Abundance from Abroad: Migrant Income and Long-Run Economic Development *

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Abstract

When international migrant incomes improve, what are the consequences for *global* income (from international and domestic sources) in migrant-origin economies? Guided by a theoretical model and using novel data, we study long-run equilibrium effects of migrant income shocks on Philippine provinces' global income. Impacts of positive shocks to migrant income magnify over time as education levels rise, migration increases, and migrants enter higher-skilled, higher-wage jobs. Higher migrant income also causes higher domestic income, primarily from household entrepreneurship. Domestic income gains account for 75% of global income gains. Education investments explain, respectively, 42% and 18% of migrant and domestic income gains.

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1 Introduction

How does international migrant income affect long-run economic development in migrants' origin areas? To fully understand how migrant incomes affect development in migrants' home countries, it is important to consider the *global* income of origin-area populations: income from both domestic (origin area) and international migrant sources. Do migrant incomes catalyze economic development back home? Migrant income could loosen liquidity constraints on investments in education and household enterprises, leading to higher domestic incomes. Are home areas able to build on initial migrant income gains by investing in education, so that migration rates rise, and future migration shifts towards higher-skilled overseas work? If so, an initial migrant income shock might have magnified effects on migrant income in the long run. What share of long-run increases in global income due to an initial migrant income shock derives from gains in migrant income versus domestic income in migrants' origin areas?

There are four challenges to answering these questions. First, it is rare to have microdata on international migrant incomes that one can combine with data on domestic income, to study the global income of origin areas. Second, unpacking intermediate mechanisms requires a model of skill upgrading and the location choices of workers. Third, it is hard to find plausibly exogenous variation to causally test the model's predictions on the effects of migrant incomes on origin areas. Finally, there are few contexts in which migrant income is large enough relative to origin-area economies that one might expect to detect aggregate effects of migrant income shocks on origin areas.

In this paper, we exploit an opportunity to address all of these challenges. First, we obtain novel administrative data on migrant income from the Philippine government's migrant worker contract database, allowing us to estimate changes in migrant income in sub-national areas. We combine these data with household survey data to analyze impacts on the global income of migrant-origin areas.[1]

Second, we build on recent theoretical developments in the economic geography

[1]Compared to most analyses in development economics, our focus on the global income of Philippines-located households incorporates incomes of international temporary migrant workers in household income. This moves towards the concept of Clemens and Pritchett (2009)'s "income per natural" (earnings of people *born* in a country, no matter where they reside).

literature with the aim of deriving meaningful relationships between migrant income changes, educational investments, long-run migration decisions and consumption welfare. The framework disciplines our empirical exercise and allows us to decompose the underlying drivers of long-run global income changes in equilibrium.

Third, to isolate causal relationships, we leverage changes in migrant incomes driven by the 1997 Asian Financial Crisis exchange rate shocks. Provinces across the Philippines had varied exposure to these shocks, as prior to the crisis they differed in rates of international migration and had varied overseas destinations (whose exchange rate shocks were heterogeneous).

Finally, in the Philippines migrant income is large enough in aggregate that migrant income shocks could be expected to have detectable impacts in the local economy. In our period of analysis, international migrant income accounted for 13.6% of the global income of Philippine households,[2] and roughly one in four Philippine households received remittances from international migrants. While this makes the Philippines somewhat unusual in a global context, international migrant income is increasingly important for a wide variety of other developing countries, as international migrant worker populations expand. Many developing country governments are emulating the Philippines and seeking to promote international migrant work. For example, Indonesia, India, and Bangladesh have sought to promote international migration of their citizens as part of their national development strategies (Ray et al., 2007; Rajan and Misha, 2007; Asis and Agunias, 2012; World Bank, 2011). Understanding the Philippines' experience is important for helping other countries decide whether to similarly seek to facilitate international labor migration.

We study impacts on global income and its international and domestic income components over roughly a decade after the 1997 migrant income shocks. On the international side, we find positive effects on migrant income that, after a decade, are substantially magnified compared to the size of the initial migrant income shock. The magnification is driven by higher participation and improved performance in the international labor market. The initial shock leads to increases in new departures for overseas jobs, and increases in migration for higher-skilled overseas jobs in particular. We find large increases in average earnings per migrant, reflecting that these

[2] For details of this calculation, please see Appendix Section A.1.1.

higher-skilled jobs have higher wages. These increases in origin-areas' aggregate migrant earnings add up to long-run gains in income that are several times the size of the initial shock to migrant income.

The positive migrant income shocks also have large impacts on household domestic income (income earned in the Philippines). The majority of the increase in domestic income derives from entrepreneurial activities, suggesting increased investment in household enterprises. By contrast, there is no indication that any of the increase in household domestic income derives from higher earnings as wage workers for other employers.

While the initial migrant income shocks lead to increases in both migrant and domestic income, the increase in domestic income amounts to a majority – 75% – of the increase in global household income. This is a new finding in the migration and development literature: while an exogenous increase in migrant earnings opportunities leads to income gains from both domestic and international sources, over the course of a decade the domestic income gains actually come to dwarf the international income gains.

These gains in global income are also reflected in key measures of household economic well-being. The positive migrant income shocks lead to higher household consumption and higher asset ownership in origin areas a decade later.

The magnitude of impacts is nontrivial. A one-standard-deviation shock to a province's migrant income per capita (total annual migrant income divided by population) leads migrant income per capita in the province to be higher by PhP 828 (19% of the mean), and domestic income per capita to be higher by PhP 2509 (7.8% of the mean) a decade later.[3] A shock of this size increases the rate of new departures for international jobs by 39.0% (0.4 std. dev.), the share of high-skilled overseas jobs by 11.6% (0.28 std. dev.), consumption per capita by 0.16 std. dev., and a household asset index by 0.18 std. dev.

Are impacts of this magnitude sensible? Through what mechanisms could these amplified effects be operating? Changes in wage opportunities in different destinations and investments in human capital simultaneously affect where workers work

[3]All monetary amounts are in real 2010 Philippine pesos. The 2010 nominal exchange rate was 45 pesos to the USD. Migrant income is deflated using cost of living adjustments in destination countries. The fraction of income remitted back to the Philippines is converted to real 2010 PhP using nominal exchange rates. The fraction not remitted is converted to real 2010 PhP using purchasing power parity (PPP) exchange rates to account for the cost of living.

and how much they earn in equilibrium. We write down a structural model of location choices and skill investments to quantify mechanisms behind our long run effects. We are particularly interested in how much of the long run gains in income are due to increased educational investments, which affect international income (via future migration and occupation choice), as well as domestic income (by making workers more productive). Isolating the contribution of various mechanisms informs us of the importance of educational investments in migration-led development.

We start with a gravity model of migration (building on Eaton and Kortum (2002), Bryan and Morten (2019), and Hsieh et al. (2019)), and augment it to allow skill heterogeneity and skill investments. Our model is tractable and generates intuitive decompositions of the overall changes in flows and incomes as a function of human capital investments and wages. Workers make educational investments to acquire skill and enter skilled occupations. Such investments are inhibited by liquidity constraints, which may be alleviated by positive migrant income shocks. Given the central role of skill acquisition, we empirically estimate impacts on educational investments. We find large positive effects: a one-standard-deviation migrant income shock increases years of schooling of 7-18 year-olds in the province by 0.1 years (0.17 std. dev.), and of college-age individuals by 0.17 years (0.15 std. dev.).

Our parameter estimates and model can rationalize the magnitudes from our reduced-form analysis. We derive meaningful comparative statics as a function of the migrant income shock, allowing us to translate our estimated reduced-form elasticities into economic parameters. With dyadic (origin-destination) data on migration flows and wages, we estimate the wage elasticity of migration, and dyad-level migration costs. We leverage the shocks and use these well-identified parameters to quantify the importance of different channels in determining long-run impacts, particularly the education channel. In validation tests we show that our model matches changes in incomes across provinces. We find that half (48.5%) of the increase in the international migration rate can be explained by the education channel, reflecting that as higher shares of the population become skilled, migration rates rise because higher-skilled individuals have higher migration rates. When it comes to the increase in migrant income, 42.3% can be attributed to the education channel. Increases in education explain 17.9% of the increase in domestic income.

All told, an exogenous improvement in migrant income in Philippine provinces led to long-run income gains in both the domestic economy and international migrant work. An important share of the global gains (24.4% of the increase in global income) can be attributed to educational investments.

In comparison to related research, our analysis has an unusual combination of features. First, we examine households' global income – international migrant income plus domestic income – and how a migrant income shock affects each of these components. Because of the rarity of migrant income data, there has been little prior research (to our knowledge) on global income in developing countries. Second, we study aggregate outcomes of migrants' origin areas. Prior work tends to focus on impacts on migrants or their origin households, rather than broader equilibrium changes in migrants' origin areas (Yang, 2008; Hanson, 2009; Gibson et al., 2010; Yang, 2011; Mendola, 2012; Clemens et al., 2016; Clemens and Tiongson, 2017; Mobarak et al., 2020).[4] These broader gains in part derive from remittances migrants send to households other than their origin households. In addition, there are gains due to future migration from households that were previously without migrants.[5] Third, we examine impacts over the long run, a decade after the initial shock. This is important, because impacts mediated by investments in education and enterprises should require long-run data to detect.

We also contribute by estimating a structural migration model to provide insights beyond the reduced-form analysis of the natural experiment. We build on prior models (Bryan and Morten, 2019; Burstein et al., 2018; Lagakos et al., 2019; Llull, 2018) by incorporating skill acquisition and its consequences for migration and wages. We use the model to estimate the impact of changes in migrant wages on migration probabilities for individuals of given skill, and estimate how changes in skill levels affect migration. The model helps us rationalize the magnitudes of effects, and quantify the contributions of educational investments in yielding long-run gains. We argue that analyses of migration that ignore the longer-run impacts of induced education

[4]The small number of prior studies on the aggregate impacts of international migration on origin areas include Orrenius et al. (2010), Lopez-Cordoba (2005), Acosta et al. (2008), Dinkelman and Mariotti (2016), Barsbai et al. (2017), Theoharides (2018), and Theoharides (2020). Barham and Boucher (1998) and McKenzie and Rapoport (2010) study impacts on income distribution in migrant home areas. Kinnan et al. (2019) examine impacts of internal migration on origin areas in China. Akram et al. (2017) examine village-level impacts of randomly inducing increases in rural-urban migration in Bangladesh.

[5]Such follow-on migration is often facilitated by prior migrants in the social network (Mahajan and Yang, 2020).

investments may substantially underestimate the overall gains from migrant income.

This paper also contributes to research on the impacts of migration on skill composition at origin. Our findings concord with studies finding that rather than leading to a net loss of skilled individuals from the population (a "brain drain"), international migration increases skill levels by stimulating educational investments (Stark et al., 1997; Mountford, 1997; Batista et al., 2012; Docquier and Rapoport, 2012; Clemens and Tiongson, 2017; Shrestha, 2017; Chand and Clemens, 2019; Khanna and Morales, 2019; Abarcar and Theoharides, 2020). These findings contrast with studies finding reductions in schooling investments in response to migration opportunities (McKenzie and Rapoport, 2011). We add to this literature by emphasizing that resulting increases in education may create a virtuous cycle, leading to more, higher-skilled, and higher-wage future migration.

2 Philippine Migration: Overview

The Philippines was the first country to facilitate large-scale temporary overseas contract migration. Migration from the Philippines is largely temporary and legal, and occurs through licensed, regulated private recruitment agencies. Filipino contract workers overseas are widely referred to as OFWs ("Overseas Filipino Workers"). In recent decades, increasing shares of the Philippine population have migrated, had a household member migrate, or received migrant remittances (Appendix Table A2). The fraction of the population currently overseas rose from 0.7% to 1.6% from 1990 to 2010. Over the same period, the fraction of households with an overseas migrant member rose from 3.2% to 6.3%. Migrant financial support extends well beyond their origin households: the share of households receiving remittances rose from 17.6% in 1991 to 26.0% in 2009.

The Philippines has perhaps the world's most elaborate government bureaucracy regulating international labor migration. The Philippine Overseas Employment Administration (POEA) approves migrant contracts and monitors recruitment by issuing operating licenses to migrant recruitment agencies. Due to concerns about worker abuses and human trafficking, recruitment agencies are typically only allowed to recruit workers in approved office locations. The Overseas Workers Welfare Administration (OWWA) works to ensure the well-being of OFWs and their families. It intercedes (via overseas consular posts) for workers experiencing abuse or contract violations, repatriates workers in conflict zones, assists OFW families in hardship, and facilitates the return and "reintegration" of OFWs to the Philippines.

Filipinos migrate to a wide variety of destinations, and the choice of destination varies substantially across origin areas. Table A1 shows the top twenty destinations for all Filipino migrants prior to the Asian financial crisis. Other than Saudi Arabia and Japan, no destination accounts for more than 10% of migrants. Migrant wages earned in different destinations are heterogeneous. Migrants to Saudi Arabia earn, on average, 306,000 Philippine pesos (Php) per year, while migrants to Japan earn Php 1.5 million. Migration rates are highly heterogeneous across provinces: the mean provincial international migration rate for 25 to 64 year olds is 2.1%, with a range of 0.1% to 7.3%.

3 Theoretical Framework

Our model relates initial migrant income shocks with educational investments and resulting future changes in migration and income. We build on recent gravity models of workers (Bryan and Morten, 2019; Tombe and Zhu, 2019; Tsivanidis, 2018), which adapt Eaton and Kortum (2002) to model migration. We build on prior work by endogenizing skill investments, and allowing for skill-dependent migration and income. The model guides our empirical specification, validates our empirical findings, and quantifies underlying channels.

3.1 Migration Decisions

An individual i's earnings w_{idost} vary across the origin province o, destination country d, skill level s, and time t. They depend on destination specific wage profiles w_{dst}, exchange rates R_{dt}, and destination-specific ability draws q_{id}.[6] ε_{dot} is any unobservable factor that makes migrants from origin o more productive in destination d. Workers lose a percentage of their wages to migration cost $0 \leq \tau_{dot} \leq 1$. Indirect utility from this destination choice is given by:

[6]Earnings w_{idost} are denominated in Philippine pesos (PhP), overseas wages w_{dst} in destination d currency units, and exchange rates R_{dt} in PhP per destination d currency unit.

$$V_{idost} = w_{idost}(1-\tau_{dot}) \equiv w_{dst}R_{dt}(1-\tau_{dot})q_{id}\varepsilon_{dot} \tag{1}$$

Here, $\tau_{oo} = 0$ and $R_{ot} = 1$ for all o. We assume ability is distributed multivariate Frechet with a shape parameter θ, as in Eaton and Kortum (2002).[7] This parameter determines the dispersion of skills across locations.[8]

$$F(q_1, \ldots\ldots, q_D) = exp\left\{-\left[\sum_{d=1}^{D} q_d^{-\theta}\right]\right\} \tag{2}$$

Let π_{dost} be the fraction of people of skill s from origin o who choose to work in d. We derive this share (see Appendix D.1) to be:

$$\pi_{dost} = \frac{(w_{dst}R_{dt}(1-\tau_{dot})\varepsilon_{dot})^{\theta}}{\sum_k (w_{kst}R_{kt}(1-\tau_{kot})\varepsilon_{kot})^{\theta}}, \tag{3}$$

where in the denominator we sum over all destinations k. Taking logs, we derive gravity equations between origin-destination pairs:

$$\log\, \pi_{dost} = \theta \log\, w_{dst} + \theta \log\, R_{dt} + \theta \log\,(1-\tau_{dot}) - \log\, \left[\sum_k (w_{kst}R_{kt}(1-\tau_{kot})\varepsilon_{kot})^{\theta}\right] + \theta\varepsilon_{dot} \tag{4}$$

3.2 Income Shocks and Human Capital Investments

Households choose schooling levels S when young, and how much to borrow b_{io}. They maximize two period utility: $u(c_1) + u(c_2)$. Period 1 consumption depends on wealth Y (including migrant income), the price of schooling p, and borrowing.

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[7] Instead of a trade elasticity, as in Eaton and Kortum (2002), this produces a migration elasticity: the elasticity between the proportion of migrants and the destination wage.

[8] Abilities may be correlated across locations with a correlation coefficient of ρ. For higher ρ, individuals that have higher ability in location d also are more able in d'. We can define $\bar{\theta}$ to measure the dispersion of skill, and θ would be a function of both the dispersion and correlation parameter: $\theta = \frac{\bar{\theta}}{1-\rho}$. The distribution would be: $F(q_1, \ldots\ldots, q_D) = exp\left\{-\left[\sum_{d=1}^{D} q_d^{-\frac{\bar{\theta}}{1-\rho}}\right]^{1-\rho}\right\}$.

Period 2 consumption depends on income and period 1 debt with interest I:

$$\begin{aligned} c_{1io} &= Y_{io} - p_o S_{io} + b_{io} \\ c_{2io} &= w_{idost} - I_o b_{io} \ , \end{aligned} \tag{5}$$

where w_{idost} is the wage after the location choice. In equilibrium, the share of skilled s workers are ℓ_{os} and unskilled u are $\ell_{ou} = (1-\ell_{os})$.[9] income depends on the distribution of worker locations. The short-run income change (due to exchange rate shocks) in the origin o depends on the share of migrants in each destination:

$$\Delta Y_o = \sum_s \left[\ell_{ost} \sum_d \left(\pi_{dost} \overline{w_{dost}} \frac{\Delta R_{dt}}{R_{dt}} \right) \right] , \tag{6}$$

where $\overline{w_{dost}}$ is the average wage in destination d for all workers of skill s from origin o, and $\frac{\Delta R_{dt}}{R_{dt}}$ is the exchange rate shock. Equation (6) motivates our empirical specifications, where we leverage variation in exchange rate shocks.[10]

We may expect that changes in migrant income help drive investments in human capital at home, for instance, by easing liquidity constraints for households. For reasonable assumptions on $u(.)$ and w (for instance, $w_{do}(s)$ linear in s, and Cobb-Douglas $u(c)$), and for credit constrained households $\bar{b} = 0$, schooling responds to shocks to migrant income: $\Delta S_o = \frac{1}{2p} \Delta Y_o$. Let $\Psi \equiv (ed_1 - ed_0)2p$, be the cost of becoming skilled. The change in the share of skilled workers in origin o is:[11]

$$\Delta \ell_{ost} = \frac{1}{\Psi} \Delta Y_o = \frac{1}{\Psi} \sum_s \left[\ell_{ost} \sum_d \left(\pi_{dost} \overline{w_{dost}} \frac{\Delta R_{dt}}{R_{dt}} \right) \right] \tag{7}$$

[9] If the average years of education for skilled workers is ed_1 and for unskilled is ed_0, then the average years of education in an origin o is simply: $S_o = \ell_{os} ed_1 + \ell_{ou} ed_0$.

[10] From Frechet properties, we know $\overline{w_{dost}} = w_{dst} \pi_{dost}^{-\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta(1-\rho)}\right)$, where Γ is the Gamma function.

[11] In Appendix D.2 we derive changes to human capital with liquidity constraints, with no liquidity constraints, or with no borrowing. We are agnostic about whether the education response is due to liquidity constraints or changing returns to education. Some combination of the two is possible, as we discuss in the appendix. Additionally, if period 2 consumption is subjectively discounted, say at rate β, then both the education and skill-share response will be scaled by $\frac{\beta}{1+\beta}$.

3.3 Changes in Migration Flows in Response to the Shock

Migration flows from origin o to destination d depend on the probability of migrating by skill level, and share of workers who are skilled (ℓ_{ost}) and unskilled (ℓ_{out}) :

$$\pi_{dost}\ell_{ost} + \pi_{dout}\ell_{out} \tag{8}$$

Changes in wages both abroad (say, via exchange rates), and at home (say, via more entrepreneurial investment), will determine migration flows. The change in aggregate outflows from an origin o has the following components:[12]

$$\begin{aligned}\Delta\, Flows_{ot} = {} & \underbrace{\Delta\ell_{sot}\sum_{d\neq o}(\pi_{dost}-\pi_{dout})}_{\text{Education channel in outflows}} + \underbrace{\theta\sum_{d\neq o}(\ell_{sot}\pi_{dost}+\ell_{uot}\pi_{dout})\frac{\Delta R_{dt}}{R_{dt}}}_{\text{Exchange rate channel in outflows}} \\ & \underbrace{-\,\theta\left(\ell_{sot}\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}+\ell_{uot}\pi_{oout}\frac{\Delta w_{out}}{w_{out}}\right)}_{\text{Domestic income stemming outflows}} - \underbrace{\chi_o}_{\text{Indirect re-sorting}}\end{aligned} \tag{9}$$

First, skilled and unskilled workers have different migration probabilities. If the skilled are more likely to migrate, then an increase in the fraction skilled will raise migration. If, on the other hand, most migrant jobs are low skilled, then the probability of migrating may fall. How skill changes affect flows are captured by the first term, "Education channel in outflows," a product of two components: the education response $\Delta\ell_{ost}$, and skill-differential in migration probabilities $\pi_{dost}-\pi_{dout}$.

Second, as exchange rates change favorably, there will be a migration response to higher compensation. This depends on the Frechet parameter (the elasticity of migration with respect to destination wages), the shock size $\frac{\Delta R_{dt}}{R_{dt}}$, and migration probabilities $\ell_{ost}\pi_{dost}+\ell_{out}\pi_{dout}$. This is the "Exchange rate channel in outflows."

