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

Gaurav Khanna, Emir Murathanoglu, Caroline Theoharides, and Dean Yang

Abstract

We study how international migrant income prospects affect long-run development in origin areas. We leverage the 1997 Asian Financial Crisis exchange rate shocks in a shift-share identification strategy across Philippine provinces. Initial migrant income shocks are magnified six-fold over time, increasing *domestic* income, education levels, migrant skills, and high-skilled migration. Remarkably, 73.6% of long-run income gains come from domestic rather than migrant income. Trade-driven impacts of exchange rate shocks are orthogonal to effects via migrant income. A structural model reveals that 19.6% of long-run income gains stem from educational investments. International migration fosters broad economic development in origin communities.

JEL codes: F22, J24, O15, O16
Keywords: Migration, global income, education, Philippines

*Khanna: University of California – San Diego (gakhanna@ucsd.edu); Murathanoglu: Oberlin College (emuratha@oberlin.edu); Theoharides: Amherst College (ctheoharides@amherst.edu); Yang: University of Michigan, NBER and BREAD (deanyang@umich.edu). We thank HeeSung Kim and Theo Kulczycki for excellent research assistance. We appreciate feedback from Ran Abramitzky, Toman Barsbai, Sam Bazzi, Gustavo Bobonis, Loren Brandt, Emily Breza, Brian Cadena, Lorenzo Casaburi, Dasha Celik, Levent Celik, Michael Clemens, Taryn Dinkelman, Michael Donihue, Christian Dustmann, Eric Edmonds, Ryan Edwards, Dennis Egger, Alejandro Estefan, Ben Faber, Xavi Giné, Joseph Gomes, Jessica Goldberg, André Gröger, Matthias Hoelzlein, Joe Kaboski, Andrea Matranga, David McKenzie, Melanie Morten, Pablo Ottonello, Owen Ozier, Dina Pomerantz, Tommaso Porzio, Imran Rasul, Yasu Sawada, Alex Scacco, Matti Sarvimäki, Mahesh Shrestha, Manisha Shah, Sebastian Sotelo, Andreas Steinmayr, Marko Terviö, Lore Vandewalle, Peter Varela, David Yanagizawa-Drott, Xiaodong Zhu, and seminar participants at Universitat Autonoma de Barcelona, U. Munich, U. Navarra, U. Zurich, Higher School of Economics, New Economic School, Helsinki Center of Economic Research (HECER), Development Network Berlin (DENeB), Asian Development Bank, U. Toronto, Australian National University, University College London, Ateneo de Manila, U. Paris 1 Panthéon-Sorbonne, the U.K. Foreign, Commonwealth, & Development Office (FCDO), Notre Dame University, the 2015 and 2018 International Conference on Migration and Development, the 2017 Centro Studi Luca d'Agliano/Colegio Carlo Alberto/FIERI Migration Conference, the 2018 Geneva Workshop on Financial Inclusion in Developing Countries (Graduate Institute Geneva), the 2018 Barcelona GSE Migration Summer Forum, NEUDC, the 2018 IZA Migration Meeting, the 2021 Asia Impact Evaluation Conference (HKUST/ADB/KDI), and the 2022 NBER Summer Institute (Development Economics Program).

1 Introduction

Moving from a developing to a developed country for work generates income gains larger than those from any known economic development program (Clemens et al., 2019; Pritchett and Hani, 2020). While international migration clearly raises incomes for migrants, evidence is scarce on how migrant income affects broader development in migrant-origin *areas*. Positive shocks to migrant income could loosen liquidity constraints on human capital and entrepreneurial investments. In addition, higher *potential* income in the international market could raise migration rates, and returns to education, as education facilitates overseas employment and earnings. Such investments should foster long-run growth. Evidence of these impacts would suggest that migration policy could play a larger role in global poverty reduction (Nunn, 2019).

