]	[0.465]	[0.171]	[0.266]
	{0.000}	{0.021}	{0.055}	{0.547}	{0.136}	{0.284}
Demeanded D	No	Yes	Yes	No	Yes	Yes
Counterfactual D	No	No	Yes	No	No	Yes
Observations	790	790	790	790	790	790
Mean Dep. Var.	34.300	34.300	34.300	549.296	549.296	549.296

Notes: Unit of observation is municipality-year (Panel A) or province-year (Panel B). All regressions include unit and year-by-island-group fixed effects. Observation numbers for Panel A columns 4-6 are lower due to municipality-years with no migration. Municipalities with no migration in baseline period are dropped from the analysis due to lacking baseline shares. In columns 4-6, observations are weighted by the number of migrants making up each cell. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. Randomization inference p-values in curly brackets. *** p<0.01, ** p<0.05, * p<0.10

demand index, as the small estimated migration response below this point leads to extreme and highly imprecise estimates. Overall, better migrant demand conditions decrease the typhoon induced migration elasticity of wages throughout the distribution of migrant wages from a municipality. Better demand conditions not only increase the migration flow response, they also dampen the per migrant drop in new contract wages.

What explains the decrease in the typhoon induced migration elasticity of wages? To

Figure 8: Migration and Migrant Wage Responses Along Migrant Demand Index



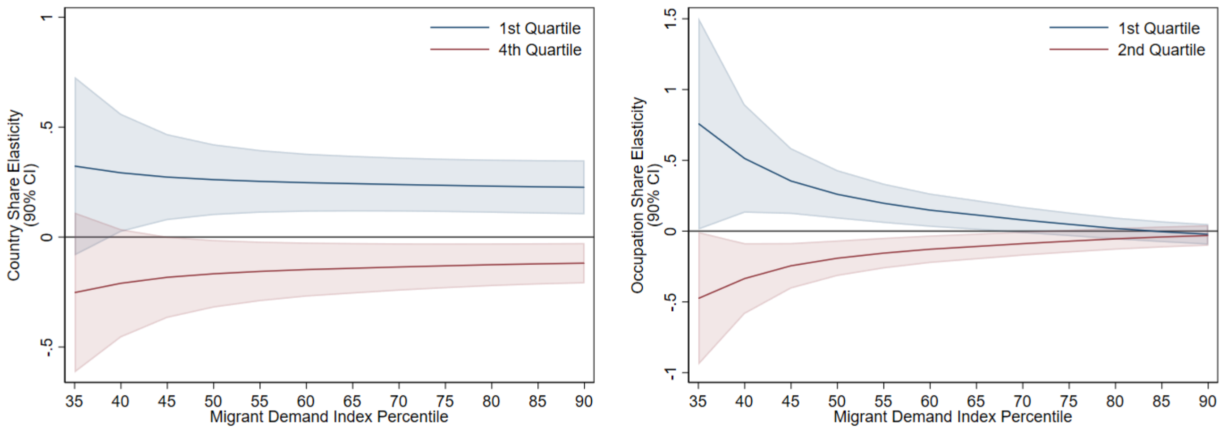
(a) Migration Response

(b) Migration Elasticity of Migrant Wages

Notes: The unit of analysis is municipality-year. Estimation uses demeaned migrant demand index with mean counterfactual demand index controls, corresponding to columns 3 and 6 of Table 6. For panel (a) traces out the migration rate response divided by mean migration rate. Standard errors are clustered at the province level. Panel (b) traces out log mean response divided by the percent migration response to typhoons. Standard errors in (b) are calculated using the delta method using the variance-covariance robust at clustering at province level.

explore this, I show analogous results for share of workers going to lowest paying occupations and countries in response to a typhoon. Figure 9b presents results for share of workers going to the lowest and second lowest quartile of occupations. Results imply that the pressure to downgrade occupations decreases as migrant demand conditions are better. At the median, a 1% increase in migration due to typhoons lead to 25% increase in the share of migrants going to the lowest paying occupations and a 20% percentage point decrease in the share going to second quartile of occupations. Around the 90th percentile, the effects are indistinguishable from zero for both quartile. Recall that Appendix Section D.4 shows that destination country GDP shocks are associated with a higher share of workers going to higher paying occupations, implying an increase in contracts available for such jobs. The current results are consistent with this: higher destination country GDP (i.e. higher migrant demand index for municipalities) increases the number of higher paying occupations available to Filipinos. When this coincides with a typhoon, typhoon induced migrants (who are on average more educated) are better able to secure higher paying occupations, decreasing the pressure to occupationally downgrade, dampening the migrant wage effects of typhoons. In contrast to the occupation results, the share of migrants going to lowest and highest wage countries are essentially flat across the distribution of migrant demand elasticity (Figure 9a). This is likely due to the fact that the migrant demand index is constructed using all destination countries, both high and low paying, therefore, on average keeping, the share of country mix in available jobs roughly constant.

Figure 9: Occupation and Country Quartile Share Response Along the Migrant Demand Index



(a) Country Share Response

(b) Occupation Share Response

Notes: The unit of analysis is municipality-year. Estimation uses demeaned migrant demand index with mean counterfactual demand index controls, corresponding to columns 3 and 6 of Table 6. Panel (a) traces out the country quartile share response divided by the percent migration response to typhoons. Panel (b) traces out the occupation quartile share response divided by the percent migration response to typhoons. Standard errors are calculated using the delta method using the variance-covariance robust at clustering at province level.

Taken together, the ability of Filipino regions to use international labor migration as an ex-post risk coping mechanism is strongly mediated by the international migrant demand conditions they face. Better demand conditions, through increasing the jobs available to Filipinos, leads to a bigger migration response with a lower migration elasticity of wages. Remembering the total annual new migrant wage response can be summarized as $(1 + \epsilon)d \ln mig$, I find that during median demand conditions we get $(1 - 0.27) \times 0.04 = 3\%$, while at 90th percentile demand conditions $(1 - 0.06) \times 0.08 = 7.5\%$. New migrant earnings response to a one SD typhoon shock is about 2.5 times larger in 90th percentile demand conditions as opposed to median.

Placebo Exercise and Robustness. To ensure that I am not merely capturing unobserved trends in migration responses to typhoons, I replicate the above analysis with future values of the migrant demand index on the right hand side. Because GDP levels of destination countries are highly correlated over time, I do this placebo exercise with both $\ln D_{p[t+3]}$ using GDP levels and with an alternative demand index using growth rates. Appendix Figure XXX plots the coefficients on the interaction term of interest, with migration rate as the outcome. Reassuringly, future levels of network gdp has a weaker and statistically insignificant effect on migration responses to typhoons. Further, while the destination gdp growth in the past two years predict a stronger migration response in response to typhoons, future gdp growth (t+1 to t+3) does not.

The analysis period includes the great recession. While this is not an identification concern, if the results are driven purely by the variation induced by the great recession, the external validity of the results in stable global economic conditions may be suspect. Appendix Figure A4 replicates the analysis with years 2009 and 2010 dropped (due to the lagging of the demand index), showing that the results go through as before. Finally, the inclusion of the mean counterfactual demand indices should ensure that the variation driving the results are not the aggregate yearly movements in the migrant demand index. However, I further show robustness to demeaning the migrant demand index both within municipality and within year in Appendix Figure A4 .

6.4 Remittance Results by Migrant Demand

To assess whether the stronger migration in times of high migrant demand translates into a stronger remittance response, I estimate the analogous specification on household level data:

$$rem_{hpt} = \beta_1 \left(T_{p,(t,t-1)} \times \ln D_{p,t}\right) + \beta_2 \ln D_{p,t} + \beta_3 T_{p,(t,t-1)} + \alpha X_{pt} + \delta' \mathbf{x_{hpt}} + \gamma_p + \gamma_{r(p),t} + \epsilon_{ipt} \tag{20}$$

where the outcome variables rem_{hpt} are at household h province p in year t. Household level controls $\mathbf{x_{hpt}}$ are included. I use the province demeaned $\ln D_{p,t}$ and show results with and without the mean counterfactual demand index as a control in the vector X_{pt}. $\ln D_{p,t}$ and the mean counterfactual demand index are standardized to be mean 0 and standard deviation 1.

Table A7 shows remittance response patterns that are parallel to that of migration response. During better migrant demand conditions, remittance response to typhoons are stronger. With the counterfactual demand index controls included , a standard deviation improvement in demand leads to 65% to 70% increase in the short term migration increase following typhoon exposure, and doubles the increase in the likelihood a household receives any remittances. (even columns. Note that RI p-values are either significant or marginally insignificant at 10 %).

6.5 Discussion and Policy Implications

This section provides among the first empirical evidence that the ability to utilize international labor migration as an ex-post coping mechanism is tempered by global migrant demand conditions the origins face at the time. Given the level of economic activity in

Table 7: Remittance Response Heterogeneity by Migrant Demand Index

	Abroad Inc Per Cap.		(Abroad Inc Per Cap.)$^{\frac{1}{3}}$		Any Abroad Inc.	
$T_{p,[t,t-1]}$	339.25***	415.48***	0.28***	0.34***	0.01**	0.01*
	(83.88)	(113.44)	(0.08)	(0.11)	(0.00)	(0.01)
$\ln D_{p,t}$	536.90***	562.13***	0.37**	0.40**	0.01	0.01
	(197.88)	(202.16)	(0.18)	(0.18)	(0.01)	(0.01)
	{0.424}	{0.284}	{0.520}	{0.388}	{0.684}	{0.556}
$T_{p,[t,t-1]} \times \ln D_{p,t}$	385.91***	276.72**	0.33***	0.24*	0.01***	0.01
	(98.13)	(123.91)	(0.09)	(0.12)	(0.00)	(0.01)
	{0.020}	{0.104}	{0.024}	{0.086}	{0.024}	{0.078}
Counterfactual D	No	Yes	No	Yes	No	Yes
Observations	306,315	306,315	306,315	306,315	306,315	306,315
Mean Dep. Var.	5134.81	5134.81	6.00	6.00	0.27	0.27

Notes: Household level regression using 2006, 2009, 2012, 2015, and 2018 FIES data. Unit of observation is a household. Typhoon exposure is at province-year level. All regressions include province and year-by-island-group fixed effects and household controls. Household controls are household size, gender of HH head, age (and age squared) of HH head, and whether the HH head completed primary school, secondary school, some college, or college. Observations are weighted by the provided sampling weights. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. Randomization inference p-values in curly brackets. *** p<0.01, ** p<0.05, * p<0.10

destination countries is not a policy lever for sending countries, what are the implications of these finding for policy?