Finally, firm behavior at home may change local wages. For instance, earnings from abroad may fund investments in firms at home. Increases in domestic income would stem the outflow of migrants, as captured by the last channel.

[12] The derivation is in Appendix D.3. The term $\chi_o \equiv \theta\sum_s \ell_{sot}\left[(1-\pi_{oost})\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)-\pi_{oost}\left(\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)\right]$ captures second-order equilibrium adjustments. We measure and include it in all accounting exercises. Intuitively, changes in wages at home or exchange rates in destinations indirectly affect the choice of specific destinations. For instance, if the US exchange rate changes favorably, it would lead to more outflows, and if the Malaysian exchange rate changes unfavorably, there will be less emigration. Yet, since both sets of exchange rates change simultaneously, a portion of the lower Malaysian emigration is redirected to the increase in US emigration. Equation A46 shows a version with these indirect effects.

We use this set up to quantify the importance of each channel. We need to causally estimate not just the change in education $\Delta\ell_{ost}$ and domestic wages Δw_{ost}, but also the migration elasticity θ, and baseline shares (ℓ and π) which determine how the shock propagates across different origins.

The equations also show that the change in flows is a function of the migrant income shock. This is true, not just for the exchange rate channel, but also for the education channel. For instance, we know from Equation (7) for $\Delta\ell_{ost}$, that the education channel directly depends on the migrant income shock:

$$\frac{1}{\Psi}\underbrace{\left[\sum_s\left[\ell_{ost}\sum_d\left(\pi_{dost}\overline{w_{dost}}\frac{\Delta R_{dt}}{R_{dt}}\right)\right]\right]}_{\Delta Y_o=\text{Migrant income shock}}\left[\underbrace{\sum_{d\neq o}\left(\pi_{dost}-\pi_{dout}\right)}_{\text{Skill bias in outmigration}}\right] \tag{10}$$

3.3.1 Change in Income and Consumption Expenditure

Global income per capita at an origin o is a weighted average of wages by skill s. The weights are the fraction in each skill group ℓ_{ost}, and probability of working in destination d given their skill level π_{dost}:

$$\sum_d \ell_{ost}\overline{w_{dost}}\pi_{dost}+\sum_d \ell_{out}\overline{w_{dout}}\pi_{dout}=\ell_{ost}\left(\sum_d\overline{w_{dost}}\pi_{dost}-\sum_d\overline{w_{dout}}\pi_{dout}\right)+\sum_d\overline{w_{dout}}\pi_{dout} \tag{11}$$

Once again, the change in global income per capita will depend on what happens to three components: (1) changes in human capital, (2) in local wages, and (3) the persistent change in exchange rates, which raises migrant income and encourages flows to favorable destinations. The education channel can be written as:

$$\Delta\ell_{ost}\left(\underbrace{\sum_{d\neq o}\overline{w_{dost}}\pi_{dost}}_{\text{skilled wage abroad}}-\underbrace{\sum_{d\neq o}\overline{w_{dout}}\pi_{dout}}_{\text{unskilled wage abroad}}\right)+\Delta\ell_{ost}\left(\underbrace{\overline{w_{oost}}\pi_{oost}}_{\text{skilled wage at home}}-\underbrace{\overline{w_{oout}}\pi_{oout}}_{\text{unskilled wage at home}}\right) \tag{12}$$

Here, we know $\Delta\ell_{ost}$ is a function of the migrant income shock from Equation

(7). We define $\beta = (\sum_d \overline{w_{dost}}\pi_{dost} - \sum_d \overline{w_{dout}}\pi_{dout})$ as the skill premium. The education channel contribution to the change in income is:

$$\frac{\beta}{\Psi}\underbrace{\left(\sum_s \left[\ell_{ost}\sum_d \left(\pi_{dost}\overline{w_{dost}}\frac{\Delta R_{dt}}{R_{dt}}\right)\right]\right)}_{\Delta Y_o = \text{Migrant Income Shock}} \tag{13}$$

The remaining change in migrant income is driven by persistent changes in the exchange rate. This captures the increase in long run migrant income, not simply due to the fact that better exchange rates directly increase migrant income, but also because they induce a greater flow of migrants (both skilled and unskilled) to places with more positive exchange rate movements. This contribution is:

$$\underbrace{\left(\sum_{d\neq o}\ell_{ost}\overline{w_{dost}}\theta\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Changes in migrant income of unskilled}} + \underbrace{\left(\sum_{d\neq o}\ell_{out}\overline{w_{dout}}\theta\pi_{dout}\frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Changes in migrant income of skilled}} = \theta\underbrace{\left(\sum_s \left[\ell_{ost}\sum_d \left(\pi_{dost}\overline{w_{dost}}\frac{\Delta R_{dt}}{R_{dt}}\right)\right]\right)}_{\Delta Y_o = \text{Migrant Income Shock}} \tag{14}$$

In other words, this is $\theta\Delta Y$. Again, the migration elasticity plays an important role in determining long-run (second-period) income. Similarly, if firms at origins respond to the inflow of money from abroad, there may be changes in domestic income. As such, domestic income may increase, not just because individuals are more skilled, but also because wages (conditional on skill) change. The overall longer term domestic income change is:

$$\Delta W_o = \underbrace{\sum_s \ell_{sot}\pi_{oost}\left(\Delta\overline{w_{oost}}\right)}_{\text{Direct wage channel}} + \underbrace{\Delta\ell_{ost}\left(\underbrace{\overline{w_{oost}}\pi_{oost}}_{\text{skilled wage at home}} - \underbrace{\overline{w_{oout}}\pi_{oout}}_{\text{unskilled wage at home}}\right)}_{\text{Education channel in domestic income}} \tag{15}$$

Here, the domestic "direct wage channel" captures the direct effect of changes in local wages. Even if $\Delta\overline{w_{oost}}$ were to be 0 for each skill group, average domestic income may rise as individuals are more educated and may work in high-paying skilled jobs. Together, the overall change in the global income of individuals is:[13]

$$\left(\frac{\beta}{\Psi}+\theta\right)\Delta Y_o+\Delta W_o-\tilde{\chi}_o \tag{16}$$

There is intuition behind this relationship. First, a higher skill-premium β implies that as individuals acquire schooling, incomes (both domestic and international) rise. Second, a lower cost of education Ψ means that easing liquidity constraints has a larger impact on education. Third, a higher migration elasticity θ means that migration flows, and thereby migrant incomes, are more responsive to favorable exchange rates. Finally, if wages rise locally, then that would have a direct impact on income as well.

In the short run, global income and expenditures increase by the migrant income shock $\Delta c_{1o}=\Delta Y_o$. In the long run, global income and household expenditures, increase by an amount greater than the initial income shock:

$$\Delta\left(c_{1o}+c_{2o}\right)=\Delta Y_o\left(1+\frac{\beta}{\Psi}+\theta\right)+\Delta W_o-\tilde{\chi}_o \tag{17}$$

Overall changes in consumption expenditure reflect changes in welfare. We use these derived lessons from our theoretical framework to discipline our empirical analysis, interpret our reduced form estimates, rationalize the magnitudes, and quantify the contribution of each channel discussed.[14]

4 Data Sources

We summarize data sources here, and provide details in Appendix A.

[13]This is a concept akin to the national product of the local region, as we are measure total economic activity generated by individuals from the region, rather than products produced in the region. Indeed, Clemens and Pritchett (2009) suggest this measure holistically captures the welfare gains to migration. The derivation for global income is in Appendix D.4. As before, the second-order indirect effects of changes in location choice are captured by $\tilde{\chi}_o \equiv \theta\sum_s\sum_d\left[\ell_{sot}\overline{w_{dost}}\pi_{dost}\left(\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)+\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)\right]-\theta\sum_s\left[\ell_{sot}\pi_{oost}\Delta\overline{w_{oost}}\right]$.

[14]A short note on the equilibrium. While simple to introduce, we do not explicitly model production to keep the analysis tractable and self-contained. Changes in production, whether at large firms or household enterprises, will affect domestic wages, changes to which are captured in our framework. Furthermore, this is not a spatial model of bilateral flows, where origins can be destinations and vice versa. With bounded migration costs, and a lack of agglomeration or congestion forces, we expect that labor and output markets clear in equilibrium (Allen et al., 2020).

4.1 Exchange Rate Shock Variables

Two administrative datasets from the Philippine government allow us to calculate the two key province-level variables needed for our analysis: 1) the income-weighted exchange rate shock, and 2) baseline (pre-shock) migrant income per capita. These datasets are from the two agencies with primary charge over OFWs, OWWA and POEA (described in Section 2 above). The first dataset is from OWWA. All Filipinos departing on overseas work contracts are required to obtain OWWA membership prior to departure, and OWWA keeps a detailed membership database that includes the migrant's home address in the Philippines. The second dataset, from POEA, provides data on migrant income. POEA uses these data to verify that contracted wages meet minimum wage requirements. Both the OWWA and POEA data include name, date of birth, destination, and gender, and so we match the two datasets in order to determine the province of origin for all migrants in the POEA database. We combine the POEA/OWWA data with monthly exchange rate data from Bloomberg LP to construct the exchange rate shock.

4.2 Data on Outcomes

We use POEA/OWWA data from 1993, 2007, 2008 and 2009 on migrant contracts. The contract data are less useful in other years because of relatively high rates of missing data on migrant origin address (discussed further in Appendix A). We focus on the numbers of new contracts, contracted annual wages, and job characteristics. The POEA/OWWA data categorize each occupational code into broad occupational groups (professionals, production workers, service workers), and we use these groups when describing the change in the occupational distribution. In the parameterization of migration costs in the structural estimation, we also use information on the locations of recruitment agency activity as recorded by the POEA.

Data on years of schooling come from four rounds of the Philippine Census of Population (1990, 1995, 2000, and 2010). The Census contains data on ownership of a number of durable goods, access to utilities, housing quality, and land and home ownership. We construct an index of household assets by taking the first principal component of these variables (Filmer and Pritchett, 2001).[15]

Data on domestic income and consumption are from the Family Income and Expenditure Survey (FIES), conducted every three years. We use the FIES to calculate annual province-level averages of household domestic income and consumption.

5 Estimation and Empirical Strategy

5.1 Gravity Equation Parameters: Migration Elasticities θ and Migration Costs τ_{do}

Our gravity equation determines migrant flows from o to d. In Equation (4) the unknown parameters are the migration elasticity θ and migration costs τ_{do}.

To estimate the Frechet parameter, θ, we use Equation (4), and leverage exogenous exchange rate shocks. The coefficient on $\log R_{dt}$ identifies θ. We implement this in two different ways by structuring our data at the origin-destination-skill-period level, and then simply at the destination-skill-period level.[16] In the former method we include origin-by-skill fixed effects and two-way cluster our errors at the origin and destination level. In the latter, we include the requisite skill fixed effects and cluster our errors at the destination level. Regression results are in the first two columns of Table A5.

We also estimate θ with another approach, recognizing from the Frechet properties that $E(q_d|d) = \pi_{do}^{-\frac{1}{\theta}}\Gamma$, where $\Gamma = \Gamma\left(1 - \frac{1}{\theta(1-\rho)}\right)$ is the Gamma function. This allows us to derive an income relationship:

$$\log\ \overline{w_{dost}} = \log\ w_{dst}R_{dt} - \frac{1}{\theta}\log\ \pi_{dost} + \log\Gamma + \varepsilon_{dot} \qquad (18)$$

As more workers from o move to d, it lowers the average wage, since the marginal migrant has lower ability than prior migrants. We use income data by origin, destination and skill-level of migrants. We include destination and origin fixed effects, where our main independent variable is the log flow from origin to destination, and

[15] These asset data are only available in the 1990, 2000, and 2010 rounds of the Census. The loadings on the individual variables are obtained from the principal component analysis for the 1990 data, and the resulting loadings are then used to construct an asset index for 2000 and 2010. The principal component loadings can be found in Appendix Table A6.

[16] Each unit of analysis is a unique origin-destination-skill-time. There are two skill groups, and in two periods: 1993 (pre shock), and an average over 2007-09 (post shock). As is often the case with such data, a large fraction of these units (81% here) have no flows, and so we use a Poisson pseudo-maximum likelihood (PPML) estimator.

two-way cluster our errors at the origin-destination pair level. We estimate the models using Poisson pseudo-maximum likelihood (PPML), which assumes that errors are uncorrelated with the exponential of the regressions. To get unbiased estimates, we use instrumental variables, following Bryan and Morten (2019).[17] Estimates of θ using this method are in the latter two columns of Table A5.

Our estimates of θ range between 3 and 3.7 across the different estimation procedures and sources of variation. IV-PPML estimates are not statistically distinguishable from PPML.

In addition to the migration elasticities, we also estimate migration costs. Since the costs help determine the persistence in migration patterns, and thereby persistence in migrant income, but does not directly affect the estimation of our primary parameters, we discuss estimating costs in Appendix B.1. One reason underlying the persistence in migration patterns is the role of recruitment agencies, who enter into contracts with overseas employers to fill specified positions (e.g., nursing positions in Qatar). Agencies source job applicants from particular localities, and specialize in placing workers in particular overseas destinations where they have contacts and past experience. The origins and destinations of workers placed by particular agencies therefore tend to be persistent over time.

As we show in the appendix, the presence of recruitment agencies serving particular corridors strongly predicts origin-destination migration flows, and this empirical relationship is stable over our study period. This helps explain the underlying heterogeneity in origin-destination flows, and the persistence in flows (and thereby migrant income) over time.

5.2 The Migrant Income Shock

As we show in Section 3, we expect migrant income to change in response to exchange rate shocks:

[17] We construct a vector of flows ($\log \pi_{do'st} \forall o' \neq o$), and squared flows ($(\log \pi_{do'st})^2 \forall o' \neq o$) to a destination from all *other* origins (i.e. excluding flows from the origin of interest). We use this vector Π_{dst-o} to predict flows from the origin π_{dost} to the destination. We predict $\widehat{\log \pi_{dost}} = \alpha_1 \log \Pi_{dst-o}$. We then run our 2SLS regression, where the first stage regresses $\log \pi_{dost}$ on $\widehat{\log \pi_{dost}}$, and the second stage implements Equation (18). We do this using IV-PPML with origin, destination and skill fixed effects, and bootstrap our standard errors.

$$\Delta Y_o = \sum_s \left[\ell_{ost} \sum_d \left(\pi_{dost} \overline{w_{dost}} \frac{\Delta R_{dt}}{R_{dt}} \right) \right] \tag{6}$$

We rewrite this relationship to facilitate estimation. Let baseline population in an origin (from the 1995 Census) be Pop_o, and the number of skilled workers L_{os}. Let the number of skilled workers going from o, to destination d be L_{dos}, so that $\ell_{ost} \equiv \frac{L_{ost}}{Pop_o}$, and $\pi_{dost} \equiv \frac{L_{dost}}{L_{ost}}$. We can rewrite Equation (6) :

$$\Delta Y_o = \sum_s \sum_d \frac{L_{ost}}{Pop_o} \frac{L_{dost}}{L_{ost}} \overline{w_{dost}} \frac{\Delta R_{dt}}{R_{dt}} = \frac{1}{Pop_o} \sum_s \sum_d L_{dost} \overline{w_{dost}} \frac{\Delta R_{dt}}{R_{dt}} \tag*{(6)'}$$

And in terms of total migrant income for those from origin o and working in destination d, since $w_{dot} \equiv \sum_s L_{dost} \overline{w_{dost}}$:

$$\Delta Y_o = \underbrace{\frac{\sum_d w_{do}}{Pop_o}}_{MigEarn_o} \times \underbrace{\frac{\sum_d w_{do} \frac{\Delta R_{dt}}{R_{dt}}}{\sum_d w_{do}}}_{Rshock_o} \tag{19}$$

We take this specification directly to the data, defining each of the components in the product above in detail. Our causal variable of interest is the province-level shock to migrant income per capita. This variable is the product of two dimensions of heterogeneity across provinces: baseline (pre-shock) migrant income per capita $MigEarn_{o0}$, and the income-weighted exchange rate shock $Rshock_o$.

5.2.1 Income-weighted exchange rate shock

Because Filipino provinces differ in the destinations of their international migrants (and their corresponding income), there was substantial heterogeneity in the income-weighted exchange rate shocks experienced by different provinces following the Asian financial crisis. The crisis was unexpected (Radelet and Sachs, 1998), and so migrants and their home areas should have been surprised by the shock. The crisis led to the devaluation of numerous currencies throughout Southeast and East Asia, including the Philippines'. As a result, the exchange rate vis-a-vis the Philippine peso changed dramatically in many of the key destinations of Filipino migrants.

An appreciation of the exchange rate in a given destination provides a positive income shock to Filipino migrants working there; each unit of foreign currency earned abroad would be convertible to more Philippine pesos.

For each destination d, we measure the change in exchange rates between the twelve months preceding July 1997 and twelve months preceding October 1998:

$$\frac{\Delta R_d}{R_d} = \frac{\text{Average country } d \text{ exchange rate from Oct. 1997 to Sep. 1998}}{\text{Average country } d \text{ exchange rate from Jul. 1996 to Jun. 1997}} - 1 \tag{20}$$

Exchange rate changes for the 20 largest destinations of Filipino migrants immediately prior to the 1997 Asian Financial Crisis are presented in Table A1. Migrants in Saudi Arabia, Hong Kong, and the United Arab Emirates experienced positive exchange rate shocks of approximately 50%. Migrants in Malaysia and South Korea actually experienced slightly negative shocks.

We then calculate the average exchange rate shock for a Philippine province, taking into account a province's baseline share of migrant income across overseas destinations. Let w_{do} be the total annual income of migrants from province o who are in country d prior to the Asian financial crisis. The weighted-average exchange rate shock for each province o is the second term in Equation (19):

$$Rshock_o = \frac{\sum_d w_{do} \frac{\Delta R_d}{R_d}}{\sum_d w_{do}} \tag{21}$$

In other words, the exchange rate shock for a province is the weighted average exchange rate change across those countries, with each country's exchange rate weighted by the fraction of a province's migrant income in that country. Table 1 shows that this variable has a mean of 0.410 and a standard deviation of 0.045.

5.2.2 Baseline migrant income per capita

We estimate average income per migrant in the province using pre-shock contract data, then multiply it by the number of migrants in each province from the 1995 Census, obtaining total migrant income for each province. We divide total migrant income by the province's population to obtain a province's pre-shock migrant income per capita; the first term of Equation (19):

$$MigInc_o = \frac{\sum_d w_{do}}{Pop_o} \tag{22}$$

Table 1 shows summary statistics for $MigInc_o$. The average is Php 4,325, and the standard deviation is Php 3,360.

5.2.3 The shock to migrant income per capita

Our causal variable of interest is the province's shock to migrant income per capita: the product of the income-weighted exchange rate shock and baseline (pre-shock) migrant income per capita. We construct this from demeaned component variables ($Rshock_o$ and $MigInc_o$). It has a mean of -0.014 (std. dev. 0.129).

Figure A1 displays the spatial distribution of the residual shock to migrant income per capita across Philippine provinces (after partialling out baseline migrant income per capita and the income-weighted exchange rate shock). The shock appears to be evenly distributed across the country. All regions contain provinces with a range of different shock values.[18]

5.2.4 Persistence of exchange rate shocks and migration patterns

There is temporal persistence in both the exchange rate shock and overseas migration patterns, leading to persistence of the shock to province-level migrant income per capita. Appendix Figure A2 shows the exchange rates for the top ten destinations. The Asian financial crisis is denoted by the dashed line in 1997, after which there is substantial dispersion of the exchange rates. The exchange rate shock is persistent through the year 2010, as can also be seen Table A1 (columns 4 and 5).

In Appendix B.2, we formally test persistence of exchange rate shocks and overseas migrant destinations across provinces, and find strong evidence of both types of persistence. The immediate (one-year) exchange rate shocks have a statistically

[18] We explore what correlates with the shock in Appendix Table A7. In Column 1, we see that $Rshock_o$ is larger (exchange rate shocks are more positive) for provinces with high baseline migrant income per capita, lower baseline years of schooling, lower female employment rates, and higher rural share of population. $MigInc_o$ (column 2) is higher for provinces with more positive exchange rate shocks, higher share rural, and with higher asset index. For $Rshock_o \times MigInc_o$, when migrant income per capita and the exchange rate shock are not included as RHS variables, there is a statistically significant positive association with years of schooling and female employment, and a negative one with the asset index. When we control for the baseline level of migrant income per capita and the exchange rate shock, only the latter is statistically significant (it is negative in sign), while the coefficients on the baseline province characteristics all decline substantially in magnitude, with only average years of schooling being statistically significantly different from zero (and positive in magnitude).

significant relationship with exchange rates up to 13 years after the Asian Financial Crisis. In addition, the pre-shock (pre-1997) international migration destination patterns of Philippine provinces have a positive and statistically significant relationship with destination patterns more than a decade after the shock.