We ask how persistent increases in international migrant income prospects affect long-run economic development in migrant-origin areas. We exploit a large-scale natural experiment: persistent changes in migrant income prospects across Philippine provinces driven by exchange rate changes due to the 1997 Asian Financial Crisis. Philippine provinces differed in the pre-crisis distribution of migrant earnings across destination countries. When exchange rates shifted in 1997, overseas incomes of migrants from different provinces experienced exogenous, heterogeneous shocks that persisted. We obtained unusual Philippine government administrative data on all migrant worker contracts, with information on migrant incomes, origins, and overseas destinations. Combining the natural experiment and these unique data, we use a shift-share strategy to examine aggregate impacts of the shock on Philippine provinces up to two decades later.

Our empirical analyses implement recent advances for identification and inference in shift-share designs, following Goldsmith-Pinkham et al. (2020). The "shares" are each province's "exposure weights": pre-shock migrant income per capita from each destination, which varies greatly across provinces. For example, in 1995 migrant income per capita from Japan was 10.7 times higher in Bulacan province (PhP 3,540 per capita) than in Leyte (PhP 332).[1] Japan's exchange rate shock should, therefore, have a greater impact in Bulacan than in Leyte.

Each destination's "shift" is its exchange rate shock. Table A1 shows shocks

[1] All Philippine peso (PhP) amounts in this paper are in real 2010 pesos (PPP exchange rate 17.8 PhP/USD).

for the top destinations in 1997–98, ranging from a 4% depreciation against the PhP (Korea) to a 57% appreciation (Libya). Other major destinations such as Japan and Saudi Arabia fall in between, with appreciations of 32% and 52%, respectively. These movements persisted for the next two decades. The shift-share variable is the shock to migrant income per provincial resident. We estimate its impacts on long-run provincial outcomes, and provide tests for the underlying identification assumptions discussed in the literature (Goldsmith-Pinkham et al., 2020).

We find, first, that each unit short-run shock (1997–1998) to migrant income prospects is magnified more than sixfold in the long run (through 2009–2015). A one-standard-deviation shock raises long-run migrant income by 14.7%, driven by both higher migration rates and higher earnings per migrant. We explore the mechanisms behind this substantial magnification with a structural model. Second, improved migrant income prospects substantially increase *domestic* Philippine income per capita (excluding migrant income or remittances) in origin provinces. Long-run domestic income rises by 6.4% for a one-standard-deviation increase in the migrant income shock. Reflecting broader local development, the increased domestic income is accompanied by structural change: the gain is concentrated on non-agricultural sources, and labor shares in primary sectors fall.

A province's "global income" per capita is the sum of its domestic and (international) migrant income per capita. Of the long-run global income increase, 73.6% comes from domestic income and 26.4% from migrant income. Household expenditure per capita rises accordingly. These gains emerge gradually over two decades after the 1997 shocks, reflecting persistence in both exchange rate changes and migrant income sources. The magnitude of the gains is nontrivial. A one-standard-deviation shock raises global income per capita 12-18 years later by 2,277 Philippine pesos (PhP) (0.2 standard deviations).

We carefully examine threats to causal identification, particularly whether our shift-share variable captures effects on international trade flows rather than migrant income. Exchange rate shocks from the 1997 Crisis could affect imports and exports, which in turn might influence provincial outcomes. We investigate whether impacts of our migrant-income shift-share variable operate via impacts on international trade. We construct additional shift-share variables capturing the exposure of provinces to exchange rate shocks affecting imports and exports. The trade shift-share variables exploit (pre-1997) variation in exchange rate shocks in trading partners, in combination with province-level employment shares in import and export industries. Our results are robust to controlling for these trade shift-share variables, which suggests that our estimates primarily reflect impacts due to changes in potential migrant income.

We also show that province-level exports are unresponsive to migrant income shocks, local price changes are unlikely to bias results, findings are robust to various controls, and foreign direct investment (FDI) is not a relevant channel. Together, these results confirm that the shocks operate through migrant income rather than alternative mechanisms.