Broadly, the evidence suggests contemporaneous increase in the availability of migrant contracts following a negative shock can lead to stronger ex-post migration response. Therefore, policies that increase the availability of jobs to affected communities in the wake of shocks can have significant shock-coping benefits. Such policies can take many forms, including the relevant government agencies intensifying efforts to secure of overseas contracts, providing incentives for private recruitment agencies to have more contracts available, reducing the costs of migrating (for example through subsidizing recruitment or processing fees), and increasing access to already available overseas jobs through job fairs. In the wake of the catastrophic 2013 Typhoon Haiyan, there are reports of the Filipino government and recruiting agencies following such policies, including the organization of job-fairs in affected areas that include overseas jobs, the government securing additional overseas contracts, and recruitment agencies waiving recruitment fees. Results are also suggestive that there may be gains from diversifying the "portfolio" of foreign markets available to Filipinos regions, as this would decrease the dependence on any individual destination contract.

These findings are also suggestive of how policies that restrict migration in destination countries can create significant negative externalities in terms of shock-coping for origin countries with strong migration ties. From the perspective of a Filipino province, a drop in availability of foreign contracts would have similar consequences whether it is due to a drop in a prominent destination's economic activity, or because more restrictive policies are enacted in the destination. In the wake of such restrictions, the capacity of a Filipino province to cope with a disaster could be greatly diminished, at least in the short run before additional adjustments can take place. This is particularly relevant given the political debates that are calling for restrictive barriers to migration.(Cinque and Reiners, 2023)

How about the impacts of a more permanent increase in the availability of overseas contracts to Filipinos? It is hard to draw firm conclusions from the current empirical case study, as the analysis is focused on short run responses to changes migrant demand. The effects therefore may partially be driven by increased search activity in the wake of typhoons leading to improved learning about the migrant demand conditions. In the absence of a shock, such shifts in migrant demand could have translated to migration outcomes slower due to information frictions (Porcher, Charly, 2022). In the case of permanent increases to availability of contracts and a long enough time horizon that such information is fully internalized, there would be a shift in the baseline rate of migrants in the economy. This predicts a possibly more robust response from migrants that are already abroad at the time of shock, though whether it would also lead to stronger ex-post migration response is unclear. Of course, persistent increase in access to overseas occupations can have effects on the origin economy beyond just migration levels in the long run, for example as documented in Khanna et al. (2022). Insofar as such increases lead to an increase in wealth available at origin over time, these regions can better invest in mitigation and adaptation technologies beyond just migration.

7 Conclusion

I investigate how temporary international labor migration responds to origin area shocks, and how this response is mediated by the demand conditions facing potential migrants. Focusing on a decade of typhoon shocks in the Philippines and using administrative data on new migrant contracts, I find that a 1 SD typhoon exposure increases out-migration from a region by about 4 % for up to 3 years. However, migrant cohorts following typhoons have lower wages primarily due to going to lower paying occupations and countries, even though supplementary evidence from Censuses and household surveys show such cohorts have higher educational attainment. This suggests that frictions in the international labor markets lead to occupation and country downgrading in response to negative home shocks. Better contemporaneous demand conditions in the wake of shocks strengthens the migration response significantly, and dampens the per additional migrant wage drop.

Given the policy debates surrounding how to facilitate and regulate this increasingly common form of migration, these findings have important policy implications. Results suggest access to such international labor markets can have substantial shock-coping benefits, even in the presence of well documented frictions. Such benefits should be considered in assessing the benefits and costs of promoting international labor migration. Further, destination policies that restrict such migration can impose significant negative externalities on origin countries with strong ties in terms of coping with shocks. These findings gain additional relevance given the extreme-weather events are expected to increase over time due to climate change.

References

Laurent Bossavie and Çağlar Özden. Impacts of Temporary Migration on Development in Origin Countries. *The World Bank Research Observer*, page lkad003, 2023.

Laurent Bossavie, Joseph-Simon Gorlach, Caglar Ozden, and He Wang. *Temporary Migration for Long-Term Investment*. Policy Research Working Papers. The World Bank, July 2021. doi: 10.1596/1813-9450-9740.

United Nations. World Population Policies 2019. 2019.

IPCC. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. 2021.

CRED. Annual Disaster Statistical Review 2017, 2017.

Solomon M. Hsiang and Amir S. Jina. The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones, July 2014.

Samuel Bazzi. Wealth Heterogeneity and the Income Elasticity of Migration. *American Economic Journal: Applied Economics*, 9(2):219–255, April 2017. ISSN 1945-7782. doi: 10.1257/app.20150548.

David McKenzie, Caroline Theoharides, and Dean Yang. Distortions in the International Migrant Labor Market: Evidence from Filipino Migration and Wage Responses to Destination Country Economic Shocks. *American Economic Journal: Applied Economics*, 6 (2):49–75, April 2014. ISSN 1945-7782. doi: 10.1257/app.6.2.49.

Ahmed Mushfiq Mobarak, Iffath Sharif, and Maheshwor Shrestha. Returns to International Migration: Evidence from a Bangladesh-Malaysia Visa Lottery. *American Economic Journal: Applied Economics*, Forthcoming. ISSN 1945-7782. doi: 10.1257/app.20220258.

HwaJung Choi. Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines. *The World Bank Economic Review*, 21(2):219–248, 2007.

Joshua E. Blumenstock, Nathan Eagle, and Marcel Fafchamps. Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters. *Journal of Development Economics*, 120:157–181, May 2016. ISSN 0304-3878. doi: 10.1016/j.jdeveco.2016.01.003.

Dean Yang. Coping with disaster: The impact of hurricanes on international financial flows, 1970-2002. *The BE Journal of Economic Analysis & Policy*, 8(1), 2008a.

Linguère Mously Mbaye and Alassane Drabo. Natural disasters and poverty reduction: Do remittances matter? *CESifo Economic Studies*, 63(4):481–499, 2017.

Alassane Drabo and Linguère Mously Mbaye. Natural disasters, migration and education: An empirical analysis in developing countries. *Environment and Development Economics*, 20(6):767–796, December 2015. ISSN 1355-770X, 1469-4395. doi: 10.1017/S1355770X14000606.

Luca Marchiori, Jean-François Maystadt, and Ingmar Schumacher. The impact of weather anomalies on migration in sub-Saharan Africa. *Journal of Environmental Economics and Management*, 63(3):355–374, 2012. ISSN 0095-0696.

Cristina Cattaneo and Giovanni Peri. The migration response to increasing temperatures. *Journal of Development Economics*, 122:127–146, September 2016. ISSN 0304-3878. doi: 10.1016/j.jdeveco.2016.05.004.

Michel Beine and Christopher R. Parsons. Climatic Factors as Determinants of International Migration: Redux. *CESifo Economic Studies*, 63(4):386–402, 2017. ISSN 1610-241X.

Jasmin Gröschl and Thomas Steinwachs. Do Natural Hazards Cause International Migration? *CESifo Economic Studies*, 63(4):445–480, 2017. ISSN 1610-241X.

Michael Berlemann and Max Friedrich Steinhardt. Climate Change, Natural Disasters, and Migration—a Survey of the Empirical Evidence. *CESifo Economic Studies*, 63(4):353–385, December 2017. ISSN 1610-241X. doi: 10.1093/cesifo/ifx019.

Cristina Cattaneo, Michel Beine, Christiane J. Fröhlich, Dominic Kniveton, Inmaculada Martinez-Zarzoso, Marina Mastrorillo, Katrin Millock, Etienne Piguet, and Benjamin Schraven. Human Migration in the Era of Climate Change. *Review of Environmental Economics and Policy*, 13(2):189–206, July 2019. ISSN 1750-6816. doi: 10.1093/reep/rez008.

Timothy Halliday. Migration, risk, and liquidity constraints in El Salvador. *Economic development and cultural change*, 54(4):893–925, 2006.

Dean Yang. Risk, migration, and rural financial markets: Evidence from earthquakes in El Salvador. *Social Research: An International Quarterly*, 75(3):955–992, 2008b.

Gianna Claudia Giannelli and Eugenia Canessa. After the Flood: Migration and Remittances as Coping Strategies of Rural Bangladeshi Households. *Economic Development and Cultural Change*, 70(3):1159–1195, April 2022. ISSN 0013-0079. doi: 10.1086/713939.

Parag Mahajan and Dean Yang. Taken by Storm: Hurricanes, Migrant Networks, and

US Immigration. *American Economic Journal: Applied Economics*, 12(2):250–277, April 2020. ISSN 1945-7782. doi: 10.1257/app.20180438.

Gordon Hanson and Craig McIntosh. Birth Rates and Border Crossings: Latin American Migration to the US, Canada, Spain and the UK. *Economic Journal*, 122(561):707–726, 2012.

Winter, Christoph. Natural Disasters, Networks, and Migration. 2020.

Andrea Cinque and Lennart Reiners. Confined to Stay: Natural Disasters and Indonesia's Migration Ban. 2023.

André Gröger and Yanos Zylberberg. Internal Labor Migration as a Shock Coping Strategy: Evidence from a Typhoon. *American Economic Journal: Applied Economics*, 8(2):123–153, April 2016. ISSN 1945-7782. doi: 10.1257/app.20140362.

Christian Dustmann, Hyejin Ku, and Tetyana Surovtseva. *Real Exchange Rates and the Earnings of Immigrants*. Centre for Research and Analysis of Migration, Department of Economics . . . , 2021.

Christian Dustmann, Uta Schönberg, and Jan Stuhler. The impact of immigration: Why do studies reach such different results? *Journal of Economic Perspectives*, 30(4):31–56, 2016.

Zvi Eckstein and Yoram Weiss. On the Wage Growth of Immigrants: Israel, 1990–2000. *Journal of the European Economic Association*, 2(4):665–695, 2004. ISSN 1542-4774. doi: 10.1162/1542476041423340.