5.3 Estimating the Impact of Migrant Income Shocks on Outcomes

The following is our regression specification:

$$
\begin{aligned}
y_{ot} = \beta_0 + \beta_1 Rshock_o \times MigInc_o \times Post_t + \beta_2 Rshock_o \times Post_t \\
+ \beta_3 MigInc_o \times Post_t + \alpha_o + \gamma_t + \delta' \mathbf{X}_{po} \times Trend_t + \varepsilon_{ot}, \quad (23)
\end{aligned}
$$

y_{ot} is an outcome of interest for province o in period t. $Rshock_o$ is the income-weighted exchange rate shock for province o (expression (21)). $Post_t$ is an indicator for periods after 1997. $MigInc_o$ is annual migrant income per capita in the province prior to the shock. α_o are province fixed effects, γ_t are period fixed effects, and $\mathbf{X}_{po} \times Trend_t$ is a vector of baseline province-level characteristics interacted with a linear time trend.[19] ε_{ot} is a mean-zero error term. Year and province fixed effects account for time-invariant locality characteristics and common time effects. Baseline province controls interacted with linear trends capture long-running linear changes in outcomes related to provinces' pre-shock characteristics. Standard errors are clustered by province.

The regression specification includes $Rshock_o$ and $MigInc_o$ interacted with $Post_t$. We do not presume $Rshock_o$ and $MigInc_o$ by themselves to be exogenous. The interactions with $Post_t$ account for changes from before to after the shock related to these variables. Our coefficient of interest is β_1 on the $Rshock_o \times MigInc_o \times Post_t$ term.

The identifying assumption is that a province's shock to migrant income is unrelated to underlying trends in outcome variables. This is the parallel-trend assumption underlying difference-in-difference estimates, which is more likely to be satisfied given our reliance on an unexpected shock. In all results tables, we show coefficient

[19] The variables in the vector $\mathbf{X}_{p0}$ are school attendance rate (age 7-18), female employment rate (age 25-64), male employment rate (age 25-64), share of population rural, asset index, share of individuals (age 25-64) working in a household enterprise, and population. When it is possible to include in the regression at least two observations in the pre-shock period and at least two in the post-shock period (e.g., in regressions for years of education), we replace $\mathbf{X}_{po} \times Trend_t$ with a province-specific linear time trend (all 82 province fixed effects interacted with a linear time trend).

estimates without and with controls for heterogeneous province trends, to gauge the robustness of results to their inclusion.

5.3.1 Human Capital, the Flow of Migrants, and Skilled Jobs

Our model predicts that schooling $\Delta S_o = \frac{1}{2p}\Delta Y_o$ changes in response to migrant income shocks. We estimate Equation (23) with years of education as the dependent variable. Equation (19) reveals that the shock affects the share of skilled workers:

$$\Delta \ell_{sot} = \frac{1}{\Psi}\Delta Y_o = \frac{1}{\Psi}\underbrace{\frac{\sum_k w_{do}}{Pop_o}}_{MigInc_o} \times \underbrace{\frac{\sum_d w_{do}\frac{\Delta R_{dt}}{R_{dt}}}{\sum_d w_{do}}}_{Rshock_o} \tag{7'}$$

We classify occupations to be high- or low-skill based on the average years of education by occupation. We consider occupations where workers have 13 or more years of education on average to be "high-skilled".[20]

Next, we divide the occupations into the three largest categories in descending order of skill: Professional jobs, production jobs, and service jobs. Professional jobs (about 14% of contracts) are the highest skilled, with a mean monthly salary of Php 1357, while service workers (about 45% of our contracts) on average earn Php 297 a month. Our model predicts that the shock may shift migration flows toward high-skill jobs as workers acquire more education (as emigration probabilities are higher for skilled workers). We study the distribution of occupations in the POEA/OWWA data to identify occupational upgrading.

Furthermore, our model suggests that migrant income shocks will affect the flow of migrants, as in Equations (9) and (10). Improved migrant incomes drive migrant flows, and skill upgrading may amplify this further. We test this hypothesis studying the number of new contracts in the POEA/OWWA data.

5.3.2 Domestic income in origin locations

As we show in our model, domestic income may rise for a few reasons. First, individuals are more educated, and skilled workers earn more at home, as captured

[20]Empirically, 13 years is a reasonable bifurcation point separating low from high skill. Figure A7 presents the density of migrant education levels, which is bimodal with peaks just below and above 13 years.

by Equation (12). Additionally, the influx of resources from abroad may encourage more firm production either by easing liquidity constraints in firm investments, or the adoption of more skill-biased capital as workers become more skilled. This second channel, if present, would raise domestic income as local wages rise. Yet, these wage changes also affect location decisions, as individuals may stay behind and earn locally rather than migrate abroad. These are captured by Equation (15), where ΔY_o affects $\Delta \ell_{sot} = \frac{1}{\Psi}\Delta Y_o$. Since we do not take a stance on the mechanisms underlying firm-side decisions, we allow $\Delta\overline{w_{oost}}$ to be a function of ΔY_o. We empirically estimate the overall association in a reduced form relationship:

$$\Delta W_o = \underbrace{\sum_s \ell_{sot}\pi_{oost}\left(\zeta_s \Delta Y_o\right)}_{\text{Direct wage channel}} + \underbrace{\frac{1}{\Psi}\Delta Y_o\left(\overline{w_{oost}}\pi_{oost} - \overline{w_{oout}}\pi_{oout}\right)}_{\text{Education channel in domestic income}} \equiv \zeta \Delta Y_o = \zeta \underbrace{\frac{\sum_d w_{do}}{Pop_o}}_{MigInc_o} \times \underbrace{\frac{\sum_d w_{do}\frac{\Delta R_{dt}}{R_{dt}}}{\sum_d w_{do}}}_{Rshock_o}, \tag{24}$$

5.3.3 Long-run income per capita and consumption

Positive shocks to migrant income will increase the flow of migrants going to places with such positive shocks. If migration rates are higher for skilled than unskilled workers, then the new flow of migrants may be disproportionately skilled. This would raise income per migrant, and further magnify migrant income per capita in the long run. We measure migrant income from the POEA/OWWA contract data. As we describe in Appendix A.2, we convert the fraction remitted to 2010 Philippine pesos, and the non-remitted portion of migrant income in purchasing power parity (PPP) terms to account for differences in costs of living at different destinations. In Equation (16), our model predicts that this initial shock to migrant income can lead to higher long-run migrant income due to both the increase in human capital accumulation (and occupational upgrading), and the increased migrant outflows to favorable destinations. We test this hypothesis by examining long-run changes in migrant income per capita.

We use the FIES dataset to examine how consumption changes, and the Census data to create an asset index for households. Income changes should affect consumption in the long run, in the manner that we describe in the model:

$$\Delta(c_{1O}+c_{2O})+\tilde{\chi}_o = \left(1+\frac{\beta}{\Psi}+\theta+\zeta\right)\Delta Y_o = \left(1+\frac{\beta}{\Psi}+\theta+\zeta\right)\underbrace{\frac{\sum_d w_{do}}{Pop_o}}_{MigEarn_o} \times \underbrace{\frac{\sum_d w_{do}\frac{\Delta R_{dt}}{R_{dt}}}{\sum_d w_{do}}}_{Rshock_o} \qquad (17)'$$

6 Empirical Results

6.1 Impacts on global income and its components

We first examine impacts of the initial migrant income per capita shock on migrant income, domestic income, and global (migrant plus domestic) income per capita in the province over the subsequent decade. We estimate regression Equation (23) where the outcome is these province-level income per capita variables (aggregate income of the given type divided by province population, in thousands of real 2010 Philippine pesos). There is one pre-shock observation (1994) and two post-shock observations (2006 and 2009) for each province.

The results for migrant, domestic, and global income are in Table 2, panel (a). Each cell in columns 1-2 is the coefficient (standard error) on the migrant income shock. By construction, the coefficient in the third row is the sum of the corresponding coefficients in the first and second rows. The shock has positive and statistically significant effects on migrant income, domestic income, and global income per capita. Coefficient estimates are stable across regressions in which controls for heterogeneous province trends are not (col. 1) and are (col. 2) included.

The effects are large in magnitude. Column 2's coefficient estimates indicate that for each one standard deviation increase in the initial shock, migrant income per capita is higher by 828 pesos (6,417 pesos×0.129) a decade later (equal to 2.3% of mean global income per capita). The coefficient estimate, 6.417, indicates that the initial shock to migrant income is substantially magnified over time: for each one-peso initial migrant income per capita shock, migrant income per capita is more than six pesos higher a decade later.

The corresponding effect sizes implied by the coefficients in the regressions for domestic income and global income are 2,509 pesos and 3,337 pesos, respectively (6.9% and 9.1% of mean global income per capita, respectively). In additional analyses shown in Appendix Table A10, we find that the increase in domestic income is not driven by higher wage income from working for employers outside the household, but rather from higher household enterprise and other income. This finding suggests that the shock may be loosening capital or other constraints that were previously constraining household entrepreneurial investments.

We also present nonparametric regression plots of the relationship between the shock and the pre-to-post change in these outcomes. In Figures 1a-1c, we plot the pre-to-post change in global income, domestic income, and migrant income per capita against the migrant income shock. Both the x and y-axis variables are residuals (partialled-out) from regressions on the exchange rate shock ($Rshock_o$) and baseline migrant income per capita ($MigInc_o$). These nonparametric regression plots all show positive relationships between the shock and the change in each outcome.

We also present an event study illustrating the dynamics of the effect of the migrant income shock on domestic income per capita, for which we have more periods of data. This also provides a test for violations of the parallel-trend assumption in pre-shock periods. The analysis uses seven waves of the triennial FIES spanning 1991 to 2009. We estimate a modified version of Equation (23) in which the migrant income shock ($Rshock_o \times MigInc_o$) is interacted with an indicator variable for each post- and pre-1997 year, with the 1997 interaction term omitted as the reference point. ($Rshock_o$ and $MigInc_o$ are also interacted with the same set of year indicators.) Results in Figure A4 demonstrate that the effect on domestic income is initially zero, but then rises substantially over time, becoming statistically significant in 2006 and 2009, nine to twelve years after the shock.

Figure A4 also highlights the importance of having long-run data, as an analysis on only the years directly following the shock would miss the substantial increase in domestic income a decade later. We argue that a meaningful driver of the increase in domestic income is investments in education and enterprises, whose returns take time to realize. The figure also shows that there are no differential pre-trends (coefficients pre-1997 are small, statistically insignificant, and show no obvious trajectory), providing assurance of the validity of the parallel trends assumption.

6.2 Consumption and assets

To see whether increases in income are accompanied by increases in household well-being, we estimate Equation (23) where the dependent variables are consumption per capita and the household asset index. Results are in Table 2, panels (b) and (c). The shock has a substantial positive impact on both consumption and the asset index.

Nonparametric regression plots of the relationship between the shock and these outcomes makes a similar point. Figures 1d and 1e reveal the upward sloping nonparametric relationships between the shock and the pre-to-post change in the asset index and consumption per capita, respectively.

6.3 Other migration outcomes

We now turn to unpacking these substantial effects on income. First, we consider: what can account for the 6.4-fold magnification of the impact of the shock on migrant income over the subsequent decade? Our theoretical framework guides us in unpacking the explanations. We examine here potential explanatory factors: increases in income per migrant, and increases in migration rates.

First, the shock caused an increase in income *per migrant* (total migrant income divided by number of migrants in a province). This is the dependent variable in the first row of Table 2, panel (d). The initial shock to migrant income per capita leads to substantially higher income per migrant a decade later. Second, the shock led to an increase in new migrant contracts per capita (total new migrant contracts divided by province population), as seen in the second row of Table 2, panel (d). These relationships can also be seen in the nonparametric plots of Figures A5a and A5b.

Theoretically, these increased flows are a result of better prospects abroad given the persistent change in exchange rates, and occupational upgrading, as provinces with positive shocks gain more education. As we show below, the shock causes increases in schooling, and the high-skilled are more likely to migrate.

Together, the education-driven occupational upgrading and the increased migration flow in response to persistent favorable opportunities abroad drive the increase in migrant income per capita. In Section 7 we quantify the role played by each of these channels in explaining the overall increase in migrant income.

6.4 Schooling

Since education investments are central to our analysis, we examine changes in schooling in detail. Our framework suggests that positive migrant income shocks could loosen financial constraints on investment in schooling (Cox-Edwards and Ureta, 2003; Yang, 2008; Gibson et al., 2011, 2014; Clemens and Tiongson, 2017; Theoharides, 2018), and also change the expected return to education in the population at large.[21] Increases in schooling could help explain increases in both long-run migrant and domestic income in response to the shock.

In Table 3, panel (a), we show that the migrant income shock led to meaningful increases in the education levels of the population. Coefficient estimates in column 2 indicate that a one-standard deviation migrant income shock leads to 0.10 and 0.17 more years of schooling, for 7-18 year olds and 19-24 year olds, respectively.

In Appendix Table A8, we present results from estimating regression Equation (23) where the dependent variables are average years of completed schooling for various narrower age and gender groupings. The unit of observation is the province by Census-year. We find positive and statistically significant effects for primary-school-aged children (age 7-12) and for young adults (aged 19-24, tertiary schooling age). For lower-secondary (age 13-15) and upper-secondary (age 16-18) children, regression coefficients are similar in magnitude, but are not consistently statistically significantly different from zero. Results are similar when we examine impacts on years of schooling separately for females and males. Comparing coefficient estimates across columns 1 and 2, results tend to be stable (or increasing in magnitude) when province-specific time trends are added to the regression. The positive impact of the shock on years of schooling is also evident in nonparametrically in Figure 1f.

6.5 Skills and occupational upgrading

The increase in education in the population helps explain the increase in migration rates, and in income per migrant, since higher-skilled populations may have migrants who engage in higher-skilled, higher-wage jobs abroad.

[21] As we discuss in Appendix D.2, positive migrant income shocks could raise schooling investments overall if the return to education is perceived to rise (Chand and Clemens, 2019; Shrestha, 2017), but could reduce schooling investments if returns to education are seen to fall (McKenzie and Rapoport, 2011).

The increase in schooling levels changes the flow and composition of migrants. Workers with more education find it relatively easier to find work abroad.[22] These workers may also be more likely to find higher-paying jobs. Alternatively, workers with more education may have more employment prospects at home, leading to negatively selected migration following migrant income shocks.

We classify each detailed occupation code as skilled or unskilled. Figure A7 shows two modes in the population skill distribution on either side of the 13 year mark. We categorize an occupation as skilled if the mean years of education among individuals engaged in the occupation is 13 or higher, and unskilled otherwise.[23] We then estimate equation (23) where the dependent variables are the share skilled in the full population (including migrants) and among migrants only.

Results are presented in Table 3, panel (b). The means of the outcomes reveal that migrants are twice as likely to be skilled than the general population. The shock increases the share skilled in both the full population and the migrant population, and the coefficients are statistically significant. Column 2 shows a that a one-standard-deviation shock leads to a 0.6 percentage point increase (0.0464×0.129) in the share skilled in the full population. Relative to a mean of 17.3 percent, this is meaningful. For migrants, the increase is about 4 percentage points, a 12% increase from the baseline mean. The shock's positive impact on the skill-upgrading of migrants is also evidence in the nonparametric plot of Figure A5c.

We also estimate equation (23) where the dependent variables related to migrant contracts by skill level. In the data, service jobs are done by workers with the least amount of skill. Production jobs typically require more education, while professionals are most likely to be skilled (Appendix Table A12). Panel (c) of Table 3 shows the results for migrant contracts in the three large occupation groupings. In the top half of the panel, we look at migrant flows as a fraction of the 1990 province level working-age population. A one standard deviation increase in the shock has substantial effects on both professional and production migrant flows, but no detectable impact on service sector migrants. In the lower half of panel (c) we study migrant

[22] In our model this depends on the relative probabilities of skilled and unskilled migrant flows, π_{dost} and π_{dout}.

[23] We calculate mean years of education by occupation among migrants engaged in this occupation in the Phliippine Labor Force Survey (LFS) data. Our results are not sensitive to varying this cutoff. Those with 12 years are likely to have a vocational degree. Those with 14 years are likely to have finished college.

occupations as a share of migrant contracts. We find a shift in the share of contracts away from service and toward professional jobs. While imprecise, the effect on service jobs is meaningful in magnitude. These effects are reflected in Figures A5d-A5 which show nonparametric relationships between the shock and changes in the occupational composition of migrants as a share of the baseline 1990 population.

In sum, migrant income shocks lead to an increase in the skilled share of the general population and of migrant workers in particular, and increases in migrant worker flows in relatively high-skilled overseas occupations. This occupational upgrading for migrants may be related to the increase in migrant flows, since (as we show later) skilled workers have a higher probability of migrating abroad. The increase in migration flows and the shift towards high-skilled jobs magnifies the gains in long-run migrant income over the long run.

6.6 Pre-trends, other channels, and selection biases

In Appendix Section C we analyze threats to identification and alternative channels. First, we discuss the possible threats to identification, given that our specifications rely on the interaction between the exchange rate shock, baseline migrant income, and a post-shock indicator. Since we condition on each of these components (and their two-way interactions), and on the possibility of different trends over time, any remaining threat would need to be driven by systemic differential trends across provinces that are somehow also associated with the interaction between exchange rate shocks and baseline income, but not correlated with controls for heterogeneity in trends across provinces.

To provide a partial test of the parallel trend assumption, we run placebo experiments in the pre-shock period, testing whether changes in outcomes *prior* to the shock have any relationship with *future* migrant income shocks. Results in Table A11 support the parallel-trend assumption. The table presents placebo test regressions for all outcomes in this paper for which we have at least two pre-shock (pre-1997) observations. For each outcome in the table, the shock coefficient is typically small in magnitude and is never statistically significantly different from zero.

Nonparametric versions of these placebo experiments also yield a conclusion that there are no apparent violations of the parallel trend assumption. Results are in Appendix Figure A6. For none of these outcomes is there a positive relationship between the future shock and changes in the pre-shock period.

We also discuss the possibility of other channels like trade and FDI. Given the lack of effects on firm production and exports (Table A9), these channels are unlikely to be important. We also address the possibility of selection bias by showing that there are no detectable effects on internal migration (Table A13).

7 The Contribution of the Education Channel

The long-run impacts of the migrant income shocks are potentially magnified by increased educational investments in origin provinces, not only because skilled workers earn more, but also because higher skilled populations migrate at higher rates, and work in skilled migrant jobs. Our model allows us to quantify how much of long-run changes in migration flows and in both domestic and migrant income can be attributed to the education channel.[24]

7.1 Contributions to the change in migration flows

The discussion in Section 3 allows us to determine the contribution of each channel to changes in flows and long-run income:

$$\Delta\, Flows_{ot} = \underbrace{\Delta\ell_{sot} \sum_{d\neq o} (\pi_{dost} - \pi_{dout}) - \chi_o}_{\text{Education channel in outflows}} + \underbrace{\theta \sum_{d\neq o} (\ell_{sot}\pi_{dost} + \ell_{uot}\pi_{dout}) \frac{\Delta R_{dt}}{R_{dt}}}_{\text{Exchange rate channel in outflows by skill}} - \underbrace{\theta \left(\ell_{sot}\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}} + \ell_{out}\pi_{oout}\frac{\Delta w_{out}}{w_{out}} \right)}_{\text{Domestic earnings stemming outflows by skill}} \tag{9}$$

The first contributor to changes in flows is investments in education. If the likelihood of migrating abroad is higher when one is skilled, then an increase in the fraction skilled will raise the flow of migrants. In Figure A8 we plot the difference in the baseline probabilities in the share of workers that migrate between skilled and unskilled workers. The figure shows that for every province, the likelihood of

[24] For data details, please see Appendix section A.7.

becoming an overseas worker is higher when the worker has more education. Therefore, increases in education should increase the flow of migrants from all provinces.

The contribution of the education channel is the product of two components: (a) the education response to income shocks $\Delta\ell_{ost}$, and (b) the skill-differential in location probabilities $(\pi_{dost} - \pi_{dout})$. The first is obtained from the regression coefficient in panel (b) of Table 3. We use the conservative specification for the full population which includes controls. The second component is obtained directly from data as in Figure A8. Together they predict the education channel in migration flows.

To estimate the role played by the exchange rate channel, we recognize that as exchange rates change favorably in a persistent manner, there will be a migration response to this higher compensation. On the other hand, increases in domestic income will induce workers to stay behind in the Philippines, stemming migration. The simultaneous changes to exchange rates across different potential locations, and increases in domestic wages, together determine the location choices of workers.[25]

These responses depend on the Frechet parameter. In Table A5 we estimate θ, and together with the size of the changes to exchange rates and to (skill-specific) domestic earnings, we determine the extent of the change in migrant flows. Again, we measure the shares of skilled and unskilled, and propensity to migrate abroad by skill group at baseline (in 1990), and use that to weight exchange rate changes by destination, as in the second part of Equation (9).

Together, the exchange rate and education channels predict the change in outflows. We validate the structure of our model by comparing model predicted flows to the simple OLS prediction from panel (c) of Table 2, which we refer to as $\widehat{Flows_{ot}}$. We plot the relationship between these predicted flows in Figure 2a.

The strong upward sloping relationship in Figure 2a indicates that the model does a good job of predicting migration flows. A number of provinces with a high predicted flow lie above the 45-degree line, suggesting that there may be other changes in those provinces or non-linearities in the empirical relationship between flows and migrant income changes. Finally, we quantify the role played by each channel. To do so, we calculate the share of the total regression based predicted flows that are attributable to the education channel. In other words, we measure: $\frac{\Delta\ell_{ost}\sum_d(\pi_{dost}-\pi_{dout})}{\widehat{Flows_{ot}}}$.

[25] As explained above, and around Equation A46, we also capture indirect effects as exchange rates change simultaneously.