Throughout, we provide two additional categories of tests of the credibility of our causal claims. First, we test whether changes in the pre-shock period ("pre-trends") correlate with future values of the shift-share variable. We find no evidence of pre-trends, ameliorating concerns of differential trends in development outcomes. Second, we consider potential omitted variables. Our estimates are not sensitive to controls for ongoing trends or heterogeneity in exposure to the Asian Financial Crisis tied to baseline characteristics such as industrial structure and development status.

We provide further insights into mechanisms and effect magnitudes with the help of a simple structural model. We use the model to quantify the contribution of various channels, and rationalize the magnification of the income gains. We augment a gravity model of migration (Llull, 2018; Bryan and Morten, 2019; Lagakos et al., 2023) to allow workers to make educational investments and enter skilled occupations. Persistent positive migrant income shocks alleviate constraints on such investments, and increase the return to migration.

Given the central role of skill, we estimate impacts on education. We find large positive effects: a one-standard-deviation migrant income shock increases the college-educated share by 0.51 percentage points (0.11 standard deviation). These skill increases are accompanied by a larger share of college-educated migrants, new high-skilled emigration, and higher migrant salaries.

Educational investments account for 19.6% of the increase in global income per capita. The model explains over 80% of the six-fold magnification of the migrant income effects, derived from higher educational investments, rising skill levels, and changing migration patterns. We also provide a framework to understand the plausibility of our estimated effects on domestic income. A reasonable set of assumptions on the share of migrant income remitted to origin economies, the multiplier on remittances, and the return on entrepreneurial investments can yield the observed long-run increase in domestic income.

Our study is made possible by two unusual elements. First, heterogeneous provincial exposure to the 1997 Asian Financial Crisis generates the persistent variation central to our shift-share identification strategy.[2] Second, we obtained unusual Philippine government administrative data on migrant worker contracts. Without these data, provincial exposure weights ("shares" in the shift-share) would be unobservable, making the shift-share strategy impossible.

We contribute to research on the economic impacts of international migration opportunities on developing-country populations, in particular impacts on the origin *areas* of migrants. Prior research establishes impacts of migrant economic conditions or opportunities on migrants' origin *households*.[3] We contribute most directly to recent research on impacts of international migration on migrant-origin *areas*, emphasizing causal identification. Related work studies the Philippines (Theoharides, 2020; Godlonton and Theoharides, 2024), South Africa (Dinkelman and Mariotti, 2016; Dinkelman et al., 2024), Mexico (Caballero et al., 2023; Bucheli and Fontenla, 2022), and Europe (Giesing and Laurentsyeva, 2018; Anelli et al., 2023; Dustmann et al., 2015; Elsner, 2013).[4]

A key feature of our paper is its focus on formal, legal migrant labor. Government-regulated migration is highly policy-relevant, with many developing-country governments actively promoting it (see Section 2). Evidence on how such flows affect origin-area development is therefore of direct interest to policymakers.

This paper has several distinguishing features, compared to prior research. First, we examine long-run impacts, up to two decades after the initial shock. Dinkelman and Mariotti (2016) and Dinkelman et al. (2024) also study long-run effects, but their causal factor is a brief historical episode of migrant work that did not persist. By contrast, we study changes to migrant income and migrant flows with long-run persistence. This allows us to examine how resulting invest-

[2]Prior studies have exploited international migrants' exchange rate shocks to study impacts on migrants and their origin households (Yang, 2006, 2008a; Kirdar, 2009; Nekoei, 2013; Abarcar, 2019; Dustmann et al., 2023).

[3]Such prior works include Dustmann and Kirchkamp (2002), Yang (2008b), Gibson et al. (2010), Gibson et al. (2011), Mendola (2012), Gibson et al. (2014), Clemens and Tiongson (2017), Gröger (2019), Cuadros-Menaca and Gaduh (2020), Mobarak et al. (2023), and Bossavie et al. (2021).