Toman Barsbai, Andreas Steinmayr, and Christoph Winter. Immigration into a Recession. Technical report, mimeo, 2019.

Barry Chiswick and Timothy Hatton. International Migration and the Integration of Labor Markets. NBER Chapters, National Bureau of Economic Research, Inc, 2003.

André Gröger. Easy come, easy go? Economic shocks, labor migration and the family left behind. *Journal of International Economics*, 128(C), 2021. ISSN 0022-1996.

María Esther Caballero, Brian Cadena, and Brian K. Kovak. The International Transmission of Local Economic Shocks Through Migrant Networks, April 2021.

IOM. Country Migration Report: The Philippines 2013. 2013.

S. Amer Ahmed and Laurent Bossavie. *Toward Safer and More Productive Migration for South Asia*. International Development in Focus. The World Bank, June 2022. ISBN 978-1-4648-1841-7. doi: 10.1596/978-1-4648-1841-7.

A. Nilesh Fernando and Niharika Singh. Regulation by reputation? quality revelation of labor intermediaries in international migration. Technical report, Working Paper, 2021.

World Bank. Indonesia's Global Workers. November 2017. doi: 10.1596/28937.

Caroline Theoharides. Manila to Malaysia, Quezon to Qatar international migration and its effects on origin-country human capital. *Journal of Human Resources*, 53(4):1022–1049, 2018.

Carl N. Morris. Parametric Empirical Bayes Inference: Theory and Applications. *Journal of the American Statistical Association*, 78(381):47–55, 1983. ISSN 0162-1459. doi: 10.2307/2287098.

Dovelyn Rannveig Agunias. Migration's Middlemen: Regulating Recruitment Agencies in the Philippines-United Arab Emirates Corridor. https://www.migrationpolicy.org/research/migrations-middlemen-regulating-recruitment-agencies-philippines-united-arab-emirates, June 2010.

Simon Franklin and Julien Labonne. Economic shocks and labor market flexibility. *Journal of Human Resources*, 54(1):171–199, 2019.

Kerry Emanuel. Global Warming Effects on U.S. Hurricane Damage. *Weather, Climate, and Society*, 3(4):261–268, October 2011. ISSN 1948-8327, 1948-8335. doi: 10.1175/WCAS-D-11-00007.1.

T. G. Conley. GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1):1–45, September 1999. ISSN 0304-4076. doi: 10.1016/S0304-4076(98)00084-0.

Simone Bertoli, Jesús Fernández-Huertas Moraga, and Sekou Keita. The Elasticity of the Migrant Labour Supply: Evidence from Temporary Filipino Migrants. *The Journal of Development Studies*, 53(11):1822–1834, November 2017. ISSN 0022-0388. doi: 10.1080/00220388.2016.1219347.

George J. Borjas. The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market. *The Quarterly Journal of Economics*, 118(4):1335–1374, 2003. ISSN 0033-5533.

Prachi Mishra. Emigration and wages in source countries: Evidence from Mexico. *Journal of Development Economics*, 82(1):180–199, January 2007. ISSN 0304-3878. doi: 10.1016/j.jdeveco.2005.09.002.

Jonathan Roth, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe. What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, 2023.

Liyang Sun and Sarah Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199, December 2021. ISSN 0304-4076. doi: 10.1016/j.jeconom.2020.09.006.

Doruk Cengiz, Arindrajit Dube, Attila Lindner, and Ben Zipperer. The Effect of Minimum Wages on Low-Wage Jobs*. *The Quarterly Journal of Economics*, 134(3):1405–1454, August 2019. ISSN 0033-5533. doi: 10.1093/qje/qjz014.

Brantly Callaway, Andrew Goodman-Bacon, and Pedro HC Sant'Anna. Difference-in-differences with a continuous treatment. *arXiv preprint arXiv:2107.02637*, 2021.

J. M. C. Santos Silva and Silvana Tenreyro. The Log of Gravity. *The Review of Economics and Statistics*, 88(4):641–658, November 2006. ISSN 0034-6535. doi: 10.1162/rest.88.4.641.

David Mckenzie and Hillel Rapoport. Network effects and the dynamics of migration and inequality: Theory and evidence from Mexico. *Journal of Development Economics*, 84(1): 1–24, 2007.

Kaivan Munshi. Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market*. *The Quarterly Journal of Economics*, 118(2):549–599, May 2003. ISSN 0033-5533. doi: 10.1162/003355303321675455.

Christian Dustmann and Josep Mestres. Remittances and temporary migration. *Journal of Development Economics*, 92(1):62–70, 2010. ISSN 0304-3878.

Patricia Cortes. The Feminization of International Migration and its Effects on the Children Left Behind: Evidence from the Philippines. *World Development*, 65(C):62–78, 2015. ISSN 0305-750X.

Gaurav Khanna, Emir Murathanoglu, Caroline B. Theoharides, and Dean Yang. Abundance from abroad: Migrant income and long-run economic development. Technical report, National Bureau of Economic Research, 2022.

Slesh A. Shrestha and Dean Yang. Facilitating worker mobility: A randomized information intervention among migrant workers in Singapore. *Economic Development and Cultural Change*, 68(1):63–91, 2019.

Rodrigo Adao, Michal Kolesár, and Eduardo Morales. Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, 134(4):1949–2010, 2019.

Kirill Borusyak, Peter Hull, and Xavier Jaravel. Quasi-Experimental Shift-Share Research Designs. *The Review of Economic Studies*, 89(1):181–213, January 2022. ISSN 0034-6527. doi: 10.1093/restud/rdab030.

Kirill Borusyak and Peter Hull. Non-random exposure to exogenous shocks: Theory and applications. Technical report, National Bureau of Economic Research, 2020.

Porcher, Charly. Migration with Costly Information, 2022.

Guofeng Cao Eric L. Naizhuo Zhao Samson, Feng Chi Hsu. Improving accuracy of economic estimations with VIIRS DNB image products. In *Remote Sensing of Night-time Light*. Routledge, 2021. ISBN 978-1-00-316924-6.

Sirish Uprety, Changyong Cao, Yalong Gu, Xi Shao, Slawomir Blonski, and Bin Zhang. Calibration Improvements in S-NPP VIIRS DNB Sensor Data Record Using Version 2 Reprocessing. *IEEE Transactions on Geoscience and Remote Sensing*, 57(12):9602–9611, December 2019. ISSN 1558-0644. doi: 10.1109/TGRS.2019.2927942.

Emmanuel Skoufias, Eric Strobl, and Thomas Tveit. Can we rely on VIIRS nightlights to estimate the short-term impacts of natural hazards? Evidence from five South East Asian countries. *Geomatics, Natural Hazards and Risk*, 12(1):381–404, January 2021. ISSN 1947-5705. doi: 10.1080/19475705.2021.1879943.

Simone Bertoli and Jesús Fernández-Huertas Moraga. Multilateral resistance to migration. *Journal of Development Economics*, 102:79–100, May 2013. ISSN 0304-3878. doi: 10.1016/j.jdeveco.2012.12.001.

M. Hashem Pesaran. Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. *Econometrica*, 74(4):967–1012, 2006. ISSN 1468-0262. doi: 10.1111/j.1468-0262.2006.00692.x.

A Appendix Figures and Tables

Table A1: Robustness: Migration Rate

Panel A: Municipality Level (1588 Municipalities)						
	Migrants Per 10,000 Capita					
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	1.110***	1.279***	1.254***	0.977***	1.244***	1.475***
	(0.309)	(0.339)	(0.314)	(0.363)	(0.413)	(0.364)
	[0.351]	[0.391]	[0.394]		[0.413]	[0.413]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	1.409**	1.490***	1.414***	0.888*	1.463***	1.622***
	(0.642)	(0.496)	(0.428)	(0.493)	(0.492)	(0.482)
	[0.529]	[0.429]	[0.428]		[0.433]	[0.433]
Year FE	Yes	No	No	No	No	No
Year-IslandGroup FE	No	Yes	Yes	Yes	Yes	Yes
Base. Char. Trend	No	No	Yes	No	No	No
Lin Muni. Trend	No	No	No	Yes	No	No
Meranti Dropped	No	No	No	No	Yes	Yes
Batanes Dropped	No	No	No	No	No	Yes
Observations	15,970	15,970	15,970	15,970	15,970	15,910
Adjusted R2	0.873	0.877	0.882	0.934	0.877	0.878
Mean Dep. Var.	33.644	33.644	33.644	33.644	33.644	33.688
Panel B: Province Level (79 Provinces)						
	Migrants Per 10,000 Capita					
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	1.307***	1.434***	1.622***	1.330***	0.981	1.895***
	(0.365)	(0.455)	(0.331)	(0.346)	(0.853)	(0.352)
	[0.440]	[0.512]	[0.406]	[0.330]	[0.804]	[0.493]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	1.398**	1.357**	1.618***	0.998**	1.292*	1.847***
	(0.634)	(0.674)	(0.482)	(0.422)	(0.711)	(0.571)
	[0.673]	[0.614]	[0.494]	[0.452]	[0.646]	[0.557]
Year FE	Yes	No	No	No	No	No
Year-IslandGroup FE	No	Yes	Yes	Yes	Yes	Yes
Base. Char. Trend	No	No	Yes	No	No	No
Lin Prov. Trend	No	No	No	Yes	No	No
Meranti Dropped	No	No	No	No	Yes	Yes
Batanes Dropped	No	No	No	No	No	Yes
Observations	790	790	790	790	790	780
Adjusted R2	0.923	0.927	0.938	0.974	0.926	0.931
Mean Dep. Var.	34.300	34.300	34.300	34.300	34.300	34.455

Notes: Unit of observation is municipality-year (Panel A) or province-year (Panel B). All regressions include province/municipality fixed effects. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. *** p<0.01, ** p<0.05, * p<0.10