Figure 2b plots the distribution of the contribution of the education channel across provinces. On average about half of the increase in migrant flows is attributable to the increased education response (Table 4).[26] We do a similar exercise for the exchange rate channel. The exchange rate changes abroad will tend to drive migration abroad as most exchange rates changed favorably relative to the Philippines. This tends to be a meaningful magnitude, almost as large as the overall change in flows. Yet, improvements on the domestic front stem such outflows, canceling out a large component of the need to emigrate. On net, changes in relative prices (exchange rates, and wages at home) help drive outflows that explain about 10% of the total new outflows. The remaining portion of the outflows are unexplained. We may not expect to explain the entirety of flows as we are building off of baseline (1990) shares of migration flows, and using the empirically conservative specification from panel (a) of Table 3.[27]

7.2 Contributions to the change in migrant income

The change in migrant income per capita can be decomposed into: (1) the education channel, and (2) the persistent change in exchange rates, which raises migrant income and encourages flows to favorable destinations.

$$\underbrace{\Delta \ell_{ost}\left(\sum_{d \neq o} \overline{w_{dost}}\pi_{dost} - \sum_{d \neq o} \overline{w_{dout}}\pi_{dout}\right)}_{\text{Education channel in migrant income}} + \underbrace{\theta\left(\sum_{s}\left[\ell_{ost}\sum_{d}\left(\pi_{dost}\overline{w_{dost}}\frac{\Delta R_{dt}}{R_{dt}}\right)\right]\right)}_{\text{Exchange rate channel in migrant income}} - \tilde{\chi}_o \tag{25}$$

Here, we know $\Delta \ell_{ost}$ is a function of the migrant income shock from Equation (7), which we again obtain with the help of linear fit of the regression shown in panel (b) of Table 3. The second component is the probability-weighted skill-premium abroad $\left(\sum_{d \neq o} \overline{w_{dost}}\pi_{dost} - \sum_{d \neq o} \overline{w_{dout}}\pi_{dout}\right)$. We plot the skill premium $(\overline{w_{dost}} - \overline{w_{dout}})$ at the origin-destination pair in Figure A9. The median origin-

[26] Theoretically, the education channel contribution can be negative if the low-skilled have a higher migration probability.

[27] Using baseline migration rates systematically produces conservative predictions. Using post-shock (but thereby endogenous) measures of the probability of migration from the 2000 Census allows us to explain roughly the entirety of flows. In the 1990 baseline data, the migration probability for skilled workers was 3.2% and for the unskilled was 0.9%. In the 2000 post-shock data, the migration probability for the skilled was 4.9% and for the unskilled was 1.6%.

destination pair offers a skill-earnings premium of about 38 percent (9.5 percent per year of education), but there is heterogeneity in returns across destinations.[28]

The remaining component of the change in migrant income is driven by persistent changes in the exchange rate. This captures the increase in long run income, not simply because better exchange rates directly increase migrant income, but also because they induce greater migration (both skilled and unskilled) to places with positive exchange rate movements. Additionally, as captured by what we call 'indirect resorting,' simultaneous changes in the exchange rate affect the location choices of migrants, which in turn affects how much they earn.[29]

A higher migration elasticity θ means that migration flows, and thereby migrant income, are more responsive to exchange rate shocks. We measure the shares ℓ_{ost} and π_{dost} at baseline (1990), multiply them with post-shock wages $\overline{w_{dost}}$ and $\overline{w_{dout}}$, and use them as weights for exchange rate changes $\frac{\Delta R_{dt}}{R_{dt}}$ as in Equation (14).

We add up the predicted migrant income estimate due to the education channel and the exchange rate channel, and create a composite measure of predicted increases in migrant income per capita. Once again, we can validate the structure of our model by comparing the model predicted migrant income per capita to the simple OLS prediction based on the regression from panel (a) of Table 2. We plot the relationship between these predicted flows in Figure 3a.

As before, we see a strong upward sloping relationship in Figure 3a which indicates that the model does a good job of predicting migrant income per capita. Predicted values are distributed around the forty-five degree line.[30]

To quantify the role played by each channel, we measure the predicted education channel in migrant income as a ratio of the predicted increase in migrant incomes (Figure 3b). We do a similar exercise for the exchange rate channel in migrant income. On average, the education channel explains about 42.3% of the increase in migrant income, whereas the exchange rate channel explains about 66% (Table 4).

[28] Returns are weighted by migration probabilities, as for many low-skilled occupations there are no migrant opportunities for certain destinations. As such, increases in skill raise earning prospects by raising employment prospects.

[29] For instance, if depreciation of the Malaysian exchange rate induces workers to stay behind in the Philippines, but simultaneous favorable changes to the US exchange rate induces a fraction of them to migrate instead to the US, then this change in location would change earnings. Equation A49 shows this indirect resorting.

[30] It is not unreasonable for our model to explain a little more than the entirety of the changes in incomes, as we base these calculations off of baseline earnings in various destinations that may change for reasons unrelated to the shocks.

7.3 Contributions to the change in domestic income

We do a similar exercise with the change in domestic income per capita. Domestic income can rise for at least two reasons. First, an increase in education and skills allows workers to work in high-paying skilled jobs (the “Education channel”). Second, the wage rates for jobs (conditional on skill) may also increase as a result of more local investment in enterprises (the “Direct wage channel”).

$$\Delta W_o = \underbrace{\sum_s \ell_{ost} \pi_{oost} \left(\Delta \overline{w_{oost}}\right)}_{\text{Direct wage channel}} + \underbrace{\Delta \ell_{ost} \left(\underbrace{\overline{w_{oost}} \pi_{oost}}_{\text{skilled wage at home}} - \underbrace{\overline{w_{oout}} \pi_{oout}}_{\text{unskilled wage at home}} \right)}_{\text{Education channel in domestic income}} \tag{15}$$

We closely follow the methods described above for migrant income to again distinguish these channels. For instance, since the shock may directly change income at home, we use the baseline skill-premium when attributing changes to the education channel. Again, we aggregate predicted domestic income due to the education channel and the exchange rate channel, and create a composite measure of predicted increases in domestic income per capita. We validate the model by comparing the model-predicted domestic income per capita with the simple OLS prediction based on the regression from panel (a) of Table 2. We plot the relationship between these predicted flows in Figure 4a. As before, we see a strong upward sloping relationship, whereby the model slightly under-predicts domestic income per capita. Predicted values are distributed around the forty-five degree line.

To quantify the role played by the direct wage channel, we estimate the impact of the migrant income shock on domestic income (including non-wage income) per worker by skill level, using the same definition of skill. These can be found in the bottom panel of Table A10. The increases in skill-specific domestic incomes are weighted by the baseline skill-shares in each province, and the probabilities that individuals do not emigrate conditional on their skill levels, as in Equation (15).

Finally we measure the role played by the education channel in domestic income, as a ratio of the predicted increase in domestic income per capita. We plot this in Figure 4b. We do a similar exercise for the direct wage channel. On average, the education channel explains about 18% of the increase in domestic income, whereas the direct wage channel explains about 56% (Table 4). The remaining component is likely driven by other aggregate changes to the income distribution.[31]

7.4 Contributions to the change in global income

Together, the changes in migrant income and domestic income allow us to decompose the changes in global income per capita. Each component of the changes in domestic and migrant income can be combined to create an aggregate measure of the change in global income per capita in the province. To test the validity of the model, we again predict the change the global income per capita using the regression estimated in Table 2 for global income. Figure 5a shows that our model again does a good job of predicting the change in global income.

Since the domestic and migrant income channels both have an education component, we can again measure the total contribution of education investments to changes in global income. Figure 5b plots the distribution of this contribution across provinces. Table 4 shows that the education channel explains about 24.4% of the overall increase in global income, while the changes in wages (both at home and abroad) explain about 59.6% of the overall increase in global income. Overall, the model explains 84.0% of the increase in global income.

8 Conclusion

We study how income from international labor migration affect origin provinces in the Philippines. Novel administrative data, a theoretical model, and large-scale natural experiment allow us unusual insight. An improvement in overseas earnings opportunities initiates a virtuous cycle: over the course of a decade, households raise their rates of international labor migration, and increasingly enter higher-skilled, higher-wage overseas work. In addition, investments in local human and physical capital raise domestic incomes in the long run, further magnifying initial gains. A structural migration model helps shed light on underlying mechanisms, revealing that education investments account for a substantial fraction of long-run gains.

[31] These estimates may be somewhat conservative, as we use baseline domestic income in calculating the contribution of the education channel.

These findings depart from the existing literature on the economic impacts of migration opportunities by focusing on the global income (international and domestic) of households in origin areas. We find meaningful impacts of improved migrant income opportunities on domestic incomes, as well as long-run increases in participation and performance in international labor markets.

We emphasize aspects of the economic development process that prior research has tended to overlook. Specifically, we provide unusual insight into the dynamics of international migrant incomes of households in migrant-origin locations, and how migrant incomes evolve in response to an initial positive shock. When there are shocks to international migrant income prospects, resulting gains are incompletely captured in analyses that focus solely on the earnings of those remaining behind in origin areas, and ignore the earnings of the migrants themselves (Clemens and Pritchett, 2009). This is particularly important when the migrant workers are only temporarily away, and remain integral (albeit geographically distant) members of their origin households. In an era of expanding international migrant work, getting a full picture of the income prospects of households requires understanding global income from both domestic and international sources.

Relative to prior work, this paper is also distinctive in that – notwithstanding the important gains in migrant income and its magnification over time – we show that the vast majority of gains from positive shocks to migrant income actually come in the form of higher *domestic* incomes in migrant-origin areas. This insight reveals to policy-makers that promoting international migration can yield substantial gains for home-country income prospects as well. Increases in earnings from international migrant work can also lead to economic development back home. The possibility emerges that origin areas of international migrants may not need to rely on migration indefinitely to maintain improved living standards in the longer run.

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Table 1: Summary Statistics

Shock Variables	Mean	Std. Dev.	10th P.	25th P.	Median	75th P.	90th P.	Obs.
Normalized Shock to Migrant Income per Capita ($Rshock_p * MigInc_{p0}$)	-0.014	0.129	-0.153	-0.065	-0.002	0.029	0.103	82
Earnings-weighted Exchange Rate Shock ($Rshock_p$)	0.410	0.045	0.366	0.389	0.414	0.434	0.458	82
Migrant Income per Capita ($MigInc_{p0}$)	4.263	3.290	1.070	1.816	3.095	6.532	8.962	82
Income								
Migrant Income per Capita	4.325	3.360	1.190	1.900	3.126	5.986	9.107	246
Domestic Income per Capita	32.147	12.708	20.986	24.432	28.234	35.654	49.017	246
Global Income per Capita	36.472	14.946	22.682	26.679	32.077	41.896	57.132	246
Consumption per Capita	29.851	12.235	18.328	21.935	26.947	34.022	47.565	246
Household Asset Index	-0.306	0.809	-1.241	-0.821	-0.357	0.104	0.571	246
Years of Schooling								
Age 7-18	4.880	0.573	4.139	4.490	4.868	5.325	5.667	328
Age 7-12	2.776	0.332	2.345	2.531	2.787	3.025	3.223	328
Age 13-15	6.401	0.619	5.602	6.000	6.404	6.874	7.161	328
Age 16-18	8.196	0.951	6.845	7.653	8.289	8.894	9.236	328
Age 19-24	9.049	1.109	7.518	8.329	9.088	9.838	10.463	328
Share skilled (13 or more years of education)	0.173	0.064	0.065	0.155	0.190	0.207	0.237	328
Share migrants skilled (13 or more years education)	0.348	0.143	0.192	0.245	0.330	0.437	0.544	328
New Migrant Contracts								
Total (share of 1990 population)	0.003	0.003	0.001	0.001	0.003	0.005	0.006	246
Professional Jobs (share of new contracts)	0.143	0.084	0.059	0.095	0.130	0.162	0.247	246
Production Jobs (share of new contracts)	0.342	0.129	0.169	0.248	0.341	0.437	0.511	246
Service Jobs (share of new contracts)	0.455	0.165	0.263	0.335	0.420	0.574	0.689	246

Notes: Unit of observation is province. Shock variables are constructed from POEA/OWWA dataset and other sources (see text). Shock to Migrant Income per Capita constructed from demeaned component variables ($Rshock_p$ and $MigInc_{p0}$). Domestic income data is from FIES and migrant income data is from POEA/OWWA dataset. Income and consumption are in real 2010 Philippine pesos (unremitted portion of migrant income is adjusted for overseas location PPP). Years of schooling and asset data are from Census (82 provinces; assets available in 1990, 2000, 2010; years of schooling available in 1990, 1995, 2000, 2010). New migrant contracts are from the POEA/OWWA dataset.

Table 2: Impact of Migrant Income Shock on Income, Assets, Income per Migrant, and New Migration Flows

	Mean (std. dev.) of dependent variable	Regressions (1) No controls	(2) Controls for heterogeneous province trends	Number of obs.
Dependent variable:				
(a) Global income and its components				
Migrant income per capita	4.325	6.068**	6.417**	246
	(3.360)	(2.405)	(3.120)	
Domestic income per capita	32.147	18.899***	19.449***	246
	(12.708)	(5.644)	(7.169)	
Global income per capita	36.472	24.967***	25.866***	246
	(14.946)	(6.205)	(7.606)	
(b) Consumption				
Total consumption per capita	29.851	11.983**	14.678**	246
	(12.235)	(4.663)	(5.711)	
(c) Assets				
Asset index	-0.306	2.059***	1.160***	246
	(0.809)	(0.521)	(0.438)	
(d) Other outcomes				
Income per migrant	329.967	350.695***	377.317**	246
	(179.051)	(93.794)	(179.000)	
New migrant contracts per capita	0.003	0.009**	0.010**	246
	(0.003)	(0.004)	(0.004)	

Notes: Unit of observation is the province-year. Each cell in cols. 1 and 2 presents coefficient (standard error) on migrant income shock for the dependent variable listed on left. Migrant income per capita, earnings per migrant, and new migrant contracts calculated from POEA/OWWA and Philippine Census data. Asset index calculated from Census. Domestic income and consumption per capita are from Family Income and Expenditure Survey (FIES). Global income per capita is migrant income per capita plus domestic income per capita. Income and consumption are in real 2010 Philippine pesos (unremitted portion of migrant income is adjusted for overseas location PPP). Data consists of three observations per province (one pre-shock and two post-shock observations). For panel (a), (b), and (d), data are for 1994, 2006, and 2009. In panel (c), data are for 1990, 2000 and 2010. Observations after 2007 are post-shock. Controls for heterogeneous province trends are baseline controls interacted with linear annual time trend. Baseline controls (all from 1990 Census) are: average years of schooling (7-18 yr olds), average female employment rate (25-64 yr olds), average male employment rate (25-64 yr olds), share of households rural, asset index, share of individuals working in household enterprises, and population. All regressions include province and year fixed effects. Robust standard errors are clustered at the province level. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Table 3: Impact of Migrant Income Shocks on Skill Share of Workforce

Dependent variable (periods included in regression)	*Mean (std. dev.) of dependent variable*	*Regressions*		*Number of obs.*
		(1) No controls	*(2) Controls for heterogeneous province trends*	
(a) Education (1990, 1995, 2000, 2010)				
Ages 7-18	4.880	0.680***	0.767***	328
	(0.573)	(0.187)	(0.209)	
Ages 19-24	9.049	0.583**	1.311***	328
	(1.109)	(0.239)	(0.418)	
(b) Share skilled (1990, 1995, 2000, 2010)				
Full population	0.173	0.0858***	0.0464*	328
	(0.0637)	(0.0245)	(0.0259)	
Migrants	0.349	0.344***	0.313***	328
	(0.143)	(0.0653)	(0.0898)	
(c) New migrant contracts (1994, 2006, 2009)				
as a percent of 1990 working-age population:				
Professional	0.048	0.446***	0.410***	246
	(0.062)	(0.107)	(0.100)	
Production	0.125	0.397**	0.460**	246
	(0.136)	(0.171)	(0.189)	
Service	0.136	0.048	0.077	246
	(0.104)	(0.141)	(0.130)	
as a share of new migrant contracts:				
Professional	0.143	0.404***	0.215	246
	(0.084)	(0.145)	(0.137)	
Production	0.342	0.008	0.001	246
	(0.129)	(0.080)	(0.097)	
Service	0.455	-0.354***	-0.152	246
	(0.165)	(0.122)	(0.125)	

Notes: Unit of observation is the province-year. Each cell in cols. 1 and 2 presents coefficient (standard error) on migrant income shock for the dependent variable listed on left. Education variables are average years of education in province population, from Philippine Census. Share skilled variables are share of province population or share of migrants. Share skilled defined as having 13 or more years of education in the Census data. Migrant contract outcomes calculated from POEA/OWWA and Census data. All regressions include province and year fixed effects. Controls for heterogeneous province trends are: for panel (a) and (b) province-specific linear annual time trend; for panel (c) baseline controls interacted with linear annual time trend. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

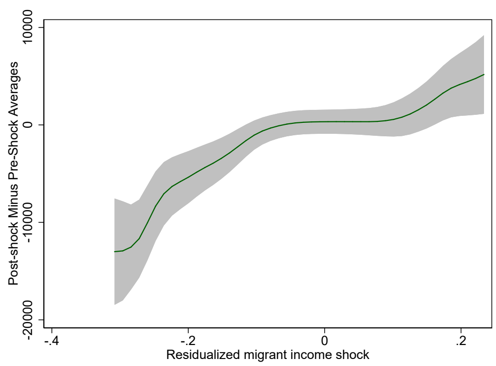
Table 4: Overall Changes and Model-based Decomposition of Flows and Income

	Migrant Flows	Domestic Income	Migrant Income	Global Income
Mean	0.003	32.147	4.325	36.472
Std. Dev.	(0.003)	(12.708)	(3.360)	(14.946)
Impact of 1-std.-dev. shock	**0.001**	**2.509**	**0.828**	**3.337**
Increase as % of mean	38.7%	7.8%	19.1%	9.1%
Share of global income increase	------	75.2%	24.8%	100.0%
Model-based decomposition:				
Education channel	48.5%	17.9%	42.3%	24.4%
Exchange rate channel	10.2%	------	66.3%	17.0%
Direct wage channel	------	56.2%	------	42.5%
Explained by model	58.7%	74.1%	108.5%	84.0%

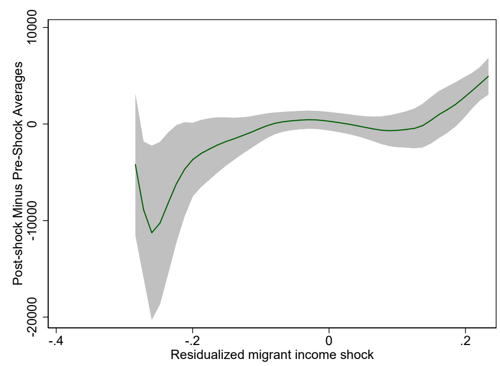
Note: The table summarizes the changes to the variables for which we decompose the overall changes and derive the changes due to the education channel component. The impact of a 1 std dev shock in migrant income is the coefficient from the regressions multiplied by 0.129 (the std. dev. of the migrant income shock). Monetary units are in thousands of Philippine pesos (PhP). The bottom panel describes the contributions of each model-based decomposition. For instance, the education channel explains 42.3% of the increase in migrant income.

Figure 1: Nonparametric Relationship Between Shock and Change in Outcomes

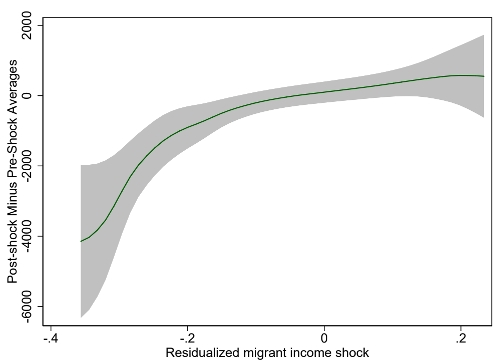
(a) Global Income Per Capita



(b) Domestic Income Per Capita

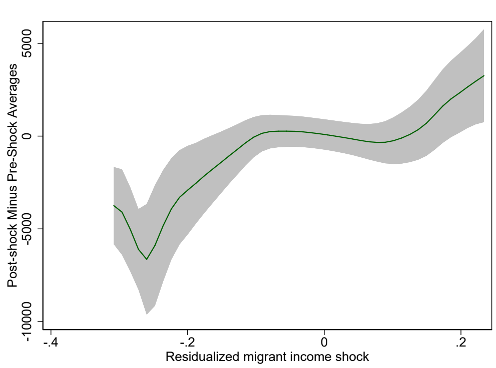


(c) Migrant Income Per Capita



(d) Household Asset Index

(e) Consumption Expenditure per capita

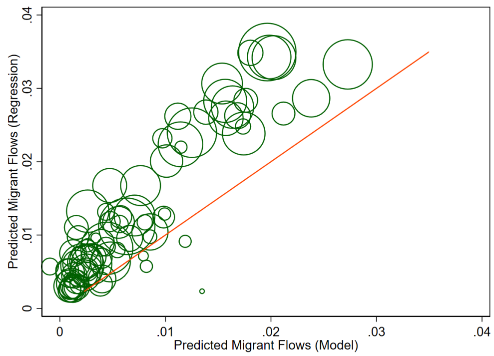


(f) Years of Education (7-18)

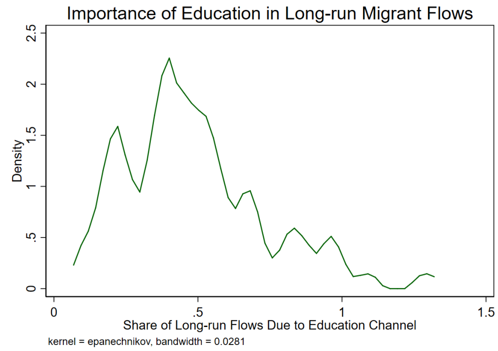
Notes: Nonparametric relationships between migrant earnings shock (income-weighted exchange rate shock times baseline migrant income per capita) and change in main outcomes from pre- to post-shock periods. Outcomes are average of post-shock years minus average of pre-shock years. The outcome and migrant earnings shock are both residualized. Residuals taken from regression of variable on income-weighted exchange rate shock and baseline migrant income per capita. Solid line is nonparametric regression estimate. Gray area is 90 percent confidence interval.