[4]There are also related studies of *internal* (within-country) migration impacts on origin areas (Kinnan et al., 2019; Akram et al., 2017; Gualavisi and Kleemans, 2024; Zheng et al., 2022).

ments in education initiate a virtuous cycle of migration, enabling high-skilled future migration, and subsequent increases in future migrant income. Indeed, by exploiting persistent exogenous variation in migrant income opportunities, we answer a fundamental question in the economics of migration: do origin areas with persistent access to high-income migration opportunities develop faster than origin areas with less attractive migration opportunities?

In addition, our work is distinct in simultaneously examining impacts on migrant, domestic, and global income, due to our novel data. We find that the vast majority of long-run gains are from increases in domestic income. Finally, we contribute by complementing our reduced-form estimates with a structural approach. The model clarifies mechanisms, quantifies the long-run magnification of gains, and helps assess the plausibility of the estimated magnitudes.

Our findings speak to recent work finding positive impacts of asset transfers to catalyze household enterprises (de Mel et al., 2008; Banerjee et al., 2015; Bandiera et al., 2017; Banerjee et al., 2021), and evidence of poverty traps (Balboni et al., 2021; Kaboski et al., 2022). In contrast to short-term, unearned transfers, we leverage persistent increases in migrant income opportunities. The variation we study could have long-run impacts, in part, by enabling escapes from poverty traps. Much of our domestic income gains come from household enterprises, suggesting that migration policy is an effective tool in the anti-poverty toolkit.

We also contribute to research on the impacts of migration prospects on skill composition. Our conclusions concord with prior findings that migration leads to "brain gain," stimulating educational investments, and raising skill levels back home (Stark et al., 1997; Mountford, 1997).[5] This contrasts with studies finding migration reduces schooling investments(McKenzie and Rapoport, 2011; de Brauw and Giles, 2017; Tang et al., 2022). We add to this literature by illustrating that increases in education may generate a virtuous cycle, leading to higher-skilled future migration, which in turn raises incomes and education levels.

[5]Such studies include Batista et al. (2012), Docquier and Rapoport (2012), Clemens and Tiongson (2017), Shrestha (2017), Theoharides (2018), Chand and Clemens (2023), Khanna and Morales (2023), Abarcar and Theoharides (2022), and Fernández Sánchez (2025). See Batista et al. (2025) for a review.

2 Context: International Labor Migration and the Crisis

In 2019, 210 million individuals from developing countries were international migrants. The largest source countries of international labor migrants are India, Mexico, and China; Bangladesh, Pakistan, the Philippines, and Indonesia also send substantial numbers abroad (United Nations, 2019a). Moving from a developing to developed country for work is associated with substantial income gains for migrants (Clemens et al., 2019). Gibson et al. (2018), Mobarak et al. (2023), and Gaikwad et al. (2024) find that random assignment to international migrant work opportunities leads to improved migrant income, and better outcomes for migrants and their origin households. Income gains from increased international migration are orders of magnitude larger than the likely impacts of further liberalization of international trade or capital flows, or of *in situ* efforts to raise domestic incomes in developing countries (Clemens, 2011; Pritchett and Hani, 2020).

Motivated by these gains, most developing country governments facilitate their citizens' international labor migration. We tabulated data on government policies on outbound international migration collected by United Nations (2019b). Out of the 70 developing countries with populations exceeding 1 million, 94% have a dedicated government agency implementing migration policy; 88% have a dedicated government agency for overseas employment, citizens abroad, or diaspora engagement; and 78% have policies promoting migrant remittances.