Table A2: Robustness: Mean Wage

Panel A: Municipality Level (1588 Municipalities)						
	mean ln(wage)					
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	-0.008***	-0.010***	-0.010***	-0.011***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
	[0.002]	[0.002]	[0.002]		[0.002]	[0.002]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	-0.001	-0.005***	-0.006***	-0.007***	-0.005***	-0.005***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.002]	[0.002]	[0.002]		[0.002]	[0.002]
Year FE	Yes	No	No	No	No	No
Year-IslandGroup FE	No	Yes	Yes	Yes	Yes	Yes
Base. Char. Trend	No	No	Yes	No	No	No
Lin Muni. Trend	No	No	No	Yes	No	No
Meranti Dropped	No	No	No	No	Yes	Yes
Batanes Dropped	No	No	No	No	No	Yes
Observations	15,788	15,788	15,788	15,788	15,788	15,731
Adjusted R2	0.902	0.904	0.905	0.926	0.904	0.904
Mean Dep. Var.	5.476	5.476	5.476	5.476	5.476	5.476

Panel B: Province Level (79 Provinces)						
	mean ln(wage)					
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	-0.007***	-0.011***	-0.011***	-0.012***	-0.011***	-0.011***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	-0.002	-0.005***	-0.006***	-0.008***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Year FE	Yes	No	No	No	No	No
Year-IslandGroup FE	No	Yes	Yes	Yes	Yes	Yes
Base. Char. Trend	No	No	Yes	No	No	No
Lin Prov. Trend	No	No	No	Yes	No	No
Meranti Dropped	No	No	No	No	Yes	Yes
Batanes Dropped	No	No	No	No	No	Yes
Observations	790	790	790	790	790	780
Adjusted R2	0.927	0.966	0.968	0.980	0.966	0.966
Mean Dep. Var.	5.493	5.493	5.493	5.493	5.493	5.492

Notes: Unit of observation is municipality-year (Panel A) or province-year (Panel B). All regressions include province/municipality fixed effects. Observation are weighted by number of migrants making up each cell. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. *** p<0.01, ** p<0.05, * p<0.10

Table A3: Full Occupation and Destination Quartile Results

Panel A: Municipality Level (1588 Municipalities)

	Share of Migrants Going To:							
	Country Quartiles				Occupation Quartiles			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	0.014***	-0.000	-0.005*	-0.009***	0.008**	-0.007***	-0.001	0.000
	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
	[0.003]	[0.000]	[0.003]	[0.002]	[0.003]	[0.002]	[0.001]	[0.001]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	0.018***	-0.000	-0.005**	-0.013***	-0.004	-0.001	0.002**	0.002**
	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
	[0.003]	[0.000]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]
Observations	15,785	15,785	15,785	15,785	15,785	15,785	15,785	15,785
Clusters	79	79	79	79	79	79	79	79
Adjusted R2	0.825	0.521	0.772	0.770	0.931	0.881	0.776	0.825
Mean Dep. Var.	0.768	0.016	0.091	0.121	0.673	0.153	0.070	0.102
SD Dep. Var.	0.141	0.025	0.075	0.101	0.166	0.107	0.060	0.077

Panel B: Province Level (79 Provinces)

	Country Quartiles				Occupation Quartiles			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	0.014***	-0.000	-0.005*	-0.009***	0.008**	-0.007***	-0.001	0.000
	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
	[0.004]	[0.000]	[0.003]	[0.002]	[0.003]	[0.002]	[0.001]	[0.001]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	0.019***	-0.000	-0.005**	-0.013***	-0.004*	-0.001	0.002**	0.003**
	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
	[0.004]	[0.001]	[0.002]	[0.003]	[0.003]	[0.002]	[0.001]	[0.001]
Observations	790	790	790	790	790	790	790	790
Clusters FE	79	79	79	79	79	79	79	79
Adjusted R2	0.935	0.854	0.911	0.907	0.978	0.960	0.958	0.921
Mean Dep. Var.	0.772	0.016	0.085	0.122	0.665	0.149	0.071	0.113
SD Dep. Var.	0.114	0.012	0.047	0.076	0.135	0.075	0.033	0.045

Notes: Unit of observation is municipality-year (Panel A) or province-year (Panel B). All regressions include unit and year-by-island-group fixed effects. Observations are weighted by number of migrants making up each cell. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. *** p<0.01, ** p<0.05, * p<0.10

Table A4: Characteristics of Sampled Household in FIES do not Change with Typhoon Exposure

	Household Size	HH Head Characteristics					
		Male	Age	Completed Prim. School	Completed High School	Completed Some College	Completed College
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	-0.016	0.003	-0.073	-0.002	-0.002	-0.005	-0.002
	(0.012)	(0.002)	(0.084)	(0.003)	(0.004)	(0.003)	(0.002)
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	-0.005	0.001	-0.034	0.000	-0.003	-0.001	-0.001
	(0.015)	(0.002)	(0.149)	(0.002)	(0.003)	(0.003)	(0.003)
Observations	306,315	306,315	306,315	306,315	306,315	306,315	306,315
Mean Dep. Var.	5134.808	5134.808	5134.808	5134.808	5134.808	5134.808	5134.808
SD Dep. Var.	15340.428	15340.428	15340.428	15340.428	15340.428	15340.428	15340.428

Notes: Household level regression using 2006, 2009, 2012, 2015, and 2018 FIES data. Unit of observation is a household. Typhoon exposure is at province-year level. All regressions include province and year-by-island-group fixed effects. Observations are weighted by the provided sampling weights. rovince clustered standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table A5: Typhoons Increase Province Level Remittance per Capita

	ln(Remittance per Capita)	
$T_{p,[t,t-1]}$ ($\beta_{ShortRun}$)	0.071	0.054
	(0.036)	(0.031)
	[0.031]	[0.029]
$T_{p,[t-2,t-3]}$ ($\beta_{MediumRun}$)	0.105	0.085
	(0.058)	(0.039)
	[0.032]	[0.037]
Linear Trend Char.	No	Yes
Observations	395	395
Adjusted R2	0.839	0.841

Notes: Province-year level regression using 2006, 2009, 2012, 2015, and 2018 FIES data. All regressions include province and year-by-island-group fixed effects. Province clustered standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table A6: Top Migration Destination Countries (2007-2016)

Destination	Number of Migrants	Percent of Migrants	Percent of Migrants in Destination that are Filipino
Saudi Arabia	1404274	35.3	4.8
United Arab Emirates	542319	13.6	6.5
Qatar	378412	9.5	8.8
Kuwait	337952	8.5	6.3
Taiwan	332949	8.4	NA
Hong Kong	264421	6.7	4.2
Singapore	113154	2.8	.6
Malaysia	74900	1.9	3.4
Bahrain	70490	1.8	6.3
Japan	57167	1.4	10.3
Oman	51640	1.3	1.9
Canada	49552	1.2	7.9
South Korea	38703	1	3.8
Brunei Darussalam	28927	.7	13.1
Papua New Guinea	19169	.5	4.7
Jordan	18474	.5	.1
Italy	18155	.5	2.5
Israel	15409	.4	NA
United States	15194	.4	4.1
Cyprus	14543	.4	3.9
Other	130423	3.3	

Notes: Last column is based on 2015 UN Department of Economic and Social Affairs estimates.

Table A7: Non-Remittance Income is not Increasing in Migrant Demand Index

	Non-Remit Income Per Cap.		Remittance Per Cap.	
$\ln D_{p,t}$	427.962	380.439	586.588***	616.882***
	(551.795)	(560.205)	(212.902)	(219.697)
HH Controls	Yes	Yes	Yes	Yes
Counterfactual D	No	Yes	No	Yes
Observations	306,315	306,315	306,315	306,315
Clusters	79	79	79	79
Mean Dep. Var.	44571.997	44571.997	5134.808	5134.808
SD Dep. Var.	46730.343	46730.343	15340.428	15340.428

Notes: Household level regression using 2006, 2009, 2012, 2015, and 2018 FIES data. Unit of observation is a household. All regressions include province and year-by-island-group fixed effects. Demand index is demeaned within provinces. Observations are weighted by the provided sampling weights. Province clustered standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table A8: Top 20 Export, Import, and FDI Partners for 2007 - 2016

Country	Total export	Percent export	Mig. Share	Country	Total import	Percent import	Mig. Share	Country	Total FDI	Percent FDI	Mig. Share
Japan	94	18.58	1.44	China	74	11.95	.14	Japan	439	24.5	1.44
USA	78	15.38	.38	USA	69	11.12	.38	Netherlands	361	20.18	.01
China	58	11.41	.14	Japan	67	10.88	1.44	USA	272	15.19	.38
Hong Kong	48	9.51	6.65	Singapore	50	8.08	2.85	BVI	125	6.99	0
Singapore	39	7.78	2.85	Taiwan	44	7.07	.1	Korea, Rep.	116	6.47	.97
Netherlands	24	4.78	.01	Korea, Rep.	42	6.77	.97	Singapore	90	5.03	2.85
Korea, Rep.	23	4.58	.97	Thailand	36	5.85	.04	Cayman	57	3.18	.04
Germany	23	4.49	.01	Saudi Arabia	28	4.52	35.32	China	46	2.59	.14
Taiwan	19	3.73	8.37	Malaysia	26	4.23	1.88	Australia	44	2.48	.36
Thailand	18	3.6	.04	Indonesia	26	4.14	.07	UK	30	1.7	.17
Malaysia	14	2.77	1.88	Hong Kong	18	2.85	6.65	Switzerland	23	1.28	.01
Indonesia	6	1.19	.07	Germany	17	2.69	.01	Germany	23	1.28	.01
Vietnam	5	1.04	.06	Vietnam	13	2.08	.06	Taiwan	21	1.15	8.37
UK	5	.9	.17	UAE	11	1.85	13.64	Hong Kong	11	.63	6.65
Australia	5	.9	.36	France	10	1.62	0	Thailand	10	.56	.04
Canada	4	.8	1.25	Australia	9	1.52	.36	India	9	.49	.03
Belgium	4	.79	.01	India	8	1.27	.03	Malaysia	8	.46	1.88
France	4	.72	0	Russia	6	.98	.08	Canada	8	.43	1.25
India	3	.58	.03	Qatar	5	.76	9.52	France	5	.26	0
Mexico	3	.56	.01	New Zealand	4	.68	.22	Denmark	3	.14	0
Others	30	5.92		Others	56	9.08		Others	90	5.03	