Figure 2: Model Validation & Contribution of Education Channel in Migrant Flows

(a) Validation: Migrant flows



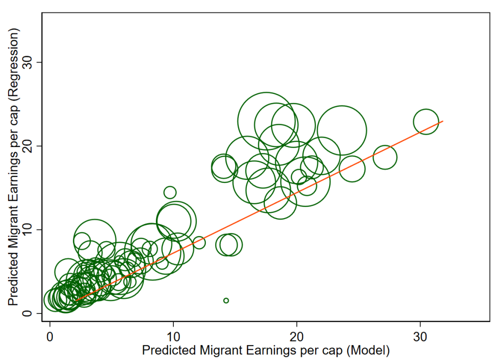
(b) Contribution of Education Channel



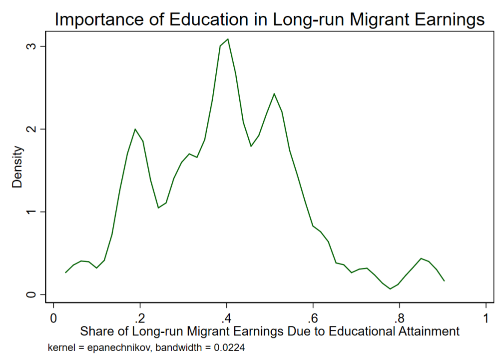
Notes: Figure 2a plots the predicted flows of migrants from the regression in panel (c) of Table 2 (vertical axis) vs the predicted flows as determined by the components of Equation (9). The red line has an angle of 45 degrees. Each point represents a province, where bubble sizes are weighted by the 1990 population. Figure 2b plots the province-level distribution of the contribution of the education channel in predicting migrant flows: $\frac{\Delta \ell_{sot} \sum_k (\pi_{kost} - \pi_{kout})}{Flows_{ot}}$

Figure 3: Model Validation & Contribution of Education in Migrant Income

(a) Validation: Migrant Income per Capita



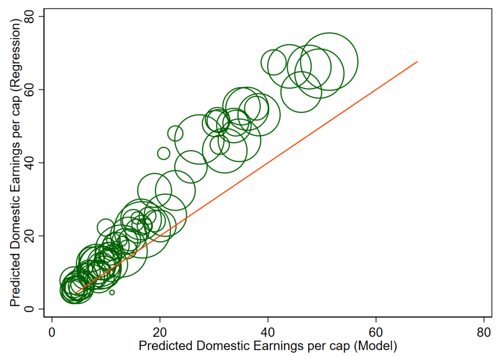
(b) Contribution of Education Channel



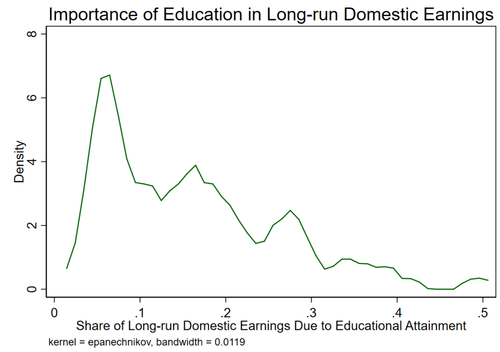
Notes: Figure 3a plots the predicted migrant income per capita from the regression in panel (a) of Table 2 (vertical axis) vs the predicted migrant income as determined by the education and exchange rate components. The red line has an angle of 45 degrees. Each point represents a province, where bubble sizes are weighted by the 1990 population. Figure 3b plots the province-level distribution of the contribution of the education channel in predicting migrant income per capita.

Figure 4: Model Validation & Contribution of Education in Domestic Income

(a) Validation: Domestic Income per Capita



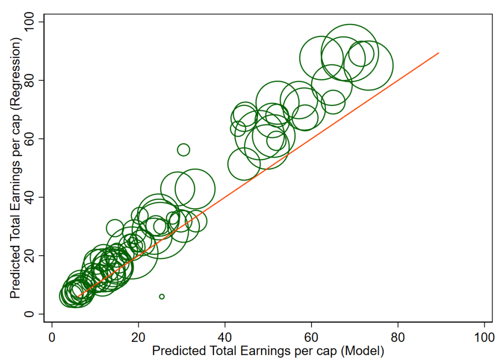
(b) Contribution of Education Channel



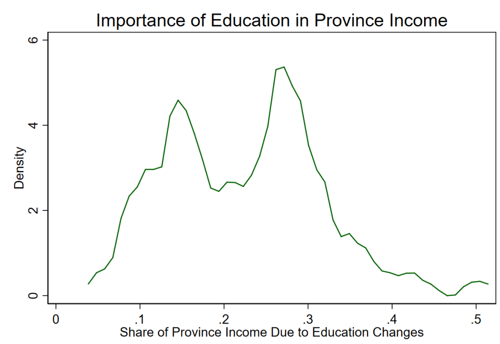
Notes: Figure 4a plots the predicted domestic income per capita from the regressions vs the predicted domestic income per capita as determined by the education and exchange rate components. The red line has an angle of 45 degrees. Each point represents a province, where bubble sizes are weighted by the 1990 population. Figure 4b plots the province-level distribution of the contribution of the education channel in predicting domestic income per capita.

Figure 5: Model Validation & Contribution of Education to Global Income

(a) Validation: Global Income per Capita



(b) Contribution of Education Channel



Notes: Figure 5a plots the predicted global income per capita (domestic plus migrant income) from the regressions vs the predicted global income per capita as determined by the education and exchange rate components. The red line has an angle of 45 degrees. Each point represents a province, where bubble sizes are weighted by the 1990 population. Figure 5b plots the province-level distribution of the contribution of the education channel in predicting global income per capita.

Online Appendix

A Data Appendix

A.1 Migration Data

Calculation of key variables in our analyses (the migrant-income-weighted exchange rate shock and migrant income per capita from each Philippine province) requires unusual data on migrant income and migrant overseas locations by province. To calculate these variables, we obtained two unique administrative datasets from agencies of the the Philippine government. The Philippine Overseas Employment Administration (POEA) is tasked with approving migrant contracts and providing exit clearance. They maintain a rich database on all new contract migrants, including data on name, date of birth, sex, marital status, occupation, destination country, employer, recruitment agency, salary, contract duration, and date deployed. The detailed occupations are also classified into broad occupation categories by the POEA. The Overseas Worker Welfare Administration (OWWA) is responsible for the welfare of overseas workers and their families, and all migrants are required to register with OWWA. OWWA maintains a database that includes migrants' name, date of birth, sex, destination country, date deployed and home address in the Philippines.

To create a dataset that includes migrant wages, destination, and province of origin, we combine the datasets from POEA and OWWA using fuzzy matching techniques for the years 1993, 2007, 2008, and 2009. In the pre-shock (pre-1997) period, we use only data from 1993 work contracts for this calculation because it has the fewest missing values for migrant origin address in the OWWA data (86% non-missing) of all pre-crisis years (1992-1996). In the post-shock (post-1997) years, several years also have relatively high rates of missing data on migrant origin address. We therefore focus on the years 2007-2009 which have low rates of missing address data, and which also span the 2007 and 2010 Philippine Censuses. This temporal overlap with census years is useful for estimating migrant income per capita, as discussed below. We match the POEA and OWWA data using first name, middle name, last name, date of birth, destination country, sex, and year of departure. We achieve a match rate of 95%.

Using the matched dataset, we then calculate the share of total province-level migrant annual income from each destination country in 1993. We aggregate migrant wages in each destination-province, and then divide these destination-province specific wage totals by the total migrant wages for the province. The wage shares are then used to create the income-weighted exchange rate shock, and the wage returns to skill. All wages are in thousands of real 2010 Philippine pesos.

To calculate migrant income per capita, we calculate total migrant income from the province by multiplying average province income in 1993 by the number of migrants in a given province reported in the 1995 Census. Since the POEA data only includes new hires, we used data from the Census to aggregate to total migrant income in the province (the Census includes all migrants, not just new hires). We then divide by the 1995 province population, obtaining migrant income per capita prior to the 1997 shock. We go through a similar calculation for migrant income per capita in 2007, 2008, and 2009. For each year, we calculate average migrant income from the POEA/OWWA data. We then multiply by the total number of migrants in the 2007 Census (for 2007 migrant income per capita), in the 2010 Census (for 2009 migrant income per capita), or the average of the 2007 and 2010 Census (for 2008 migrant income per capita).

We use the POEA/OWWA classification of broad occupation categories to create migration rates by occupation. There are three broad categories we examine: (1) Professional occupations include performing artists, engineers, medical professionals and teachers, among other professions. (2) Service workers are usually caretakers and caregivers, cooks and waiters, and domestic helpers among other occupations. (3) Production workers comprise of brick-layers and carpenters, electrical workers, and plumbers among other occupations. Together, these three categories cover about 94 percent of migrant contracts.

There is one caveat with using the home address variable to calculate province-level wages: the home address variable in the OWWA data includes municipality, but not province. Out of 1630 municipalities in the Philippines, 332 have ambiguous names that are used in more than one province. This accounts for between 10 and 19% of migration episodes depending on the year. Thus, to calculate province-level variables, we assign municipalities with such duplicate names their population share of the total wages across municipalities with the same name. In addition, a small minority of migrants fail to report municipality in the OWWA data (14% in 1993). Theoharides (2018), who also uses the matched POEA/OWWA dataset, shows that municipalities appear to be missing at random, so we simply drop observations with missing municipalities from our analysis.

A.1.1 Calculation of aggregate migrant income as share of global income

In the introduction we report that migrant income makes up 13.6% of global income in the Philippines in our period of analysis. For each province, we calculate migrant income per capita and domestic income per capita in each of years 1994, 2006, and 2009. We then use provincial population in each year to calculate provincial migrant income and domestic income in each year. Then, we take the sum of each across provinces within year to get Philippine aggregate migrant and domestic income in each year. We then take the sum of migrant and domestic income across years 1994, 2006, and 2009. Finally, we divide aggregate migrant income by aggregate global income, yielding the percentage 13.6%.

A.2 Cost-of-living Adjustment for Migrant Incomes

To calculate the PPP adjusted migrant earnings for each year and province, we undertake the following steps:

1. **Calculating share of remittances as a fraction of total migrant earnings:** For each province and year, we divide the remittance per capita with the migrant earnings per capita. Remittances are measured as "assistance from abroad" in the FIES data. For province-year pairs where remittances are above total migrant earnings, we cap the share at 1.

2. **Creating a price-ratio adjuster:** For this analysis, we use the World Bank WDI "Price Level Ratio of PPP Conversion Factor over Exchange Rate" data.[32] We normalize it so that Philippines price levels are 1. Using 1993 migrant destination earning shares as weights, we average each country's price levels to get a province-year level price ratio adjuster. We use 1993 migrant destination earnings shares as weights for all years, as this is pre-shock data. Any migrant destination distributions after 1997 would presumably be impacted by the shock itself. However, we use the relevant year's price ratio levels from WDI to create the price ratio adjuster.

   Taiwan is a prominent destination country for which the WDI data is missing. So, we use FRED data on "PPP over GDP" and "Taiwan / U.S. Foreign Exchange Rate" to calculate the price level ratio by dividing the conversion factor with the exchange rate.[33]

3. **Calculating PPP adjusted migrant earnings:** First, for each province-year migrant earnings, using the share of remittances we calculate above, we determine the unremitted portion of the earnings. We then adjust the unremitted portion by dividing it with the price ratio adjuster. The remitted portion is not adjusted, as it is spent in the Philippines. PPP adjusted migrant earnings are the sum of the remitted earnings and the adjusted unremitted earnings. We then go from nominal income to real 2010 PhPs.

[32] For more information about and access to the data, see `https://data.worldbank.org/indicator/PA.NUS.PPPC.RF?end=2019&start=2019&view=bar`

[33] For more information about and access to the data, see `https://fred.stlouisfed.org/series/PPPTTLTWA618NUPN` PPP over GDP data and `https://fred.stlouisfed.org/series/DEXTAUS` for the exchange rate.

A.3 Census Data

We created a panel of schooling and asset outcomes using the 1990, 1995, 2000, and 2010 Philippine Census of Population from the Philippine Statistical Authority. Each census wave includes 100% of the non-institutionalized Philippine population. In each round of the census, we take the average within the province across all households (for the asset index) or individuals within age groups (for years of schooling).

To study the impact on the skill composition of jobs, we use information on occupations and educational attainment from the Survey of Overseas Filipinos (SOF). The survey ask families about the education and occupations of household members, and we calculate an average education level for each occupation in the Philippine Standard Occupational Classification (PSOC), which we match to the Census data.

A.4 Labor Force Survey Data

Data on employment rates are from the 1992-2011 quarterly Philippine Labor Force Survey (LFS). The LFS is widely used by the Philippine Statistical Authority (PSA) to calculate official government statistics, such as employment statistics, as well as by academic researchers. The data are collected in January, April, July, and October. We have five years of pre-shock data, and 14 years of post shock data. The first two quarters of 1997 are assigned to the pre-shock period, while the latter two quarters of 1997 are considered post-shock. Each survey round includes approximately 200,000 individuals and 44,000 households, and includes sampling weights.[34] One-quarter of households are rotated out of the sample in each quarter, and the data are repeated cross-sections.

Labor force participation, international migration status, and employment-related variables are available for all household members aged 15 and above, while employment status is available for individuals age 10 and above. Individuals are defined as employed if they did some work, even for an hour, during the past week. Households are asked about migrant members and their demographics, but employment status is not asked about migrant members. We assume that all household members who are currently overseas on a work contract are employed. We calculate the employment rate by dividing by the province population in a given age-gender group. We also create variables for the share of employed workers engaged in each employment class out of the province population. Labor supply outcomes in Table A9 exclude international migrants in the rate calculations.

[34] More technical details on the LFS can be found here: https://psa.gov.ph/content/technical-notes-labor-force-survey-lfs

A.5 Firm Production Data

Data on firm revenue, exports, inventories, employment, hours and compensation are from the Annual Survey of Philippine Business and Industry (ASPBI). This is a sample-survey covering the entire country. We obtain data between 1988 and 2015 only for province-year observations that had more than 3 manufacturing firms in their survey. This means that at most we have information for about 76 (out of 82) provinces, and some years have fewer observations. Yet, to the best of our knowledge, this is the longest detailed comprehensive panel of firm activity. The survey uses the official List of Establishments (LE) as their sampling frame. An establishment is the unit of enumeration in the survey, defined to be an “economic unit under a single ownership or control." The sampling design is stratified systematic sampling with employment size-group as the stratification variable. In our analysis, we use sample weights when examining the ASPBI data. Unweighted regressions produce qualitatively similar results.

Our main variables of interest include employment (the number of workers on payroll in November of the survey year) and number of hours workers by production workers (including wait time and overtime, but excluding sick and vacation leave). Revenue includes cash received for goods sold and services rendered, while inventories refer to the stock of goods by and under the control of establishment regardless of where the stocks are located.

A.6 Domestic Income and Consumption

Data on household income and consumption are from the 1994, 2006, and 2009 Philippine Family Income and Expenditure Survey. The FIES is a rider survey to the LFS, and is similarly used widely by the PSA to calculate official income and expenditure statistics. FIES enumeration occurs over two visits: the first in July of the survey year, with January to June as the reference period, and the second in January of the subsequent year, with July to December as the reference period. The same households interviewed for the LFS in July of the survey year and January of the subsequent year are interviewed for the FIES. We have one year of pre-shock data (1994) and two years of post-shock data (2006 and 2009). Each survey also includes sampling weights.

The FIES includes detailed household income and consumption categories. Domestic income and consumption, as included in Table 2, are the aggregation of these detailed categories. We also calculate total income by adding migrant income from the POEA/OWWA data and domestic income from the FIES.

To analyze global income's domestic and migrant components over our period of analysis (which come from different data sources), we need to focus on a subset of time periods when both domestic and migrant income data are available. The intersection of the two datasets allows us to examine one pre-shock year and two post-shock years in analyses of global income. For domestic income from the FIES, the pre-shock year is the 1994 FIES round, and the post-shock years are 2006 and 2009 FIES rounds.

For migrant income from the POEA/OWWA dataset, we use 1993 as the pre-shock year for migrant income. In the analyses we consider these data "1994" for the purposes of calculating global income (the sum of migrant and domestic income) in 1994. For the post-shock years, we use migrant income calculated using the 2007 data as "2006" migrant income to combine with 2006 domestic income in the FIES. We use the average of the 2008-2009 migrant income as the "2009" migrant income to combine with 2009 domestic income in the FIES.

A.7 Data for Quantifying Contribution of the Education Channel

We create a database at the origin-destination-skill group-by-year level from our raw data in order to perform the quantification exercise. From the 1990 Census we construct the baseline shares of the working-age population that migrated abroad for each skill group. We use these baseline shares as the probability of migration by skill-group. In addition, we use the POEA/OWWA data to construct measures of migrant income for each origin-destination pair, by skill group and year. We use the post-shock period to determine the returns to skill using these income. We exclude origin-destination-skill-time observations where there were no flows. We trim the salary data at the 99th percentile.

Our quantification exercise also requires us to rely on a measure of the predicted change in education levels at the origin. We use the results in panel (a) of Table 3, for the full population sample, and the specification that includes all the controls, to create an out-of-sample linear prediction at the origin level. When we compare our quantification exercise to predicted changes in flows and income-per-capita from Table 2, again we use the estimates that rely on the full set of controls to be consistent.

B Additional Empirical Analyses

B.1 Estimating Migration Costs

Migration costs help drive the persistence in migration patterns, and thereby persistence in migrant income. One reason underlying the persistence is the role of recruitment agencies, who enter into contracts with overseas employers to fill specified positions (e.g., nursing positions in Qatar). Agencies source and interview job applicants in licensed branches in particular localities. Agencies specialize in placing workers in particular overseas destinations where they have contacts and past experience. The origins and destinations of workers placed by particular agencies therefore tend to be persistent over time.

As a result, the costs of migrating from a particular Philippine origin location to a particular destination country are heterogeneous. We parameterize migration costs between origin o and destination d as depending on the presence of recruitment agencies, and their overseas areas of operation. Competition between agencies in origin o placing workers in destination d should lower how much they charge potential migrants, also lowering o to d migration costs:

$$\log\left(1-\tau_{dot}\right) = \lambda_1 \,\#\, Rec\, Agen_{dot} + \lambda_2 HHI\, Rec\, Agen_{dot} + \varepsilon^1_{dot} \quad \text{for } t = T, \qquad \text{A26}$$

where $\#\, Rec\, Agen_{dot}$ is the number of recruitment agencies in province o that send at least one migrant to destination d, and $HHI\, Rec\, Agen_{dot}$ is the Hirschman-Herfindahl Index for the competitiveness of the market that sends migrants from o to d.[35]

We use Equation A26 in conjunction with Equation (4). The migration costs we estimate vary at the od-pair level. In Equation (4), $\theta \log\, w_{dst} + \theta \log\, R_{dt}$ are absorbed by destination fixed effects μ_d, and $\log\, \left[\sum_k \left(w_{kst}(1-\tau_{kot})\right)^{\theta} \varepsilon_{kot}\right]$ by origin fixed effects, μ_o.[36]

$$\log\, \pi_{dot} = \mu_o + \mu_d + \theta\lambda_1 \,\#\, Rec\, Agen_{dot} + \theta\lambda_2 HHI\, Rec\, Agen_{dot} + \varepsilon^2_{dot} \quad \text{for } t = T \qquad \text{A27}$$

That recruitment agencies play such a meaningful role in determining migration flows can be seen by the raw data scatter-plot version of Equation A27 in Figure A3. While this relationship is not meant to be causal, it quantifies the migration costs for workers who wish to migrate from origin o to destination d. The relationship between flows and agencies is strong, and also stable over our study period. This may explain the underlying heterogeneity in origin-destination flows, and the persistence in flows (and thereby migrant income) over time.

B.2 Persistence of exchange rate shocks and migration patterns

We present here empirical analyses of the persistence of exchange rate shocks and of overseas migration destination patterns from Philippine provinces.

We first provide evidence of long-run persistence of the exchange rate shocks generated by the Asian Financial Crisis. In Appendix Table A3, we test whether the initial (short run) exchange rate shock persists over three and thirteen years after the shock. In Columns 1 through 3, we regress the three-year (1997-2000) change

[35] If h_{aod} is the share of workers sent by agency a to d, then $HHI_{od} = \sum_a h^2_{aod}$.