In the Philippines, two government agencies facilitate international labor migration during our study period. The Philippine Overseas Employment Administration (POEA) regulates migrant recruitment, issuing operating licenses to recruitment agencies and reviewing and approving migrant work contracts. The Overseas Workers Welfare Administration (OWWA) works to ensure the wellbeing of overseas Filipino workers (OFWs) and their families. It intercedes (via Philippine consulates worldwide) for workers experiencing abuse or contract violations, repatriates workers in conflict zones, assists migrant families in hardship, and facilitates the return and "reintegration" of migrant workers to the Philippines. POEA and OWWA are the sources of the contract data we use.[6]

[6]There are several prominent examples of government agencies facilitating temporary contract migration in other developing countries. In Pakistan, the Bureau of Emigration and Overseas Employment regulates and licenses recruitment agencies. The Ministry of Labor, Migration, and Employment of the Population in Tajikistan regulates migration and facilitates job matching. Agencies in Bangladesh (the Bureau of Manpower, Employment, and Training and the Welfare Fund for Migrant Workers) and in Indonesia (the National Authority for the Placement and Protection of Indonesian

In recent decades, increasing shares of the Philippine population have migrated, had a household member migrate, or had overseas income. From 1990 to 2015, the fraction of the population currently overseas rose from 0.7% to 2.2%, and the fraction of households with an overseas migrant member rose from 3.2% to 7.5%. The share of households with overseas income rose from 16.6% in 1991 to 29.7% in 2018.[7] The vast majority of migration outflows from the Philippines is migration for temporary, legal work by workers who expect to return to their origin areas after one or more labor contracts. Approximately 60% of contract migrants are female, and migrants work in a wide range of destination countries across Asia and the Middle East, as well as in Canada and Europe (see Table A1).

Migrant income in the Philippines comes from numerous overseas destinations, and migrant destinations vary substantially across origin provinces. Such origin-destination migration corridors are highly persistent due to migrant networks resulting from both social connections and migrant recruitment agencies. Table A1 shows the top 20 migrant destinations, ranked by mean "exposure weight" across provinces (1995 migrant income per capita, for province-destination dyads). Our empirical approach exploits the fact that, for each destination, there is substantial variation in the exposure weight across provinces.

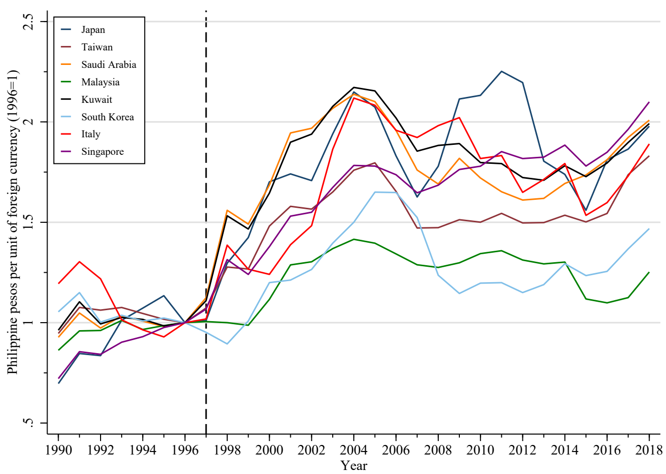
Asian Financial Crisis. The 1997 Asian Financial Crisis was largely unanticipated by policymakers, international organizations, and financial markets (Radelet and Sachs, 2000). The crisis began in Thailand in July 1997 and rapidly spread across East Asia, triggering sharp currency depreciations, capital flight, and economic contractions throughout the region. The Philippines experienced significant economic disruption, with GDP contracting by 0.6% in 1998, inflation rising sharply, and the peso depreciating by approximately 40% against the US dollar (Park and Lee, 2002). However, the Philippines was less severely affected than neighboring countries like Thailand, Indonesia, and South Korea, in part due to more conservative banking practices and lower levels of short-term foreign debt. While the real economic effects of the crisis were relatively short-lived – with most affected countries experiencing rapid recovery by 1999-2000 – the exchange rate changes

Overseas Workers) play similar roles to the Philippines' migration agencies. Such migration flows differ from the case of migration between, for example, Mexico and the United States, where such temporary visas are largely limited to agricultural work and are small in scope.