Notes: Export and Import data are from COMTRADE. Values in billions \$. FDI data from Philipines Statistical Agency reports. Values in billions of real 2010 Phps. Mig share corresponds to the fraction of all migrants in my data (from 2007-2016) going to the relevant destination (in percent)

Table A9: Robustness: Migrant Demand Index Heterogeneity with Alternative Migration Variables

Panel A: Municipality Level (1550 Municipalities)

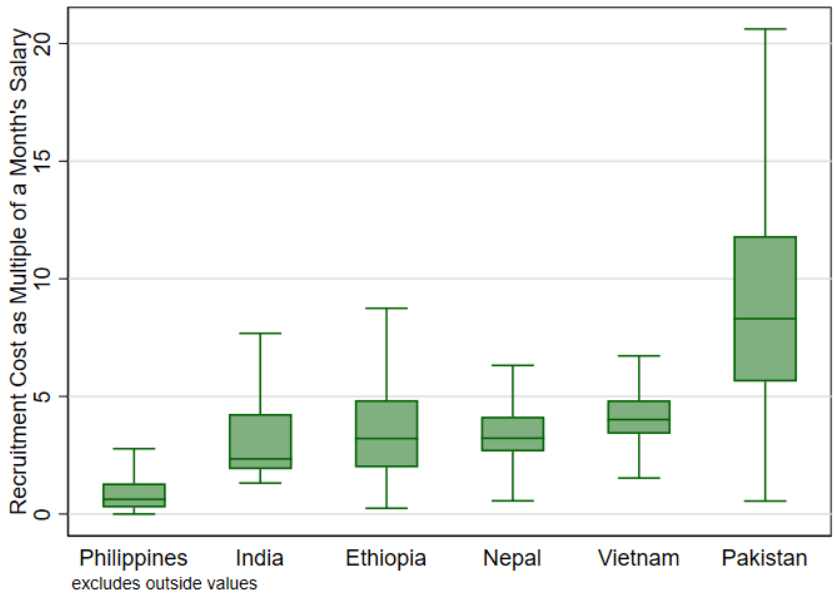
	Migration Rate per 2007 Capita			ln(Migrants)		
$T_{p,[t,t-1]}$	0.977**	1.049**	1.021**	0.029**	0.033***	0.031***
	(0.413)	(0.433)	(0.432)	(0.012)	(0.012)	(0.012)
	[0.436]	[0.455]	[0.456]			
$D_{p,t}$	7.389***	2.727***	3.115***	0.100***	0.093***	0.106***
	(1.825)	(0.617)	(0.692)	(0.029)	(0.027)	(0.026)
	[0.575]	[0.539]	[0.540]			
	{0.24}	{0.216}	{0.140}	{0.194}	{0.229}	{0.229}
$T_{p,[t,t-1]} \times D_{p,t}$	0.991***	1.976***	1.980***	0.028***	0.046***	0.043***
	(0.277)	(0.542)	(0.515)	(0.010)	(0.013)	(0.012)
	[0.341]	[0.678]	[0.658]			
	{0.000}	{0.000}	{0.000}	{0.017}	{0.126}	{0.164}
Demeaned D	No	Yes	Yes	No	Yes	Yes
Counterfactual D	No	No	Yes	No	No	Yes
Observations	13,550	13,550	13,550	13,550	13,550	13,550
Clusters	79	79	79	79	79	79
Mean Dep. Var.	43.063	43.063	43.063	262.064	262.064	262.064

Panel B: Province Level (79 Provinces)

	Migration Rate per 2007 Capita			ln(Migrants)		
$T_{p,[t,t-1]}$	0.944	1.267*	1.054*	0.021**	0.029**	0.023*
	(0.583)	(0.642)	(0.595)	(0.010)	(0.012)	(0.012)
	[0.589]	[0.635]	[0.540]			
$D_{p,t}$	7.522**	3.226**	4.538***	0.135***	0.127***	0.144***
	(3.372)	(1.428)	(1.413)	(0.040)	(0.038)	(0.034)
	[1.360]	[1.336]	[1.318]			
	{0.374}	{0.370}	{0.158}	{0.077}	{0.175}	{0.175}
$T_{p,[t,t-1]} \times D_{p,t}$	2.360***	2.240***	2.570***	0.043**	0.040***	0.033**
	(0.799)	(0.701)	(0.844)	(0.017)	(0.015)	(0.013)
	[0.880]	[0.789]	[0.904]			
	{0.000}	{0.008}	{0.010}	{0.051}	{0.260}	{0.420}
Demeaned D	No	Yes	Yes	No	Yes	Yes
Counterfactual D	No	No	Yes	No	No	Yes
Observations	790	790	790	790	790	790
Clusters	79	79	79	79	79	79
Mean Dep. Var.	40.658	40.658	40.658	4698.152	4698.152	4698.152

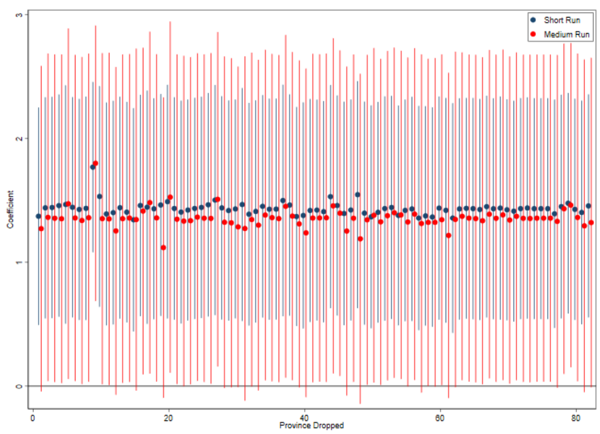
Notes: Unit of observation is municipality-year (Panel A) or province-year (Panel B). All regressions include unit and year-by-island-group fixed effects. Municipalities with no migration in baseline period are dropped from the analysis due to lacking baseline shares. Province clustered standard errors in parenthesis. Standard errors robust to spatial (200 km) and serial (10-year) correlation in square brackets. Randomization inference p-values in curly brackets. *** p<0.01, ** p<0.05, * p<0.10

Figure A1: Total Migration Costs as a Multiple of a Month's Salary, Across Countries

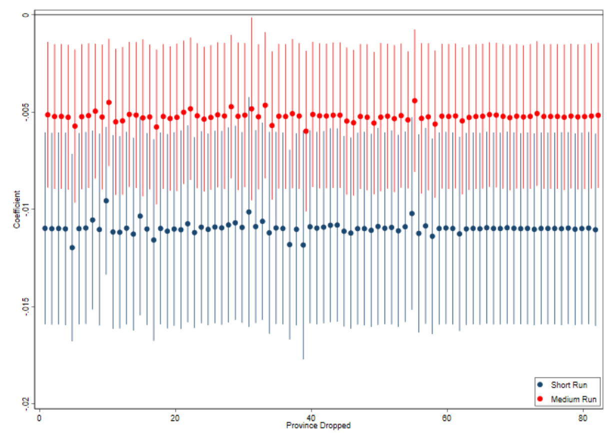


Notes: Box plot summarizing the distribution of total recruitment and migration costs as a multiple of a month's salary. Limited to countries where over 80 % of migration took place through recruitment agencies or manpower agencies. Only includes migrants who applied to their jobs through private recruitment agencies or manpower agencies. Outside values are dropped. Source: KNOMAD/ILO 2015, 2016 Migrant Cost Survey

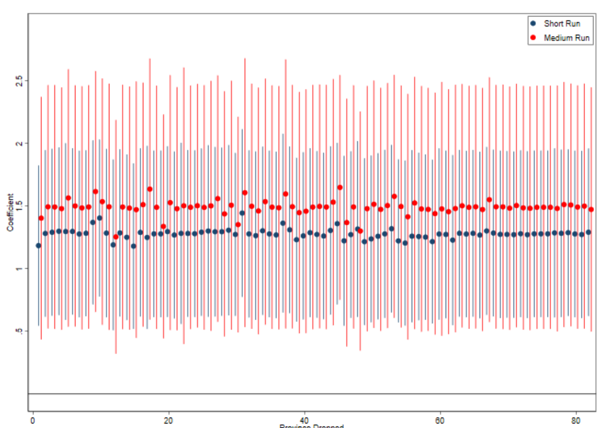
Figure A2: Robustness: Dropping Provinces One-by-One



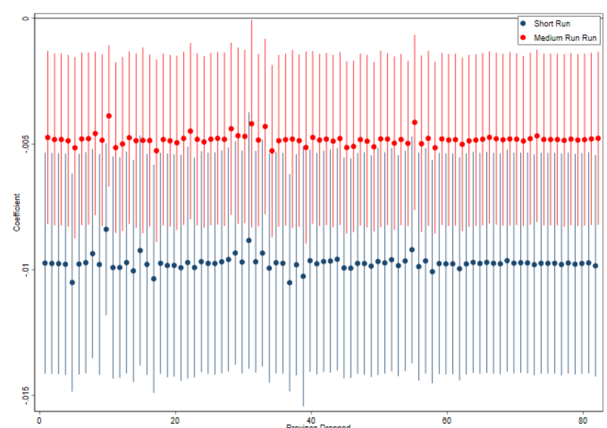
(a) Prov. Level: Migration Rate



(b) Prov. Level: Mean ln(Wage)



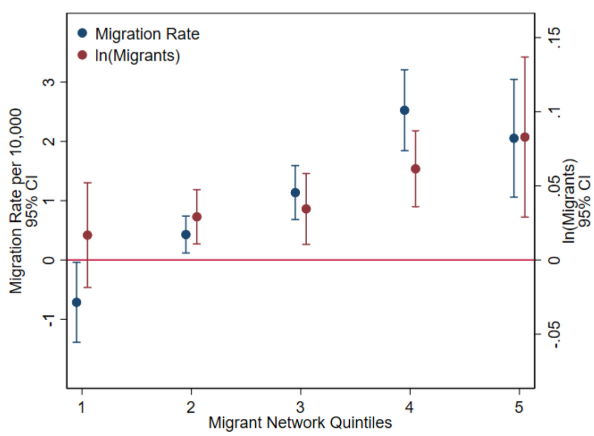
(c) Muni. Level: Migration Rate



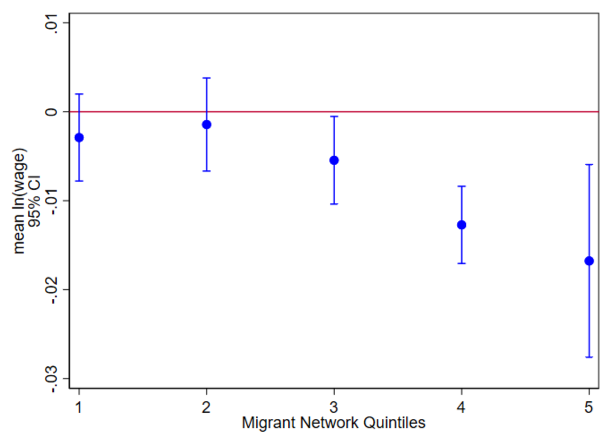
(d) Muni. Level: Mean ln(Wage)

Notes: β_{SR} and β_{MR} from summary specification (13) are plotted. Provinces are dropped one-by-one from the sample. Province number 9 corresponds to Batanes. Confidence intervals based on province clustered standard errors.