[36] This means that whether the origin is a big city or a small town, or whether the destination is a rich or a poor country, is not associated with the migration cost estimates.

in the exchange rate on the one-year (1997-1998) change in the exchange rate. The shocks are persistent across various country subsamples (all countries, as well as only countries with large numbers of Filipino migrants). Columns 4 through 6 show the correlation of the 13-year (1997- 2010) and one-year exchange rates, showing that the exchange rate shocks are also highly persistent over this longer time window.

Also crucial to the analysis is that the destinations of migrants from particular provinces (and thus the locations of their migrant income) show persistence or "stickiness" over time. We provide evidence of persistence in origin-province/overseas-destination in Appendix Table A4. In Appendix Table A4, we first show that total province-level international migration rates are highly persistent: when regressing post-shock (2000 or 2010) migration rates on the initial (1995, pre-shock) migration rate, the coefficient on the initial migration rate is highly statistically significant and the regression with this single RHS variable has a very high R-squared (close to 0.8). Appendix Table A4 then tests persistence of specific overseas destinations by province. We run one regression for each of the top 20 pre-shock overseas destinations, regressing the share of the province's population migrating to the destination in 2009 on the corresponding share in 1995. Each row presents the coefficient on the 1995 share. The positive and statistically significant coefficients indicate strong persistence in overseas destinations at the province level: knowing a province's pre-shock migrant destination pattern has strong predictive power for its post-shock destination pattern. While not every coefficient in this set of 20 is statistically significant at conventional levels (three are not), a test of joint significance of these 20 coefficients rejects the null of no statistical relationship (p-value$<$0.001).

C Details behind pre-trends, other channels, and selection biases

In this section, we provide additional discussion and empirical analyses to address key concerns related to causal identification.

C.1 Omitted variable bias

Most prominently, there are concerns of omitted variable bias: third factors could be correlated with the shock and changes in key outcomes. To address omitted variable concerns, all our regression specifications focus only on the *interaction* between the exchange rate shock and baseline migrant income per capita as the right-hand-side variable of interest. Second, we give the most weight to regression specifications that include controls for heterogeneous province trends. In all results tables, we directly compare coefficient estimates from regressions that do not (column 1) and do (column 2) include these strong controls for heterogeneity in time trends across provinces; coefficient estimates are stable across these specifications for most key outcomes.

In addition, for most outcomes we can run "placebo" experiments in the pre-shock period to show that changes in outcomes prior to the shock have no relationship with the future shock to migrant income per capita. This is a partial test of the parallel-trend assumption underlying difference-in-differences.[37] In Appendix Table A11 and Figure A6 we present the relationships from placebo experiments. We keep only observations prior to the June 1997 shock, and partition the pre-shock observations in to an earlier "control" period and a later "false treatment" period. We run regressions where $Post_t$=1 in this "false treatment" period, and 0 otherwise. For instance, we show non-parametric relationships for different education outcomes in the pre-period in Figure A6c, for domestic income in Figure A6a and for consumption expenditure in Figure A6b. As we have multiple pre-periods, we also show trends in domestic income in an event study analysis in Figure A4. No patterns emerge in this analysis that mirror our main results; trends in key outcome variables in the pre-1997 period do not appear to be related to the size of their (future) shocks to migrant income per capita. We take this as support for the validity of the parallel trend assumption.

C.2 Channels other than migrant income

A key question is whether the shock variable we construct affects outcomes only via its effect on migrant income, or whether other channels might be operative. In particular, trade or foreign direct investment (FDI) patterns (between Philippine provinces and overseas destinations) might reflect migration patterns. It is imaginable that positive shocks to migrant income per capita might be collinear to some degree with shocks to domestic income due to increased trade and FDI. Our results are inconsistent with trade- and FDI-mediated effects, however, since the shock does not affect domestic employment rates or firm production outcomes (Table A9). Indeed, we directly estimate the effects on exports for manufacturing firms in Table A9 and fail to find any detectable changes. In Appendix Table A12, we present impacts on employment rates (share of population working) of adults (age 25-64) and young adults (age 16-24), in total and by gender.[38] Coefficients in nearly all regressions are small in magnitude (and actually negative for young adults) and not statistically significantly different from zero.[39]

[37] Data are not available for us to be able to run these placebo experiments for the household asset index (only one pre-shock year is available, the 1990 Census), and migrant contracts (the only available pre-shock year is 1993).

[38] In Table A9, discussed previously, we presented regressions for labor force participation rates in these age groups. Impacts on employment rates for children (age 10-15) were already shown in Table A9.

[39] The exception is the negative and statistically significant coefficient in the regression for male adults, which declines to zero and loses statistical significance when province-specific linear time trends are added to the regression in column 2.

C.3 Selection bias

Finally we address the possibility of selection bias: changes in the composition of households or individuals across rounds of data (since we have a panel of localities, not a panel of households or individuals). We check for the possibility of selection bias via internal migration by examining the impact of the migrant income shock on internal migration rates. Results are in Appendix Table A13. We find no large or statistically significant relationship between internal migration and the shock.

D Model Derivations

D.1 Deriving share of flows from o to d

Wages for workers are as defined in the text, to be:

$$w_{idost} = w_{dst} R_{dt} (1 - \tau_{dost}) q_{id} \varepsilon_{dot} \equiv \widetilde{w_{dost}} q_{id} \tag{A28}$$

Workers will pick the destination p with the highest value of $w_{idost} = \widetilde{w_{dpst}} q_{id}$. The probability that they pick destination 1 is given by:

$$\begin{aligned} \pi_{1ost} &= Pr\left[\widetilde{w_{1ost}} q_1 > \widetilde{w_{d'ost}} q_{d'}\right] \;\; \forall d' \neq 1 \\ &= Pr\left[q_{d'} < \frac{\widetilde{w_{1ost}} q_1}{\widetilde{w_{d'ost}}}\right] \;\; \forall d' \neq 1 \\ &= \int \frac{dF}{dq_1} (q_1, \alpha_1 q_1, ..., \alpha_D q_D) \, dq_1 \end{aligned} \tag{A29}$$

where we define $\alpha_d \equiv \frac{\widetilde{w_{1ost}}}{\widetilde{w_{d'ost}}}$. We assume that the abilities are distributed with the following Frechet distribution:

$$F(q_1, ..., q_D) = exp\left\{ - \left[\sum_{d=1}^{D} q_d^{-\theta} \right] \right\} \tag{A30}$$

So the derivative of the CDF is given by:

$$\frac{dF}{dq} = \theta q^{-\theta-1} exp\left\{ - \left[\sum_{d=1}^{D} q_d^{-\theta} \right] \right\} \tag{A31}$$

This derivative evaluated at $(q_1, \alpha_1 q_1, ..., \alpha_D q_D)$, allows us to determine the probability of choosing destination 1:

$$\begin{aligned}
\pi_{1ost} &= \int \theta q^{-\theta-1} exp\left\{-\left[\sum_{d=1}^{D}(\alpha_d q)^{-\theta}\right]\right\} dq \\
&= \frac{1}{\sum_{d=1}^{D}\alpha_d^{-\theta}} \int \left(\sum_{d=1}^{D}\alpha_d^{-\theta}\right) q^{-\theta-1} exp\left\{-\left[q^{-\theta-1}\left(\sum_{d=1}^{D}\alpha_d^{-\theta}\right)\right]\right\} dq \\
&= \frac{1}{\sum_{d=1}^{D}\alpha_d^{-\theta}} \int dF(q) \\
&= \frac{1}{\sum_{d=1}^{D}\alpha_d^{-\theta}}.1 \\
&= \frac{\widetilde{w_{1ost}}^{\theta}}{\sum_{d=1}^{D}\widetilde{w_{dost}}^{\theta}} \qquad \text{A32}
\end{aligned}$$

The third line comes from the properties of the Frechet distribution, where we know that the term in the integral of the second line is simply the PDF with a shape parameter θ, and a scale parameter $\sum_{d=1}^{D}\alpha_d^{-\theta}$. Expanding on the definitions for $\widetilde{w_{dost}}$, and including the subscripts, we have:

$$\pi_{dost} = \frac{(w_{dst}R_{dt}(1-\tau_{dot})\varepsilon_{dot})^{\theta}}{\sum_k (w_{kst}R_{dt}(1-\tau_{kot})\varepsilon_{kot})^{\theta}} \qquad \text{A33}$$

D.2 Extensions on Education Responses

Non Credit Constrained Households and Changes in Returns: Non constrained households may also respond to exchange rate shocks. Exchange rate shocks may not change the returns to education as they change both the educated and non-educated wage. For those who are not constrained, we derive that for a cost of education $= p_1S + p_2S^2$, the optimal amount of schooling does not depend on Y, but only on the returns to education:

$$S_i^u = \frac{w'(s)_d(1-\tau_{dost})R_{dt}q_{id} - p_1}{2p_2} \qquad \text{A34}$$

where S_i^u are the years of schooling for unconstrained households. The average education levels of non-constrained households from origin o to destination d are:

$$S_{do}^u = \frac{w'(s)_d(1-\tau_{dost})R_{dt}\pi_{dot}^{\frac{-1}{\theta}}\Gamma - p_1}{2p_2} \qquad \text{A35}$$

And the average change in education for unconstrained households from origin o is:

$$S_o^u = \sum_d S_{do}\pi_{dot} = \sum_d \frac{w'(s)_d(1-\tau_{dost})R_{dt}\pi_{dot}^{\frac{-1}{\theta}+1}\Gamma - p_1}{2p_2} \qquad \text{A36}$$

Since $\frac{\Delta\pi_{dot}^{\frac{-1}{\theta}}}{\Delta R_{dt}} = -\frac{\pi_{dot}^{\frac{-1}{\theta}}}{R_{dt}}$, we know that:

$$\Delta S_o^u = \sum_d \frac{w'(s)_d(1-\tau_{dost})\theta\pi_{dot}\Gamma}{2p_2}\frac{\Delta R_{dt}}{R_{dt}} \qquad \text{A37}$$

If δ fraction of the population is credit constrained, then the education response will also depend on δ. Notice that for unconstrained households to respond, students must also expect the exchange rate shocks to be permanent.

Constraints on borrowing from future: For borrowing constrained households, the amount of schooling will depend on the income in the first period (and thereby any shocks to the income from abroad). Consider the two period consumption problem in Equation (5), and the lifetime utility $u(c_1)+u(c_2)$. If $b=\bar{b}$ is binding, then schooling is the only choice. From the first order conditions with respect to schooling, we know that:

$$pu'(c_1) = w'(S)u'(c_2) \qquad \text{A38}$$

For continuous, increase and concave utility and earnings functions, using the implicit function theorem, we can show education is an increasing function of income $\frac{\Delta S}{\Delta Y} > 0$. [40] We can also derive meaningful closed form solutions under other assumptions, such as for a linear earnings function: $w(S) = w'(S)S$, and Cobb-Douglas utility, say $u(c) = \alpha logc$, we can show that for $\bar{b}=0$ (completely constrained households), the first order condition is simply: $\frac{p\alpha}{Y-pS} = \frac{\alpha}{w(S)}w'(S)$. We can derive a simple closed form relationship: $S_o = \frac{1}{2p}Y_o$.

For partially binding credit constraints, we can show $\Delta S = \frac{-I\bar{b}}{4p\gamma_d(1-\tau_{do})q_{id}R_{dt}}\frac{\Delta R_{dt}}{R_{dt}}$, where I is the rate of interest on borrowing

[40] To be specific: $\frac{\Delta S}{\Delta Y} = p + \frac{u''(c_2)}{u''(c_1)}\frac{w'(S)}{p} + \frac{u'(c_2)}{u''(c_1)}\frac{w''(S)}{p}$. Since $u'(c)>0$, $u''(c)<0$, $w'(S)>0$, $w''(S)<0$, we know $\frac{\Delta S}{\Delta Y} > 0$.

D.3 Deriving the changes in flows

We know that flows from a specific origin to a specific destination can be characterized by.

$$\pi_{dost}\ell_{sot} + \pi_{dout}\ell_{uot} \tag{8}$$

Suppose, only R_{dt} changed for one destination, and there were no changes to domestic wages at the origin, then the direct effect would just be:

$$\Delta\, Flows_{dot} = \underbrace{\Delta\ell_{sot}\left(\pi_{dost} - \pi_{dout}\right)}_{\text{Education channel in flows}} + \underbrace{\theta\left(\ell_{sot}\pi_{dost} + \ell_{uot}\pi_{dout}\right)\frac{\Delta R_{dt}}{R_{dt}}}_{\text{Exchange rate channel in flows}} \qquad \text{A39}$$

Yet, simultaneously every exchange rate and every origin's wage changes as a result of the shock. So how does the π_{dost} change when there are multiple changes. From Equation (4), we know that there is a direct effect, and an indirect effect to go to specific destination d:

$$\begin{aligned}\frac{\Delta\pi_{dost}}{\pi_{dost}} &= \theta\frac{\Delta R_{dt}}{R_{dt}} \qquad \text{A40}\\ &- \frac{\theta}{\sum_d\left(w_{dst}R_{dt}(1-\tau_{dot})\varepsilon_{dot}\right)^{\theta}}\left[\sum_{d\neq o}\left(\left(w_{dst}R_{dt}(1-\tau_{dot})\varepsilon_{dot}\right)^{\theta}\frac{\Delta R_{dt}}{R_{dt}}\right) + \left(\left(w_{ost}\varepsilon_{oot}\right)^{\theta}\frac{\Delta w_{ost}}{w_{ost}}\right)\right]\end{aligned}$$

This can be rewritten as:

$$\Delta\pi_{dost} = \theta\pi_{dost}\left[\underbrace{\frac{\Delta R_{dt}}{R_{dt}}}_{\text{Direct effect}} - \left(\underbrace{\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Indirect resorting}} + \underbrace{\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}}_{\text{Domestic earnings stemming flows}}\right)\right] \qquad \text{A41}$$

Change in flows depends on shock on own destination, but also how flows would change to other destinations, and how increases to domestic income would stem such flows. This captures how flows to other destinations change, indirectly affecting flows to the current destination.

We can sum up across destinations, and rewrite this equation

$$\sum_{d\neq o}\Delta\pi_{dost}=\theta\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\left[1-\sum_{d\neq o}\pi_{dost}\right]\right)-\left(\theta\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\left[\sum_{d\neq o}\pi_{dost}\right]\right) \tag{A42}$$

$$\sum_{d\neq o}\Delta\pi_{dost}=\underbrace{\pi_{oost}\left[\theta\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)\right]}_{\text{Exchange rates driving outflows*}}-\underbrace{[1-\pi_{oost}]\left(\theta\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)}_{\text{Domestic earnings stemming outflows*}} \tag{A43}$$

Alternatively, we could separate out the indirect sorting effects:

$$\begin{aligned}\sum_{d\neq o}\Delta\pi_{dost}= &\underbrace{\theta\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Exchange rates driving outflows}}-\underbrace{\theta\left(\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)}_{\text{Domestic earnings stemming outflows}}\\ &\underbrace{-\theta\left[\sum_{d\neq o}\pi_{dost}\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)-\left[1-\sum_{d\neq o}\pi_{dost}\right]\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right]}_{\text{Indirect resorting}}\end{aligned} \tag{A44}$$

Equation A43 allows us to derive:

$$\begin{aligned}\Delta\,Flows_{ot}=&\underbrace{\Delta\ell_{sot}\sum_{d\neq o}(\pi_{dost}-\pi_{dout})}_{\text{Education channel in outflows}}+\underbrace{\theta\sum_{d\neq o}(\ell_{sot}\pi_{oost}\pi_{dost}+\ell_{uot}\pi_{oout}\pi_{dout})\frac{\Delta R_{dt}}{R_{dt}}}_{\text{Exchange rate channel in outflows}}\\ &\underbrace{-\theta\left(\ell_{sot}[1-\pi_{oost}]\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}+\ell_{out}[1-\pi_{oout}]\pi_{oout}\frac{\Delta w_{out}}{w_{out}}\right)}_{\text{Domestic earnings stemming outflows}}\end{aligned} \tag{A45}$$

We can split this up by skill group:

$$\Delta\, Flows_{ot} = \underbrace{\Delta\ell_{sot} \sum_{d \neq o} \left(\pi_{dost} - \pi_{dout}\right)}_{\text{Education channel in outflows}} \tag{A46}$$

$$+\,\theta \left[\underbrace{\ell_{sot}\,\pi_{oost} \sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Exchange rate driving skilled outflows*}} \;+\; \underbrace{\ell_{uot}\,\pi_{oout} \sum_{d \neq o} \left(\pi_{dout} \frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Exchange rate driving unskilled outflows*}} \right]$$

$$-\,\theta \left[\underbrace{\ell_{sot}\left[1-\pi_{oost}\right]\pi_{oost} \frac{\Delta w_{ost}}{w_{ost}}}_{\text{Domestic earnings stemming skilled outflows*}} \;+\; \underbrace{\ell_{out}\left[1-\pi_{oout}\right]\pi_{oout} \frac{\Delta w_{out}}{w_{out}}}_{\text{Domestic earnings stemming unskilled outflows*}} \right]$$

Here, the channels above include the indirect re-sorting to the alternative destinations. Alternatively, we can keep the indirect re-sorting separate:

$$\Delta\, Flows_{ot} = \underbrace{\Delta\ell_{sot} \sum_{d \neq o} \left(\pi_{dost} - \pi_{dout}\right)}_{\text{Education channel in outflows}} - \underbrace{\chi_o}_{\text{Indirect re-sorting}} \tag{9}$$

$$+\,\theta \left[\underbrace{\ell_{sot} \sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}}\right) + \ell_{uot} \sum_{d \neq o} \left(\pi_{dout} \frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Exchange rate driving outflows by skill group}} \right]$$

$$-\,\theta \left[\underbrace{\ell_{sot}\,\pi_{oost} \frac{\Delta w_{ost}}{w_{ost}} + \ell_{out}\,\pi_{oout} \frac{\Delta w_{out}}{w_{out}}}_{\text{Domestic earnings stemming outflows by skill group}} \right]$$

where $\chi_o \equiv \theta \sum_s \ell_{sot} \left[(1-\pi_{oost}) \sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}}\right) - \pi_{oost} \left(\pi_{oost} \frac{\Delta w_{ost}}{w_{ost}}\right) \right]$

D.4 Contributions to changes in global income

The changes to income consist of two main components. First, let us look at domestic income (for those who do not migrate):

$$\sum_s \ell_{sot} \pi_{oost} \overline{w_{oost}} \tag{A47}$$

The direct effect on the domestic income would exist if wages increased $\Delta \overline{w_{oost}} \neq 0$. The first is just the direct "wage channel" – higher wage rates imply higher domestic income. The second is driven by the fact that measured income rises only because education levels rise, and skilled workers are paid more.

$$\Delta W_o = \underbrace{\sum_s \ell_{sot} \pi_{oost} \left(\Delta \overline{w_{oost}}\right)}_{\text{Direct wage channel}} + \underbrace{\Delta \ell_{ost} \left(\underbrace{\overline{w_{oost}} \pi_{oost}}_{\text{skilled wage at home}} - \underbrace{\overline{w_{oout}} \pi_{oout}}_{\text{unskilled wage at home}} \right)}_{\text{Education channel in domestic earnings}} \tag{15}$$

Yet, overall income generated by the individuals that originate from these regions changes by more than simply these components.[41] This is because, the location choices of individuals change as well, in response to lucrative exchange rates, and domestic wage increases. If wage rates increase, then more people may remain behind locally, and earn at home: $\Delta \pi_{oost}$

$$\Delta \pi_{oost} = \theta \pi_{oost} \left[\underbrace{\frac{\Delta w_{ost}}{w_{ost}}}_{\text{Remainers}} - \underbrace{\left(\sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}} \right) + \pi_{oost} \frac{\Delta w_{ost}}{w_{ost}} \right)}_{\text{Indirect resorting}} \right] \tag{A48}$$

There is also the indirect effect again, as described before. Even if wages do not increase at home, more workers may stay behind if exchange rates abroad become less favorable.

Similarly, the direct effects on income based on more favorable exchange rates are driven by higher persistent income, and more flows abroad to avail of these favorable exchange rates. To a specific destination d, this is again given by:

$$\Delta \pi_{dost} = \theta \pi_{dost} \left[\underbrace{\frac{\Delta R_{dt}}{R_{dt}}}_{\text{Direct effect}} - \underbrace{\left(\sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}} \right) + \pi_{oost} \frac{\Delta w_{ost}}{w_{ost}} \right)}_{\text{Indirect resorting}} \right] \tag{A49}$$

Again, the indirect resorting channel depends on the relative changes to exchange

[41] This concept of global income of individuals from a region is similar to the concept of national product, rather than domestic product.