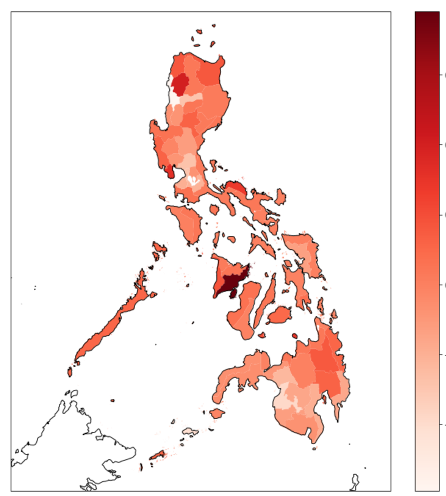
[7] Overseas income includes cash received from family members abroad and cash gifts from abroad (97%) as well as pensions (2.7%) and investment income from abroad (0.57%).

proved highly persistent.[8] Figure 1a shows nominal exchange rates (foreign currency units per PhP, normalized to 1 in 1996) for eight major destinations. These exchange rate movements have a clear persistence over the next two decades, as discussed further in Appendix Section B.3. The unanticipated nature of the initial shocks, combined with the province-level exposure, generates spatial variation in the shift-share variable across provinces, as we show in Figure 1b. This provides the foundation for our identification strategy.

(a) Exchange Rate Shocks: 1997 Asian Financial Crisis



(b) Distribution of Migrant Income Shock Across Philippine Provinces



Notes: Left panel shows exchange rate changes for selected countries. Data are from World Development Indicators, annual average nominal exchange rates in units of foreign currency per Philippine peso, normalized to 1 in 1996, for 8 large sources of international migrant income for Philippine provinces. Vertical dashed line indicates 1997 (year of the Financial Crisis). The right panel shows the spatial variation in province-o shift-share variable (migrant income shock) $Shiftshare_o = MigInc_{o0} Rshock_o$ after partialling out weighted average exchange rate shock $Rshock_o$ and pre-shock migrant income per capita $MigInc_{o0}$, for 74 Philippine provinces. See Section 4 and Appendix Section C.2 for details.

3 Data and Measurement

We summarize data sources here; details are in Appendix A. We examine outcomes of 74 Philippine provinces.[9]

[8]During the crisis, the various country central banks, and the Asian Development Bank (Rana, 1998) acknowledged that their currencies were pegged either "too high" or "too low". Allowing the exchange rates to correct and to float was the suggested solution, which later reports claim helped the speedy recovery (Park and Lee, 2002). There was a short-term change in capital flows from various countries. While the real economies recovered rapidly, the exchange rates stayed persistently at their new level.

[9]To deal with changes in provincial definitions and borders, we combine geographic areas and work with a consistent definition of 74 provinces with borders as they were defined in 1990.

3.1 Migrant Contract Data for Construction of Exposure Shares

Our shift-share research design requires data on migrant income per capita of each Philippine province (indexed *o*) from every migrant overseas destination (*d*), prior to the 1997 crisis. These data constitute the exposure shares (a.k.a., exposure weights ω_{do0}) in the shift-share variable $Shiftshare_o$ (defined in Section 4.1 below). A key challenge is that these data are not available in any Philippine Censuses or surveys. In general, data on migrant income flows from the full set of overseas migrant destinations to specific subnational areas (e.g., Philippine provinces) are very rare in any context worldwide. Our access to data for measuring these exposure shares for Philippine provinces is one of the key innovations of our paper, making possible our shift-share research design.

We estimate exposure weights ω_{do0} using two administrative datasets we obtained from Philippine government agencies, OWWA and POEA. The OWWA dataset contains the Philippine home address of individuals departing on overseas work contracts. The POEA dataset provides data on migrant income and occupation. Both the OWWA and POEA data include name, date of birth, destination, and gender. The two datasets were matched to determine migrant-origin province in the POEA database (Theoharides, 2018), allowing us to estimate ω_{do0}.