Figure A3: Robustness: Baseline Migrant Network Size Results Using Alternative Measurement from 1995 Census



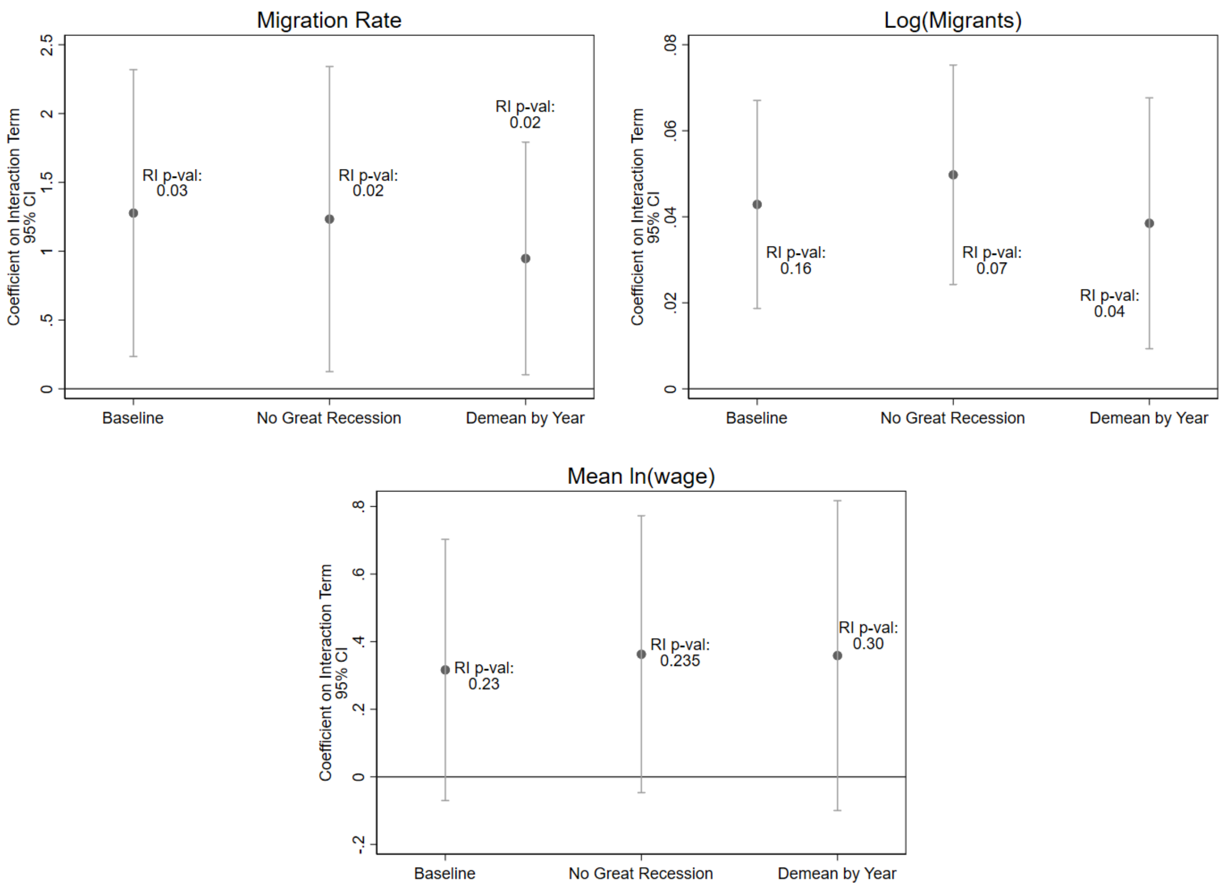
(a) Migration



(b) Migrant Wages

Notes: Coefficients estimates for the interaction between short run typhoon exposure $T_{m,(t,t-1)}$ and dummies for baseline network size quintiles are plotted. Unit of analysis is municipality-year for both panels. Municipality and year-by-island-group fixed effects are included. Confidence intervals based on province clustered standard errors. Log migrant regression is estimated using PPML in panel (a). Observations are weighted by number of migrants making up each cell in panel (b).

Figure A4: Robustness: Migrant Demand Index Heterogeneity (Municipality Level)



Notes: Figures plot the interaction term of interest from estimating equation (19) run at the municipality level. Regressions use the demeaned migrant demand index and includes the mean counterfactual demand index. The left estimates are the baseline estimates from the body, the middle estimates drop the Great Recession years, and the right estimates further demean the migrant demand index by province and year. Confidence intervals based on province clustered standard errors. Randomiztion inference p-values are shown on the figure.

B Data

To BE CONCLUDED

C Model Derivations

TO BE COMPLETED

D Additional Analyses

D.1 Typhoon Index and Contemporaneous Damages

To validate my constructed typhoon exposure index T, I assess the relationship between T and two outcomes: (1) province level tropical cyclone damage and casualty estimates I obtained from the Philippines National Disaster Risk Reduction and Management Council (NDRRMC) for 2003-2020 (excluding 2014) and (2) nightlight data from the Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB) for 2012-2020.

D.1.1 Typhoon Index is Predicts with Damages and Casualties

I start with assessing whether NDRRMC damage and casualty estimates are increasing with province-year level T_{pt}. I aggregate the NDRRMC data at the province-year level. The three outcomes of interest are total number of dead, injured, and missing persons (casualties), total number of affected persons, and the total cost of the damage in real 2010 PhPs. I also run the analysis with the outcomes of interest normalized by the province population.[45] For total number of casualties and affected, I use a ppml specification given the outcome is count data. For damages, I take a cubic root to deal with right skewness of the data. Results are highly robust to other reasonable transformations and empirical models.

Panel A of Table A10 shows results from running a simple bivariate regression between outcome of interest and the standardized typhoon index at the province-year level. The typhoon index is highly correlated with all three outcomes of interest, with an adjusted R^2 of 47%, 19 %, and 34% for casualties, affected people, and damages respectively using the non-normalized outcomes (columns 1- 3). Panel B shows results from a panel regression of the form that includes province and year fixed effects, overall finding a similar strong association between the typhoon exposure index and government damage and casualty estimates.

[45] Province level GDP data to normalize the damages is unfortunately not available.

Table A10: Typhoon Exposure Index Predicts Damage and Casualty Estimates

Panel A: Cross Sectional Regressions

	Raw			Per Prov. Capita		
	Num. Casualties	Num. Affected Persons	(Damages)$^{\frac{1}{3}}$	Num. Casualties	Num. Affected Persons	(Damages)$^{\frac{1}{3}}$
T_{pt}	0.889	0.484	237.138	0.808	0.534	2.929
	(0.106)	(0.027)	(17.633)	(0.055)	(0.033)	(0.174)
Observations	1,343	1,343	1,343	1,343	1,343	1,343
Adjusted R2	0.466	0.189	0.344	0.195	0.218	0.369

Panel B: Panel Regressions (w/ Province and Year FE)

	Raw			Per Prov. Capita		
	Num. Casualties	Num. Affected Persons	(Damages)$^{\frac{1}{3}}$	Num. Casualties	Num. Affected Persons	(Damages)$^{\frac{1}{3}}$
T_{pt}	0.917	0.425	198.955	0.899	0.438	2.377
	(0.093)	(0.048)	(18.664)	(0.087)	(0.038)	(0.191)
Year, Prov FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,258	1,248	1,343	1,258	1,248	1,343
Adjusted R2			0.563			0.557

D.1.2 Typhoon Index Predicts a Decrease in Average Nighttime Light Density

I next turn to nighttime light density. Using a processed version of VIIRS DNB that aims to remove noise, ambient light, and other background factors, I create a quarter-province level average nighttime light intensity measure by averaging the monthly NTL values of pixels falling within the borders of a Filipino province in a given quarter. Two known issues with this data is that cells with low levels of light can have negative values due to airglow contamination or noise (Samson, 2021; Uprety et al., 2019) and some monthly observations are calculated from a very low number of cloud free day observations, potentially leading to higher variance (Skoufias et al., 2021). I replace the negative values with 0s in creating my estimate (following an approach by Skoufias et al. (2021)) and show unweighted results along with results weighted by the number of cloud free days in the province-quarter of interest, giving higher weights to presumably less noisy observations.

I present results from an estimating equation of the form:

$$\ln(lights)_{pt} = \alpha + \beta T_{pt} + \gamma_p + \gamma_t + \epsilon_{pt} \qquad \text{A21}$$

where $\ln(lights)_{pt}$ is the quarterly average nighttime light density for province p and quarter t, T_{pt} is the quarter-province typhoon exposure index (standardized to be mean 0 and standard deviation 1), and γ_p γ_t are province and quarter fixed effects. I additionally show results with a province specific trend to account for secular trends in $\ln(lights)_{pt}$ for each province, and quarter-by-island group fixed effects (consistent with my main empirical specifications) to additionally account for any island-group specific trends or shocks.

Results are presented in Table A11. Across all specifications, I find that a one SD typhoon exposure leads to contemporaneous drop in nighttime lights by 1.7 - 1.9 %, further providing evidence that the typhoon exposure index captures destruction and economic damage caused by typhoons in Filipino provinces.