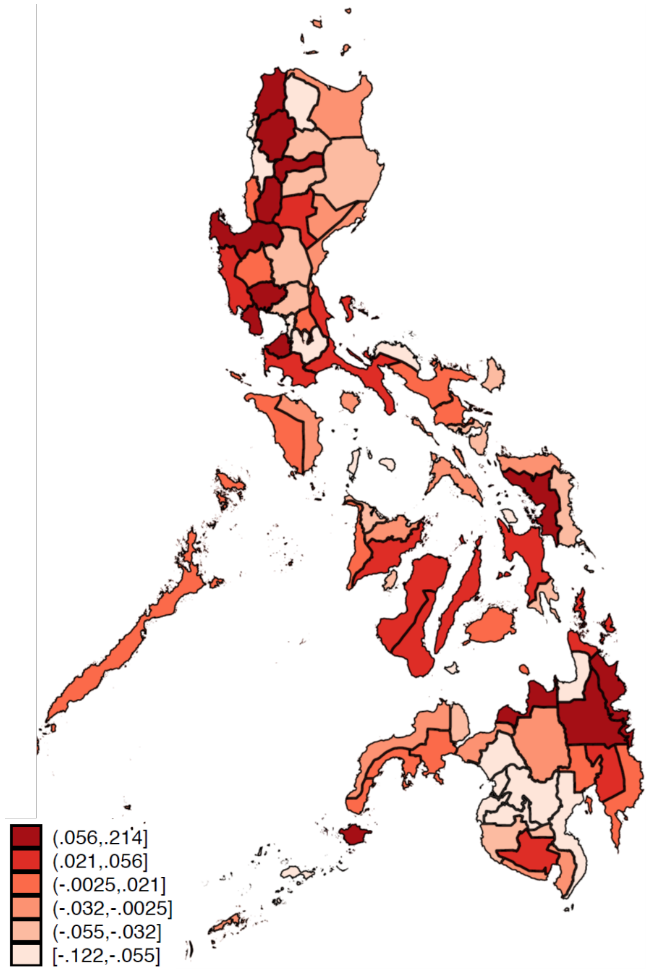
rates in other destinations. So together the global income generated by individuals from these regions (whether they are located at home or abroad) increase by:

$$\underbrace{\sum_s \left[\ell_{sot}\pi_{oost}\left(\underbrace{\Delta\overline{w_{oost}}}_{\text{Direct wage channel}} + \underbrace{\theta\Delta\overline{w_{oost}}}_{\text{Remainers channel}}\right)\right]}_{\text{Domestic earnings due to firm-side responses}} - \tilde{\chi}_o + \underbrace{\theta\underbrace{\left(\sum_s \ell_{ost}\sum_d \pi_{dost}\overline{w_{dost}}\frac{\Delta R_{dt}}{R_{dt}}\right)}_{\Delta Y_o=\text{Migrant Earnings Shock}}}_{\text{Earnings from Abroad: Exchange Rate Channel}} \tag{A50}$$

where $\tilde{\chi}_o \equiv \theta\sum_s\sum_d\left[\ell_{sot}\overline{w_{dost}}\pi_{dost}\left(\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)+\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)\right]$

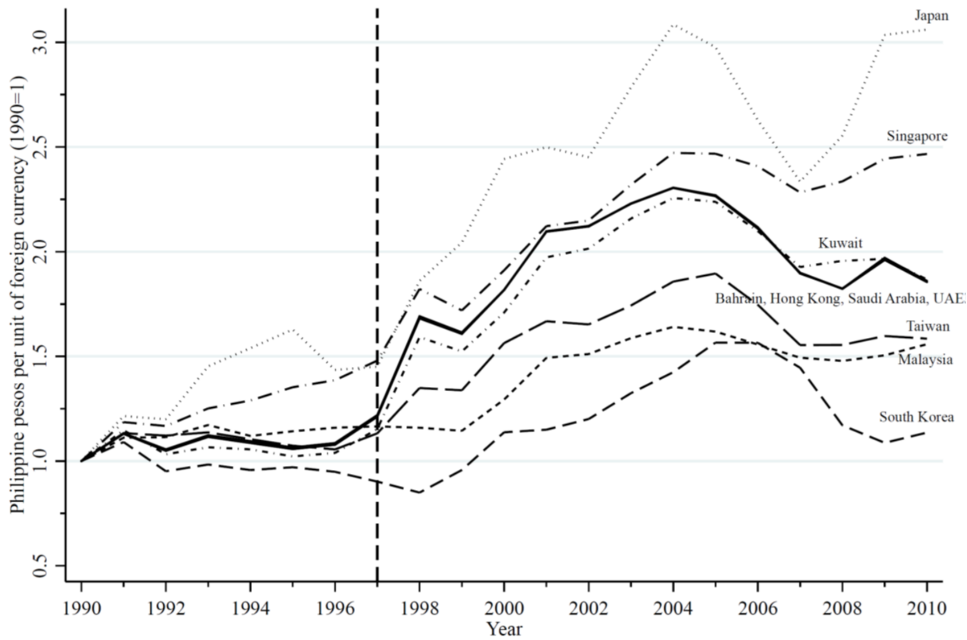
E Additional Tables and Figures

Figure A1: Spatial Distribution of Migrant Income Shock Across Philippine Provinces



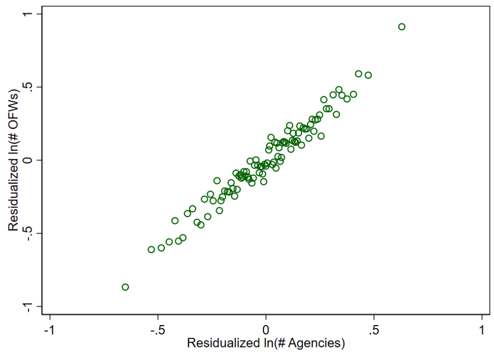
Notes: Figure presents ranges of residual migrant income shock (earnings-weighted exchange rate shock times baseline migrant income per capita) after partialling-out main effects of income-weighted exchange rate shock and baseline migrant income per capita.

Figure A2: Exchange Rate Shocks Due to 1997 Asian Financial Crisis

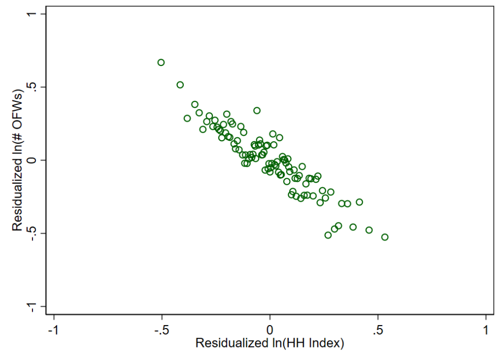


Notes: Data are from World Development Indicators. Annual average exchange rates are in units of foreign currency per Philippine peso, normalized to 1 in 1990, for key destinations of Philippine labor migrants. Vertical dashed line indicates 1997 (year of the Asian Financial Crisis).

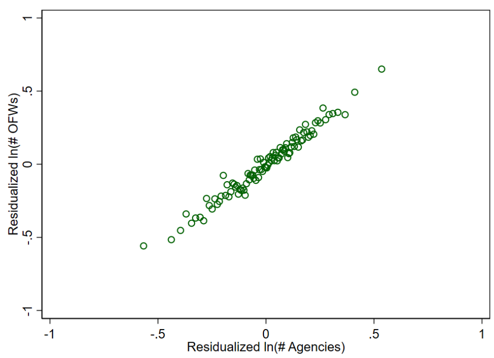
Figure A3: Migrant Flows at Recruitment Agencies at the Origin-Destination Level



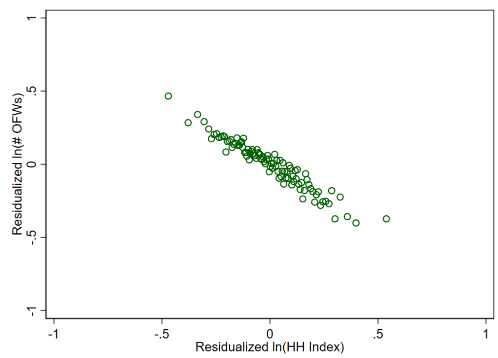
(a) Migrants Flows and # of Agencies 1993



(b) Migrant Flows & HHI of Agencies 1993



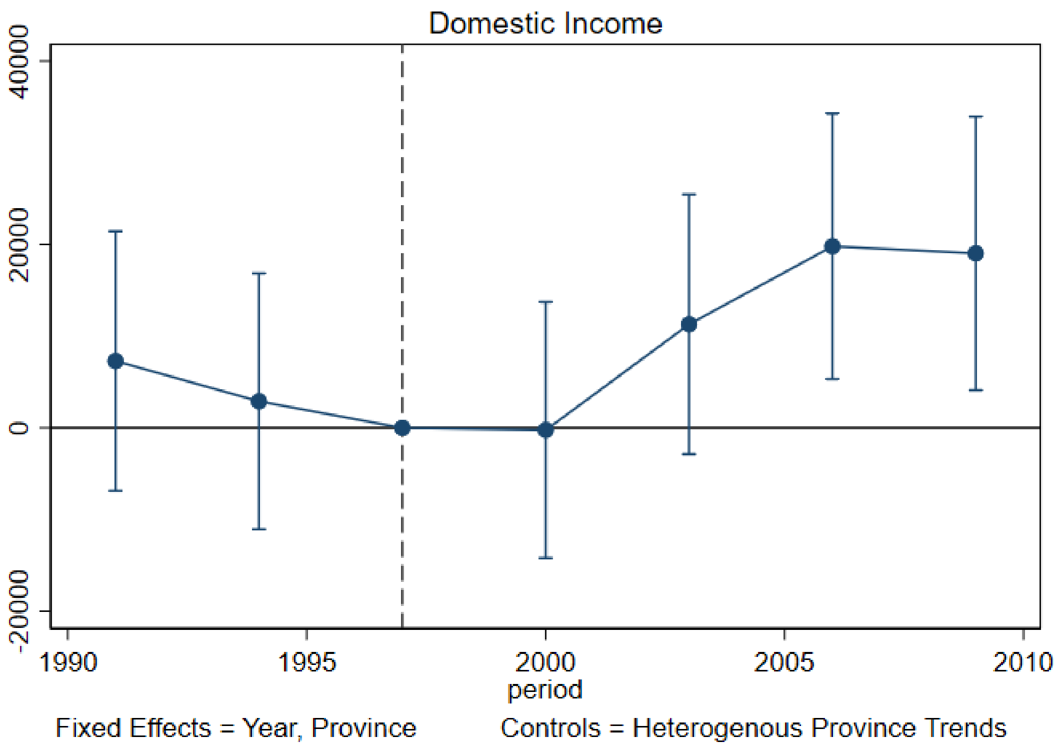
(c) Migrants Flows & # of Agencies 2007-9



(d) Flows & HHI of Agencies 2007-9

Notes: Figures plot the relationship between Log(Number of Oversees Foreign Workers (OFWs)) on the vertical axis recruitment agencies on the horizontal axis. In panel (a) and (c) we plot the Log(Number of Recruitment Agencies) on the horizontal axis. In panel (b) and (d) we plot the Log(Hirschman-Herfindahl Index of Agencies) on the horizontal axis. Panel (a) and (b) are for 1993, whereas panel (b) and (d) are averaged over the 2007-9 period. The data are at the origin-destination pair level, and all variables are residualized by origin μ_o and destination μ_d fixed effects.

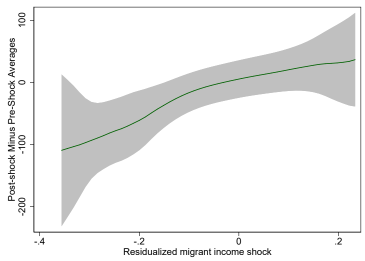
Figure A4: Event Study of Impacts on Domestic Income



Notes: Figure A4 plots the coefficient estimates on migrant income shocks for all years with FIES data (1991, 1994, 1997, 2000, 2003, 2006, and 2009). Province fixed effects, year fixed effects, and heterogenous province trends are used as controls. Standard errors are clustered at the province level.

Figure A5: Nonparametric Relationship Between Shock and Change in Outcomes Related to Skill Composition of Migrants and the Population

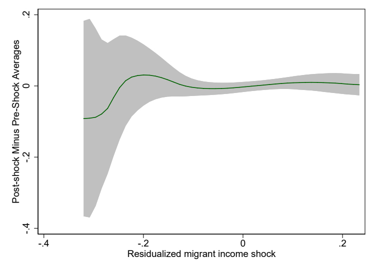
(a) Income per Migrant



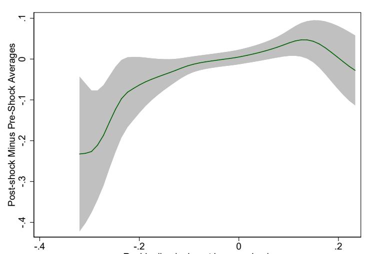
(b) New Migrant Contracts

(c) Migrants: Share Skilled

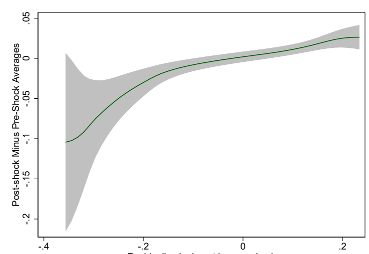
(d) Migrants: Share Services



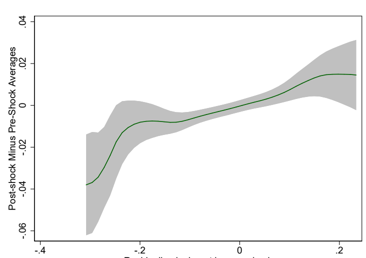
(e) Migrants: Share Production



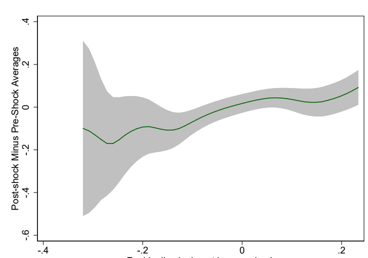
(f) Migrants: Share Professional



(g) Share Skilled (All)



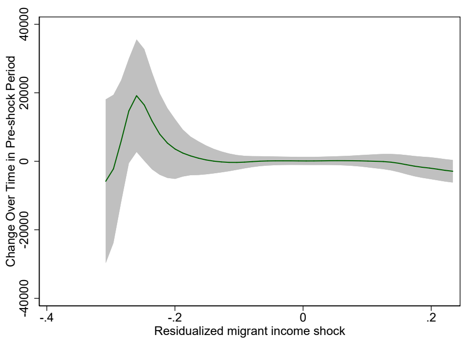
(h) Years of Schooling (19-24)



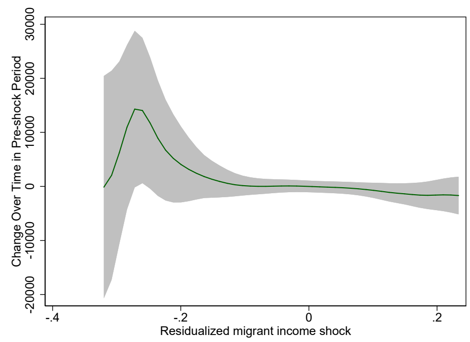
Notes: Nonparametric relationships between migrant income shock (income-weighted exchange rate shock times baseline migrant income per capita) and change in outcomes from pre- to post-shock periods. Outcomes are average of post-shock years minus average of pre-shock years. Outcomes and migrant income shocks are both residualized. Residuals taken from regression of variables on income-weighted exchange rate shock and baseline migrant income per capita. Solid line is nonparametric regression estimate. Gray area is 90 percent confidence interval.

Figure A6: Pre Period Growth

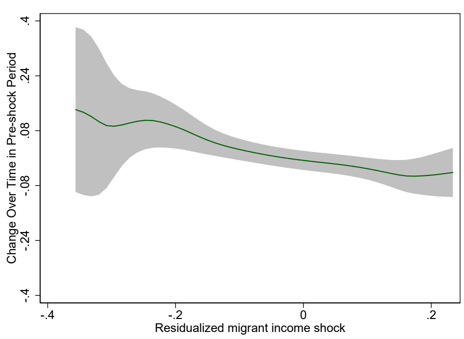
(a) Domestic Income Per Capita



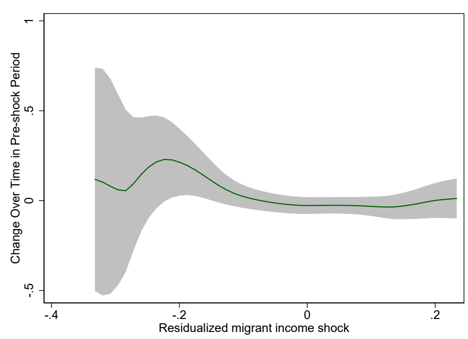
(b) Consumption Expenditure per capita



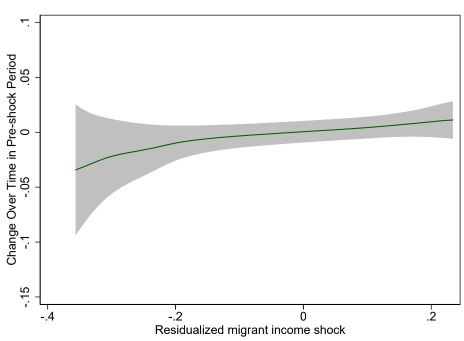
(c) Years of Schooling (7-18)



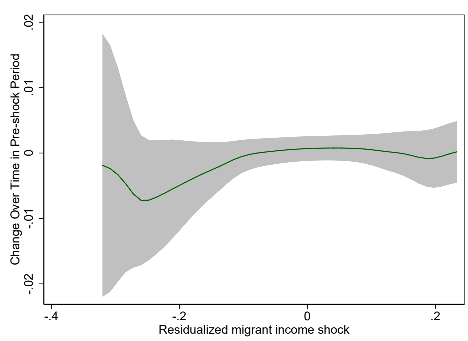
(d) Years of Schooling (19-24)



(e) Share Skilled (Migrants)

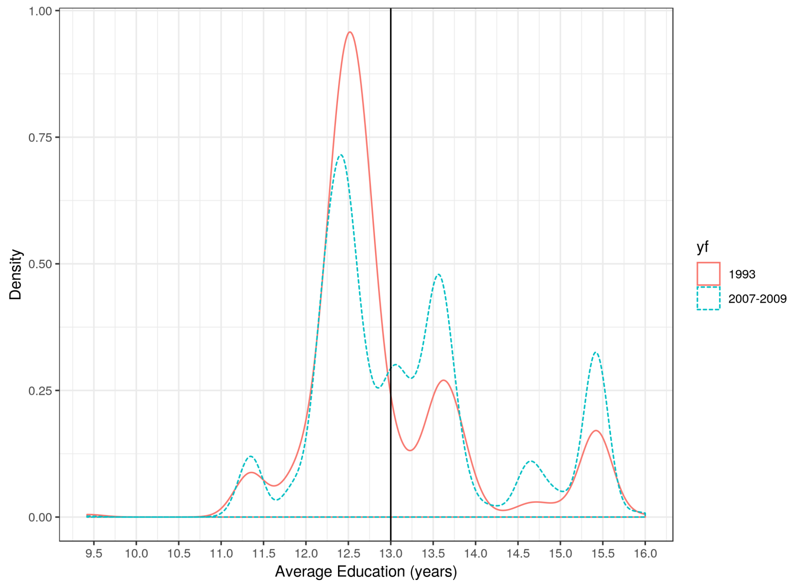


(f) Share Skilled (Full Population)



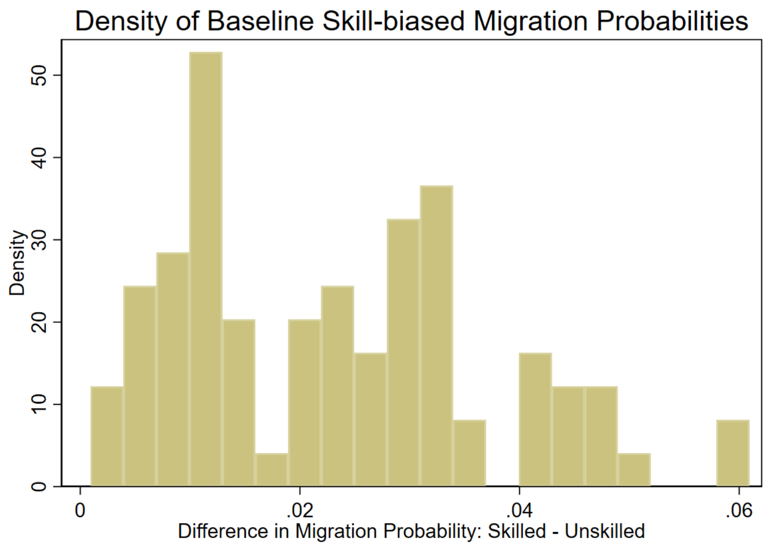
Notes: Nonparametric relationships between migrant income shocks (income-weighted exchange rate shock times baseline migrant income per capita) and change in outcomes in the pre-shock period. Outcomes are last pre-shock period minus first pre-shock period. For years of schooling this is growth between 1990 and 1995. For consumption per capita and domestic income per capita, it is growth between 1991 and 1997. Outcomes and migrant income shocks are both residualized. Residuals taken from regression of variables on income-weighted exchange rate shock and baseline migrant income per capita. Solid line is nonparametric regression estimate. Gray area is 90 percent confidence interval.