Table A11: Typhoon Exposure Index Predicts a Drop in Nightlight Intensity

	Dependent Variable: Log(Night Light Intensity)					
T_{pt}	-0.019	-0.019	-0.019	-0.018	-0.018	-0.017
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Prv. Trend	No	Yes	Yes	No	Yes	Yes
Year X Isl. Gr. FE	No	No	Yes	No	No	Yes
CFD Weight	No	No	No	Yes	Yes	Yes
Observations	2,765	2,765	2,765	2,765	2,765	2,765
Adjusted R2	0.921	0.934	0.941	0.931	0.948	0.952

D.2 Stacked Regression with Binary Typhoon Exposure Measure

This section provides event study results for my main outcomes of interest using the stacked regression procedure of Cengiz et al. (2019) on a binary transformed typhoon exposure index. The goal of this analysis is to assess whether the TWFE results in the body of the paper are biased (or leads and lags in the event study graphs contaminated) due to the staggered nature of typhoon exposure and possibly heterogeneous treatment effects across provinces and time.

The analysis is done in bi-quarterly periods. I first create a binary typhoon exposure measure using a cutoff rule, and then, for each bi-quarterly period in the analysis, construct a control group based on whether a province has had a binary typhoon exposure = 1 for 3-years before or after the bi-quarterly period of interest (referred to as a cohort).[46] Choosing the cutoff value for the binary typhoon exposure measure presents a tradeoff. Low cutoffs create a control group that is more likely to have typhoon exposure that is approximately 0, yet given the prevalence of typhoons in this setting, leads to a progressively smaller control groups as many provinces are exposed to typhoons to some degree in the 6 year event windows I construct. Smaller cutoff values also group together provinces with strong typhoon exposure with others that have progressively weaker typhoon exposures, weakening the treatment. On the other hand, high cutoffs lead to bigger control groups, yet increases the likelihood that control provinces have non-negligible typhoon exposure. Higher cutoffs also ensure that the treated cohorts have had strong typhoon exposure. Given this trade-off, I present results using two alternative cutoffs, corresponding to 90th and 50th percentile of the typhoon exposure index (conditional on non-zero exposure).

The estimating equation for the outcome y_{ptc} for province p, in bi-quarterly period t, for treatment cohort c:

$$y_{ptc} = \sum_{\tau=-6,\tau\neq-1}^{\tau=6} \delta_\tau \times 1[T]_{p,c,t-\tau} + \gamma_{p,c} + \gamma_{r(p),t,c} + \epsilon_{ptc} \qquad \text{A22}$$

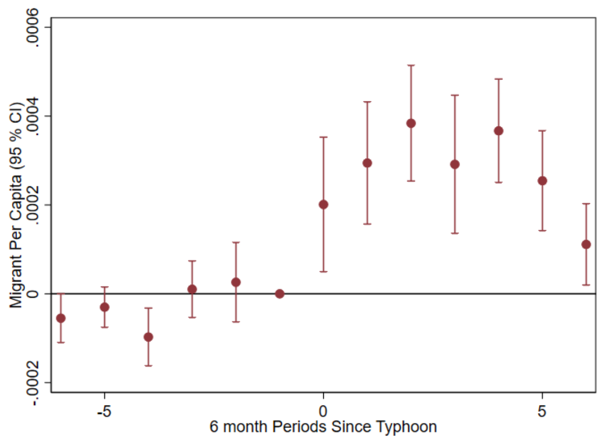
where $1[T]$ is the binary treatment index and included fixed effects are also appropriately at province by treatment cohort and year by island group by treatment cohort level. Standard errors are clustered at the province by cohort level.

Figures A5 , and A6 presents results for the two cutoff values. First focusing on the 90th percentile cutoff, I find reassuring evidence that both the migration and wage responses are generally in line with the results in the body of the paper, without evidence of strong

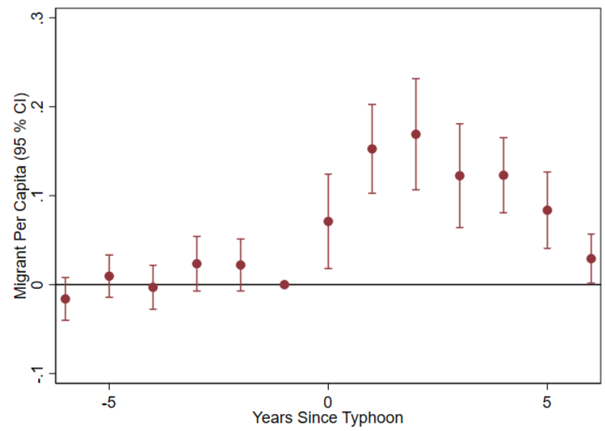
[46] If treatment effects persist beyond three years, yet do not flip signs (i.e. migration response is always positive or wage response is always negative), the coefficients would be biased towards 0.

pre-trends. Given the binary measure corresponds to extreme typhoons, the coefficients are larger than the estimates corresponding to one SD values in the body.[47] On the other hand, using the median cutoff leads to highly noisy results, likely due to the significant drop in the number of control provinces.

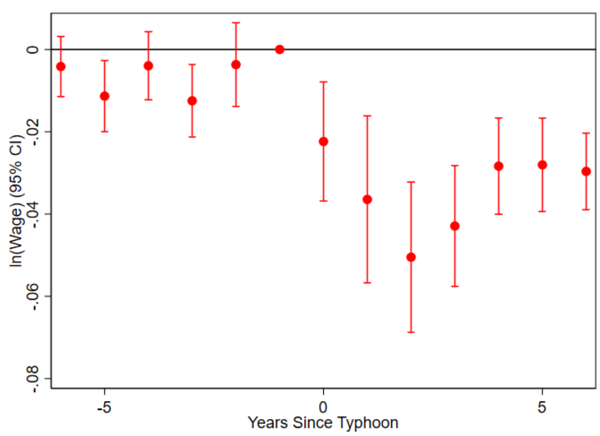
Figure A5: Stacked Regressions Results with 90th Percentile Cutoff of Typhoon Exposure



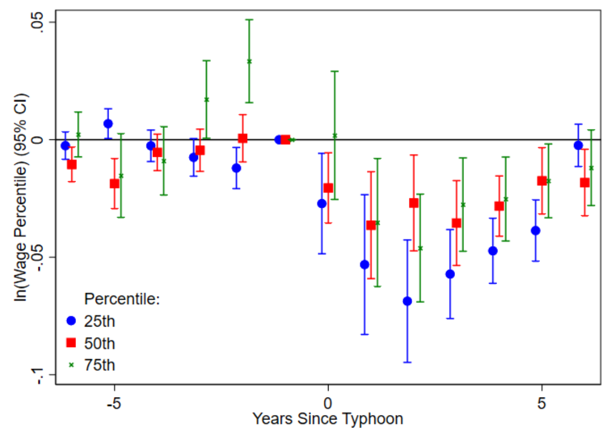
(a) Migrant Per Capita



(b) Log Migration



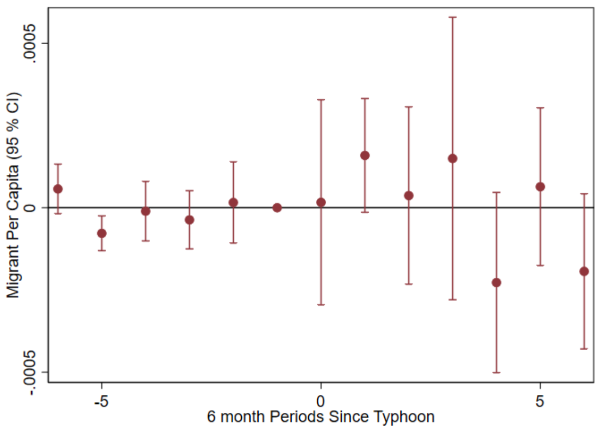
(c) Mean Wage



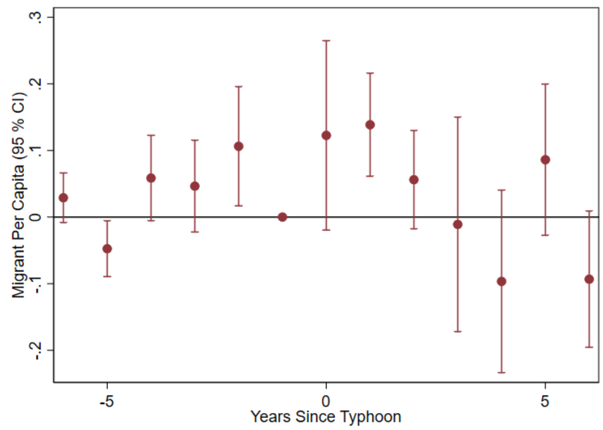
(d) Log Wage Percentiles

[47] Again, given some "control" provinces in this design have also had significant typhoon exposure, these estimates are likely underestimates.

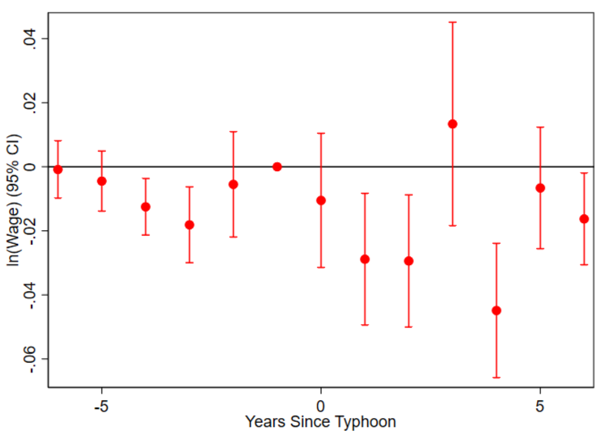
Figure A6: Stacked Regressions Results with Median Cutoff of Typhoon Exposure



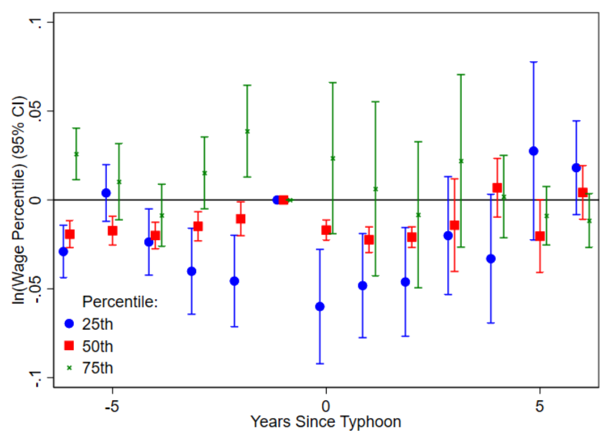
(a) Migrant Per Capita



(b) Log Migration



(c) Mean Wage



(d) Log Wage Percentiles

D.3 Variance Decomposition of Migrant Contract Wages

To document how contract wages vary with migrant characteristics present in the data (age and sex), destination country, and occupation, I estimate the OLS specification of the following to undertake a variance decomposition:

$$\ln w_{idot} = \mathbf{D}_{dt} + \mathbf{O}_{ot} + \mathbf{X}_{it} + \epsilon_{iodt} \quad \text{A23}$$

where w_{idot} denotes contract wages of migrant i, going to destination country d for occupation o, in year t. $\mathbf{D}_dt$ and $\mathbf{O}_dt$ are fixed effects for destination country by year and occupation by year. $\mathbf{X}_it$ is the full set of fixed effects for 5 year age bins interacted with sex by year. I also show results from an analogous decomposition without year interaction. The analysis covers 2007-2016.

Panels A and B of Appendix Table A12 presents the results, with and without the year interactions. Overall, across both specifications, the destination country explains the most of the variance (34 to 37%), followed by the occupation (24 %). The positive covariance term between occupation suggests higher paying occupation pay diferentially more in higher paying countries, though the magnitude of the covariance is small. Conditional on country and occupation, age and sex by themselves explains a negligible portion of the variation (1.3 %). 31 to 34 % of the variation remains unexplained.

Given the substantial fraction of the variance still in the residual, I further check whether undertaking a decomposition of the form in Equation A23 but with destination by occupation by year fixed effects. If the slope of the wage gradient of occupation are substantially different across countries, this approach can account for significantly more of the variation than occupation and destinations individually (though this will partially be captured by the covariance term between variation explained by country and occupations in Panels A and B). Results are presented in Panel C. While occupation-destination cells now explain 69 % of the variation (more than the sum of their parts and the covariance term in Panels B and C), majority of the unexplained variation persists. Some of this residual variation might be driven by the fact that my occupation definition groups together multiple sub-occupations available in the data.

Table A12: Variance Decomposition of Migrant Wages

Panel A

	Share of Variance
Occupation	.2381601
Country	.3424736
Demographics	.013193
Cov(Country - Ocuupation)	.0338566
Cov(Occupation - Demographics)	.0226764
Cov(Country - Demographics)	.0070321
Residual	.3426082

Panel B

	Share of Variance
OccupationXYear	.2413466
CountryXYear	.3739901
DemographicsXYear	.0131872
Cov(Country - Ocuupation)	.030391
Cov(Occupation - Demographics)	.0218857
Cov(Country - Demographics)	.0056281
Residual	.3135712

Panel C

	Share of Variance
OccupationXCountryXYear	.6994294
DemographicsXYear	.0100141
Cov(OccupationXCountryXYear - DemographicsXYear)	.0266728
Residual	.2638836

D.4 Destination GDP and Aggregate Migration from the Philippines

The migrant labor demand condition proxy I describe in Section 6 uses the destination country GDP as the country specific proxy for migrant labor demand. Therefore, it is important to establish destination country GDP is a meaningful proxy for migrant labor demand. This appendix investigates the relationship between aggregate migration from the Philippines and destination country GDP shocks, following a broadly similar approach to McKenzie et al. (2014).

I construct aggregate migration from the Philippines to individual destination countries using the administrative microdata for years 1998 to 2016. I only include countries for which there is a positive migrant flow in every year included in my analysis, which leaves me with 66 destination countries that covers over 99 % of migration out of Philippines in this period.

The estimating equation I primarily employ throughout this is as follows:

$$\ln y_{dt} = \beta_0 + \beta_1 \ln GDP_{d,t-1} + \alpha_d + \alpha_t + \delta_d \times t + \epsilon_{jt} \qquad \text{A24}$$

where y_{dt} is the outcome of interest (migration, wages, or occupation share) to country d in year t, $GDP_{d,t-1}$ is the level of real per capita GDP in country d lagged by one year, α_d and α_t are destination and year fixed effects, and $\delta_d \times t$ is a destination specific trend to account for longer run linear trends.

D.4.1 GDP Shocks and Migrant Flows

Table A13 shows the migration results, with log number of migrants as the outcome variable. Column 1 presents results from equation A24, and shows a 1 % percent increase in destination GDP causes a 1.6% increase in migration to the country. In column 2, I follow Bertoli and Fernández-Huertas Moraga (2013) and Bertoli et al. (2017), who argues that a reduced form estimating model of the kind A24 implicitly restricts all destination countries to be equally substitutable. Their proposed solution is to implement the common correlated effects estimator of Pesaran (2006) which adds a set of auxiliary regressors that allows for countries to have differing substitution patterns. The results from the CCE show a higher elasticity of 2.8 %, consistent with Bertoli et al. (2017). While both point estimates are above unity, their 90% interval contains the unit elasticity of 1.[48]

[48] I do not include destination country linear trends in the CCE estimator as this leads to an issue of more variables than observations due to the additional controls included in this estimator. However, the increase in elasticity estimate between the two models is not driven by the lack of time trends in column 2, as estimating equation A24 without the linear time trends gives an estimate of 1.43, which is very close to the estimate in column 1 of Table A13.

Table A13: Responsiveness of Migrant Flows to Destination GDP

	Log(Migration)	
	OLS	CCE
$GDP_{p,t-1}$	1.587**	2.847**
	(0.688)	(1.204)
Observations	1,249	1,249
Adjusted R2	0.914	0.659

D.4.2 GDP Shocks and Migrant Hiring Wages

Next, I focus on hiring wages of new migrants. I again employ equation A24, with mean $ln(wages)$ and median $ln(wages)$ as outcome variables. Consistent with the body of the paper, I weight each observation by the number of migrants making up each cell.

Starting with mean wages, column 1 of Table A14 shows a positive but marginally insignificant increase in average new migrant wages of about 0.3 % in response to a 1 % GDP shock. In column 3, I replicate this analysis, focusing on the main analysis period (2007 - 2016), finding a 1 % GDP shock leads to a statistically significant increase of 0.4 % in average wages. Column 3 investigate whether the wage responses are driven by composition of occupations by additional controlling for share of occupations in each occupation wage quartile. The results suggest that the increase in wages is primarily due to changing occupation composition, as opposed to a complete shift in the full wage distribution. Columns 4-6 shows results for log median wages. Overall the median wage response is much smaller in magnitude and insignificant. An overall shift in the wages of all occupations would have moved the median wages as well, again suggesting that equilibrium contract wages do not meaningfully respond to destination GDP shocks, consistent with the conclusion of McKenzie et al. (2014).

Finally, I directly check if GDP shocks lead to an increase in higher paying occupations in Table A15. As expected from above results, positive GDP shocks lead to a significant drop in share of contracts for lowest paying occupations and an increase in share for the top 3 quartiles of occupations. This is consistent with the results in the body of that paper, showing that migrant demand index primarily allows more robust migration responses and lower wage drops to typhoons through lowering the pressure to downgrade occupations.

Table A14: Responsiveness of New Migrant Wages to Destination GDP

	ln(mean wage)			ln(median wage)		
$GDP_{p,t-1}$	0.287	0.403***	0.089	0.168	0.095	0.095
	(0.175)	(0.141)	(0.144)	(0.180)	(0.150)	(0.150)
2007 - 2016 Only	No	Yes	Yes	No	Yes	Yes
Occ. Share Control	No	No	Yes	No	No	Yes
Observations	1249	660	660	1249	660	660
Adjusted R2	0.940	0.984	0.989	0.936	0.982	0.982

Table A15: Responsiveness of Migrant Occupation Shares to Destination GDP

	Share of Contracts with Occupation Quartile:			
	1st	2nd	3rd	4th
$GDP_{p,t-1}$	-1.009***	0.516***	0.225***	0.255***
	(0.229)	(0.094)	(0.052)	(0.093)
Observations	660	660	660	660
Adjusted R2	0.954	0.934	0.923	0.899

D.5 Spillover Analysis

TO BE COMPLETED.

I operationalize this idea by first calculating the baseline period share of migrants from each province p going to each destination country d, $\pi^0_{p \to d}$. This provides me with the vector $\pi^{\mathbf{0}}_{\mathbf{p}} = [\pi^0_{p \to 1}, ..., \pi^0_{p \to D}]$, which denotes the baseline destination network of each province. I calculate the pairwise destination network similarity across all provinces using cosine similarity. I then define a typhoon exposure measure for each province-year that is the weighted average of the typhoon exposure of all other provinces weighted by the cosine similarity and the baseline number of migrants from the province.

Table A16: Spillovers: Effects of Exposure As Measured by Baseline Network Similarity

	Migration Rate			Mean ln(salary)		
Exposure	1.035	0.726	0.643	-0.003	-0.003	-0.004
	(0.451)	(0.451)	(0.444)	(0.002)	(0.001)	(0.002)
$T_{p,[t,t-1]}$		1.116	0.991		-0.011	-0.009
		(0.504)	(0.560)		(0.003)	(0.004)
$T_{p,[t-2,t-3]}$		1.219	1.241		-0.005	-0.006
		(0.675)	(0.661)		(0.002)	(0.002)
Inv. Dist. Exposure			0.424			-0.010
			(0.467)			(0.004)
Mig. Sh. Exposure			-0.095			0.002
			(0.168)			(0.001)
Avg. Neighbour Typh.			-0.055			0.005
			(0.404)			(0.003)
Constant	34.300	34.301	34.300	5.529	5.529	5.530
	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)
Observations	790	790	790	790	790	790
Adjusted R2	0.936	0.937	0.937	0.970	0.971	0.972

D.6 Randomization Inference Details

TO BE COMPLETED.