Figure A7: Density of Migrant Worker Education



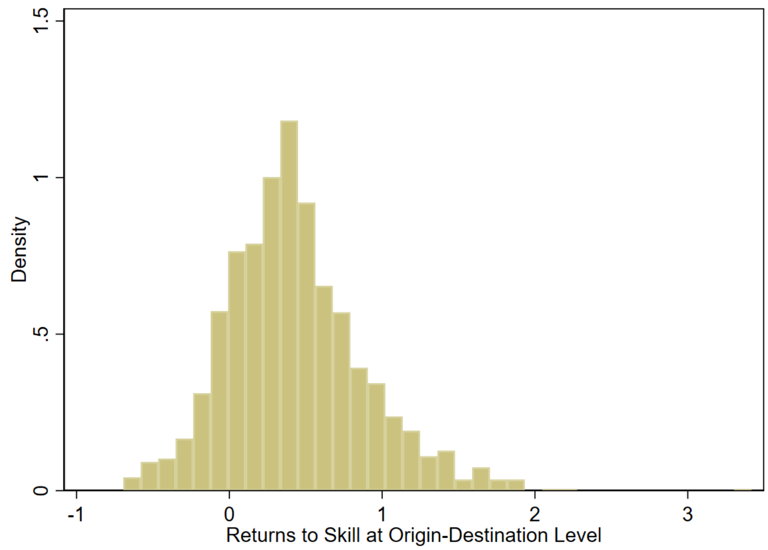
Notes: This figure presents density plots of the distribution of education of migrant workers, separately for worker contracts in the 1993 and the 2007-9 periods. For each worker contract in the POEA/OWWA contract data, workers are assigned the average level of education observed for Overseas Filipino Workers (OFWs) reported in the Philippine Census in the same detailed occupational category.

Figure A8: Skilled-Unskilled Migration Probabilities



Notes: Figure plots a binned histogram of the difference in migration probabilities by skill, across provinces in 1990. We calculate the share of the skilled population that in the age-group 25-64 that is an overseas worker in destination d to be π_{dos}. We similarly do this for unskilled workers in π_{dou}. We then aggregate the difference across destinations, and plot $\sum_k (\pi_{kos} - \pi_{kou})$.

Figure A9: Wage skill-premium among migrants



Notes: Figure plots the distribution of $\overline{w_{dost}} - \overline{w_{dout}}$ at the origin-destination pair level

Table A1: Top 20 Locations of Filipino Migrants Prior to Asian Financial Crisis

Destination	% of Total	Average Annual Earnings (000, Real 2010 Php)	Exchange Rate Shock (June 1997-Oct 1998)	Exchange Rate Shock: 2000	Exchange Rate Shock: 2010
Saudi Arabia	41.85	305.93	0.52	0.69	0.72
Japan	16.09	1457.57	0.32	0.70	1.13
Taiwan	8.45	426.99	0.26	0.48	0.50
Hong Kong	7.31	379.98	0.52	0.67	0.71
United Arab Emirates	5.66	246.97	0.52	0.69	0.72
Malaysia	3.70	216.19	-0.01	0.12	0.34
Singapore	2.28	243.72	0.29	0.38	0.78
Italy	1.96	497.01	0.38	0.24	0.82
Qatar	1.85	217.71	0.52	0.69	0.72
Brunei Darussalam	1.71	271.96	0.30	0.38	0.78
Kuwait	1.24	366.61	0.50	0.65	0.80
United States	1.20	1903.52	0.52	0.69	0.72
Bahrain	1.17	275.66	0.52	0.69	0.72
Northern Mariana Islands	1.11	298.79	0.52	0.69	0.72
Libya	1.09	527.83	0.57	0.44	-0.41
Oman	0.49	267.11	0.52	0.69	0.72
Lebanon	0.34	177.74	0.55	0.76	0.79
Guam	0.32	1309.29	0.52	0.69	0.72
South Korea	0.26	546.72	-0.04	0.20	0.20
India	0.11	380.18	0.35	0.33	0.33
Other	2.41	484.43	0.34	0.16	0.25
Total	100.00				

Notes: Average annual earnings (in thousands) calculated using data from POEA and OWWA in 1993 and is based on 269,990 new migrant contracts in 1993. "Other" includes all migrant destinations outside the top 20 (142 destinations). Exchange rate shock is change in Philippine pesos (Php) per local currency unit prior to the Asian Financial Crisis. The change is defined as the fractional change between July 1996-July 1997 and October 1997-September 1998 (e.g., 10% appreciation is 0.1). The exchange rate shock in 2000 and 2010 are defined as the fractional change in the exchange rate between 2000 and 1997, and 2010 and 1997 respectively. Sources: POEA, OWWA, World Development Indicators.

Table A2: Share of Households with Migrant Connections

Year	Migrants as % of population	% of households with a migrant member	% of households receiving remittances
1990	0.7%	3.2%	
1991			17.6%
1994			19.8%
1995	1.1%	5.0%	
1997			17.3%
2000	1.3%	5.2%	18.1%
2003			20.7%
2006			23.3%
2009			26.0%
2010	1.6%	6.3%	

Source: Authors' calculations from the Philippine Census (1990, 1995, 2000, and 2010) and the triennial Family Income and Expenditure Survey (FIES) from 1991-2009 inclusive. Migrants as % of population is number of individuals reported as migrants divided by total population in Census. % of households with a migrant member is fraction of all households reporting a migrant member in Census. % of households receiving remittances is share of households receiving remittances from overseas (not necessarily from a household member), from FIES (nationally representative survey of households).

Table A3: Persistence of Exchange Rate Shock

	2000 Exchange Rate Shock			2010 Exchange Rate Shock		
	All destinations	Destinations with >1000 migrants	Destinations with >5000 migrants	All destinations	Destinations with >1000 migrants	Destinations with >5000 migrants
	(1)	(2)	(3)	(4)	(5)	(6)
1997-1998 exchange rate shock	1.194***	1.310***	0.840***	1.191***	1.034***	0.511***
	(0.068)	(0.169)	(0.117)	(0.103)	(0.316)	(0.179)
N	163	41	25	163	41	25
R2	0.746	0.642	0.593	0.319	0.192	0.088

Notes: Results from regressions of the exchange rate shock through 2000 or 2010 on the 1997-1998 exchange rate shock. Reported coefficients are the coefficient on the 1997-1998 exchange rate shock variable. Exchange rate shocks are defined as Philippine pesos per local currency unit exchange rate in a given year, divided by the 1997 exchange rate minus 1. Robust standard errors are in parentheses. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.
Source: POEA, OWWA, and Census.

Table A4: Persistence of Total OFW Rate

Panel A: Persistence of Total OFW Rate

	2000 Migration Rate (1)	2010 Migration Rate (2)
1995 Migration Rate	0.740***	0.977***
	(0.034)	(0.055)
N	82	82
R2	0.779	0.797

Notes: The unit of observation is the province. Migration rates are the number of migrants in province j out of the total population in province j. Outcome variables are reported in the column headings. Robust standard errors are in parentheses. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Panel B: Persistence of Migrant Shares Over Time

Bahrain	0.796***
	(0.161)
Brunei Darusssalam	0.209**
	(0.095)
Guam	1.149***
	(0.157)
Hong Kong	0.885***
	(0.072)
India	0.453
	(0.584)
Italy	0.466***
	(0.031)
Japan	0.027***
	(0.005)
Kuwait	0.642
	(0.581)
Lebanon	-0.000
	(0.000)
Libya	1.009***
	(0.184)
Malaysia	0.046***
	(0.013)
Northern Mariana Islands	0.022***
	(0.004)
Oman	0.725***
	(0.271)
Qatar	2.573***
	(0.442)
Saudi Arabia	0.698***
	(0.128)
Singapore	0.856***
	(0.311)
South Korea	0.034**
	(0.013)
Taiwan	0.419***
	(0.107)
United Arab Emirates	1.521***
	(0.308)
United States	0.212***
	(0.029)
P-val.: Joint signif. of all coeffs.	*0.000*

Notes: The unit of observation is the province. N=82. Reported coefficients are from regressions of the number of migrants from province j going to a given destination in 2009 divided by the population in province j regressed on the the number of migrants from province j going to a given destination in 1995 divided by the population in province j. Results are reported for the top 20 pre-shock migrant destinations. Robust standard errors are in parentheses. Bottom row of the table reports the p-value on a F-test of joint significance of the migrant shares in 1995 from a seemingly unrelated regression (SUR) model. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Table A5: Estimating θ using Poisson Pseudo-maximum Likelihood

	Change in Migrant Flows		Earnings	
Log(EX Rate Change)	3.424*	3.024*		
	(1.808)	(1.748)		
Log(Migrants)			-0.317*	-0.268**
			(0.168)	(0.113)
Observations	23,127	258	7,684	7,282
Specification	Origin-Dest-Skill	Destination-Skill	PPML	IV PPML
Clusters	Origin Destination	Destination	Origin Destination	Bootstrap
Fixed Effects	Origin x Skill	Skill	Origin Destination Skill	Origin Destination Skill
Theta			3.155*	3.728**
Std Error			(1.670)	(1.568)

Notes: PPML estimates of theta. First two columns estimate theta using the migration response to a destination shock. Last two columns study the wage change as migrant flows increase -- the estimate of theta is the negative reciprocal of the coefficient reported in the last 2 rows. Migrant earnings and migrant flows are from the POEA/OWWA dataset. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Table A6: First Principal Component Loadings

Refrigerator	0.322
Television	0.3521
Radio	0.175
Water	0.2271
Phone	0.1736
Electricity	0.3305
Metal Roof	0.2944
Brick Walls	0.2339
Trash collection	0.2678
Wood Fuel	0.3414
High Quality Fuel	0.3476
Flush Toilet	0.2945
Home Ownership	0.1123
Land Ownership	0.0278

Notes: This table shows the principal component loadings for each asset in the the asset index. Source: Philippine Census.

Table A7: Correlates of shock variables

	Exchange Rate Shock (1)	Migrant Earnings Per Capita (2)	Exchange Rate Shock times Migrant Earnings Per Capita (3)	Exchange Rate Shock times Migrant Earnings Per Capita (4)
Migrant Earnings Per Capita	0.008***			-0.003
	(0.003)			(0.008)
Exchange Rate Shock		12.177***		-1.757***
		(4.502)		(0.311)
Average Years of Schooling (ages 7-18)	-0.064***	0.968	0.220***	0.112***
	(0.015)	(0.588)	(0.049)	(0.039)
Female employment rate (ages 25-64)	-0.116***	0.468	0.265*	0.054
	(0.040)	(2.060)	(0.144)	(0.093)
Male employment rate (ages 25-64)	-0.017	-1.444	0.048	-0.014
	(0.036)	(1.540)	(0.118)	(0.080)
Share rural	0.077*	5.698***	-0.141	0.115
	(0.043)	(1.971)	(0.105)	(0.089)
Asset index	0.006	3.086***	-0.108***	-0.038
	(0.014)	(0.475)	(0.031)	(0.028)
Rate of employment in enterprises	-0.033	0.802	0.168	0.125
	(0.062)	(2.077)	(0.171)	(0.120)
Population (1000's)	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
p-val.: joint significance of all coeffs.	*0.000*	*0.000*	*0.000*	*0.000*
N	82	82	82	82
R2	0.427	0.841	0.403	0.655
Mean Dependent Variable	-0.000	-0.000	-0.014	-0.014

Notes: The outcome variables are indicated in the column headers, and are regressed on 1990 province characteristics. Robust standard errors. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Table A8: Impact of Migrant Income Shocks on Years of Schooling Completed

Dependent variable: Years of schooling of...	*Mean (std. dev.) of dependent variable*	*Regressions*		*Number of obs.*
		(1) *No controls*	*(2)* *Province-specific linear time trends*	
Children aged 7-18	4.880	0.680***	0.767***	328
	(0.573)	(0.187)	(0.209)	
Children aged 7-12	2.776	0.484***	0.484**	328
	(0.332)	(0.127)	(0.188)	
Females	2.874	0.495***	0.506***	328
	(0.331)	(0.122)	(0.174)	
Males	2.684	0.473***	0.462**	328
	(0.337)	(0.134)	(0.207)	
Children aged 13-15	6.401	0.342**	0.269	328
	(0.619)	(0.156)	(0.279)	
Females	6.656	0.310**	0.304	328
	(0.601)	(0.155)	(0.281)	
Males	6.157	0.375**	0.242	328
	(0.649)	(0.162)	(0.288)	
Children aged 16-18	8.196	0.217	0.998	328
	(0.951)	(0.259)	(0.759)	
Females	8.621	0.221	1.167	328
	(0.977)	(0.275)	(0.789)	
Males	7.795	0.262	0.875	328
	(0.943)	(0.264)	(0.752)	
Young adults, aged 19-24	9.049	0.583**	1.311***	328
	(1.109)	(0.239)	(0.418)	
Females	9.447	0.532**	1.314***	328
	(1.137)	(0.263)	(0.421)	
Males	8.674	0.681***	1.383***	328
	(1.104)	(0.232)	(0.440)	

Notes: All regressions include province fixed effects, year fixed effects, baseline migrant earnings per capita times post, and weighted-average exchange rate shock times post. Regressions in column 2 include province-specific linear time trends. Average years of schooling are calculated from the 1990, 1995, 2000, and 2010 Philippine Censuses. Post equals 1 in 2000 and 2010, and 0 in 1990 and 1995. Robust standard errors are clustered at the province level. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Table A9: Impact of Migrant Income Shocks on Manufacturing Firm Production

Dependent variable	Mean (std. dev.) of dependent variable	Regressions (1) No controls	Regressions (2) Province-specific linear time trends	Number of obs.
(a) Firm production				
Log total revenue	14.79	-0.306	0.699	1388
	(1.527)	(0.774)	(1.091)	
Log value of exports	0.264	-0.0272	-0.227	1388
	(0.709)	(0.343)	(0.515)	
Log total inventories	9.698	0.419	2.139	1388
	(3.079)	(1.910)	(2.528)	
Log total employment	2.785	0.061	0.069	1388
	(1.024)	(0.401)	(0.558)	
Log gross salaries and wages	11.96	-0.318	-2.186	1388
	(2.751)	(1.227)	(2.604)	
Log total hours worked	9.541	-0.665	-1.086	1388
	(2.010)	(0.785)	(1.666)	
(b) Domestic labor supply (no migrants)				
Labor force participation, adults	0.763	-0.064*	0.021	6159
(aged 25-64)	(0.070)	(0.033)	(0.041)	
Labor force participation, young adults	0.521	-0.046	-0.077	6159
(aged 16-24)	(0.105)	(0.064)	(0.054)	
Employment rates, children	0.129	-0.039	-0.033	6159
(aged 10-15)	(0.123)	(0.067)	(0.061)	
(c) Household and small entreprenuership, adults (aged 25-64)				
Self employed, no employees	0.300	-0.056	0.009	6159
	(0.094)	(0.0395)	(0.0267)	
Self employed, >0 employees	0.0326	0.038*	-0.009	6159
	(0.094)	(0.0225)	(0.0172)	
Working in family enterprise	0.0909	-0.119***	-0.051	6159
	(0.094)	(0.0380)	(0.0442)	
Working for other household	0.0248	0.007	0.006	6159
	(0.094)	(0.0097)	(0.0138)	

Notes: All regressions include province fixed effects, year fixed effects, baseline migrant earnings per capita times post, and weighted-average exchange rate shock times post. Regressions in column 2 include province-specific linear time trends. Manufacturing firm production, panel (a), data are from the Annual Survey of Philippine Business and Industry (ASPBI). The data are annual from 1988 to 2015, except 1995, 2000, 2002, 2004, 2007 and 2011, when there was no survey. The sample only includes province-year observations that have more than 3 firms recorded in the year. Employment outcomes and household entreprenuership data are from the Philippine Labor Force Survey, and cover the years 1992-2011. The unit of observation is the province-quarter-year. Labor force participation rate is share in the labor force out of total population in the age group. Employment rate is share working out of total population in age group. International migrants are excluded in calculation of outcome variables in panel (b). Post equals 1 in 1997, quarter 3 to 2011, and 0 in 1992-1997, quarter 2. Robust standard errors clustered at the province level. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Table A10: Components of the Changes in Domestic Income

Dependent variable (periods included in regression)	*Mean (std. dev.) of dependent variable*	*Regressions* (1) *No controls*	*Regressions* (2) *Controls for heterogeneous province trends*	*Number of obs.*
Income (1994, 2006, 2009)				
Domestic income per capita	32.147	18.899***	19.449***	246
	(12.708)	(5.644)	(7.169)	
Domestic wage income per capita	14.232	3.959	2.247	246
	(8.771)	(2.713)	(3.509)	
Domestic entrepreneurial and rental income per capita	10.211	10.289***	9.463**	246
	(2.994)	(3.030)	(4.037)	
Domestic other income per capita	7.704	4.652*	7.739**	246
	(3.391)	(2.527)	(3.040)	
Income by Skill (1994, 2006, 2009)				
Domestic income per worker (skilled)	121.564	62.618***	50.890*	246
	(35.684)	(22.218)	(30.249)	
Domestic income per worker (unskilled)	62.347	30.478	14.527	246
	(22.658)	(21.371)	(22.927)	

Notes: All regressions include province and year fixed effects. Controls for heterogeneous province trends are baseline controls interacted with linear annual time trend. The baseline controls use 1990 data and include: average years of schooling for 7 to 18 year olds, average female employment rate for 25 to 64 year olds, average male employment rate for 25 to 64 year olds, share of households that are rural, the asset index, the share of individuals working in household enterprises, and the population. Skilled workers are workers in a household where the worker with the median education level has completed high school. We use 1994, 2006, and 2009 FIES data. Robust standard errors are clustered at the province level. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Table A11: Falsification Tests (Test for Pretrends)

Dependent variable	*Mean (std. dev.) of dependent variable*	*Regressions* (1) *No controls*	*Regressions* (2) *Controls for heterogeneous province trends*	*Number of obs.*
(a) Income and Consumption				
Domestic income per capita	34.569	-6.162	7.384	160
	(16.463)	(11.810)	(11.810)	
Consumption per capita	30.542	-11.315	-0.958	160
	(14.809)	(10.712)	(9.853)	
(b) Years of Schooling				
Children, aged 7-18	4.617	-0.425**	-0.097	164
	(0.512)	(0.205)	(0.215)	
Young adults, aged 19-24	8.612	-0.394	-0.279	164
	(1.047)	(0.442)	(0.329)	
Share skilled in full population	0.196	0.0119	-0.0024	164
	(0.024)	(0.0185)	(0.0199)	
Share skilled migrants	0.302	0.120	0.0826	164
	(0.095)	(0.0759)	(0.0969)	

Notes: All regressions include province fixed effects, year fixed effects, baseline migrant income per capita times post, and weighted-average exchange rate shock times post. In panel (a), observations are at province/FIES-year level, for 1991 and 1997; post=1 if 1997, and 0 in 1991. In panel (b), observations are at province/census-year level, for 1990 and 1995; post=1 if 1995, and 0 in 1990. Controls for heterogeneous province trends are baseline controls as included in Table 3. Robust standard errors are clustered at the province level. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.

Table A12: Distribution of Education by Occupation

Occupation	*Years of education*	1993	2007-9
Professional	*Mean*	13.6	15.1
	Std. dev.	(1.28)	(0.85)
Production	*Mean*	12.8	12.8
	Std. dev.	(0.80)	(0.79)
Services	*Mean*	12.5	12.7
	Std. dev.	(0.24)	(0.39)

Notes: Table shows the education distribution by major occupation category. The last column (2007-9) takes the average across 3 years of the data: 2007, 2008 and 2009.

Table A13: Impact of Migrant Income Shocks on Internal Migration

Fixed effects regressions. Columns 1 and 2 report coefficients (standard errors) on migrant earnings shock.
Data from each of 77 provinces over three periods (1990, 2000, 2010).

Dependent variable: Internal Migration	*Mean (std. dev.) of dependent variable*	*Regressions*		*Number of obs.*
		(1) No controls	*(2) Province-specific linear time trends*	
Inmigration rate				
Aged 25-64	0.029	0.071**	0.054	231
	(0.022)	(0.032)	(0.053)	
Aged 16-24	0.035	0.099***	0.048	231
	(0.029)	(0.036)	(0.052)	
Aged 7-12	0.022	0.061*	0.043	231
	(0.017)	(0.031)	(0.044)	
Aged 13-15	0.021	0.077***	0.053	231
	(0.018)	(0.029)	(0.039)	
Outmigration rate				
Aged 25-64	0.030	-0.018	-0.056	231
	(0.024)	(0.025)	(0.041)	
Aged 16-24	0.046	-0.044	-0.079	231
	(0.036)	(0.034)	(0.057)	
Aged 7-12	0.021	-0.011	-0.030	231
	(0.019)	(0.019)	(0.040)	
Aged 13-15	0.022	-0.019	-0.039	231
	(0.020)	(0.019)	(0.034)	
Net migration rate				
Aged 25-64	0.000	-0.089*	-0.111	231
	(0.025)	(0.046)	(0.078)	
Aged 16-24	0.011	-0.143***	-0.127	231
	(0.043)	(0.053)	(0.090)	
Aged 7-12	-0.001	-0.072*	-0.074	231
	(0.020)	(0.042)	(0.072)	
Aged 13-15	0.001	-0.096**	-0.092	231
	(0.022)	(0.038)	(0.064)	

Notes: All regressions include province fixed effects, year fixed effects, baseline migrant earnings per capita times post, and weighted-average exchange rate shock times post. Regressions in column 2 include province-specific linear time trends. Internal migration rates are calculated from the 1990, 1995, 2000, and 2010 Philippine Censuses. There are 77 provinces per year rather than the 82 shown in the other tables using Census data due to corrupt internal migration data for five provinces in 1990. At the recommendation of the PSA, we have dropped these 5 provinces in all years. Net migration rate is outmigration rate minus inmigration rate. Post equals 1 in 2000 and 2010, and 0 otherwise. Robust standard errors are clustered at the province level. *** indicates significance at the 1% level. ** indicates significance at the 5% level * indicates significance at the 10% level.