3.2 Exchange Rate Data

Data for the exchange rate shock $\tilde{\Delta} R_d$ in $Shiftshare_o$ comes from Bloomberg LP. As we discuss in Subsection 4.1, our shift-share variable uses only the immediate, short-run change in exchange rates. We calculate the short-run exchange rate change, $\tilde{\Delta} R_d$, as the proportional change in the average exchange rate (foreign currency per PhP) from immediately before (mean from Jul 1996 - Jun 1997) to immediately after (mean from Sep 1997 - Oct 1998) the shock (e.g., a 10% appreciation of the foreign currency against the Philippine peso is 0.1).

3.3 Outcome Data

Provincial mean household income and expenditure per capita are available from the Family Income and Expenditure Survey (FIES), conducted every three years by the Philippine Statistics Authority (PSA). Each triennial FIES round samples roughly 40,000 households nationwide. We use up to twelve rounds of the FIES from 1985 to 2018 (inclusive), covering up to four pre-shock observations (prior to 1997), the "partially-treated" 1997 observation, and up to seven post-shock observations for each province.

Key outcomes include migrant income, domestic income, and (their sum) global income per capita. We analyze these outcomes at the same triennial frequency as the FIES, the data source for domestic income. The POEA/OWWA contract data are available for fewer years, and also have missing data on migrant origin address in the early-to-mid 2000s (details in Appendix A), preventing us from calculating migrant income in 2000, 2003, and 2006. It is also not available after 2016. Analyses of migrant, domestic, and global income therefore involve the following triennial periods: 1994, 1997, 2009, 2012, and 2015. Also in triennial periods, we examine secondary outcomes such as average migrant salaries, migrant contracts as a share of province population (by occupation), and domestic income sub-components (wage, entrepreneurial, other). Income and expenditure outcomes are in 2010 real Philippine pesos (17.8 PhP/US$ PPP).

We also examine impacts on provincial educational attainment and migrant worker share in population from six rounds of the Philippine Census of Population (1990, 1995, 2000, 2007, 2010, and 2015). Further, we examine share of the workforce in different sectors from four rounds of the Census where this information is available (1990, 1995, 2000, 2010).

4 Empirical Approach

Our goal is to estimate the impact of migrant income on development outcomes in Philippine provinces. As is well known, simply regressing (say) provincial domestic income per capita on migrant income per capita in a panel regression with province and year fixed effects would not yield a credible estimate of the causal effect of migrant income. First, there may be reverse causation: higher domestic income may lead to more migrant income. Omitted variable bias is also a concern. For example, provinces with more college graduates may have both higher domestic income and higher migrant income, but this does not mean that more migrant income causes higher domestic income.

To alleviate such concerns, it is important to identify a source of exogenous variation in migrant income. We take an "exogenous shares" shift-share approach to causal identification, following Goldsmith-Pinkham et al. (2020). We first derive our regression equation. We then discuss causal identification, and the temporal persistence of the shock measured by our shift-share variable.

4.1 Regression Equation

Our independent (right-hand-side) variable of interest measures the shock to migrant income prospects in the province. The measure takes into account that migrants and their income are unevenly spread across overseas destinations, exchange rate shocks varied across the overseas destinations, and provinces varied in their baseline (pre-shock) share of migrant income in overall province income.

First, we define the average exchange rate shock affecting a province's overall migrant income, $Rshock_o$, as the weighted average exchange rate shock in province o, where the weights are pre-shock shares of migrant income from each destination d:

$$Rshock_o = \frac{\sum_d \omega_{do0} \tilde{\Delta} R_d}{\sum_d \omega_{do0}} \tag{1}$$

$\tilde{\Delta} R_d$ is the fractional change in the destination-d exchange rate from before to after the crisis (e.g., a 10% appreciation against the Philippine peso is 0.1).[10]

ω_{do0} is province o's pre-shock aggregate migrant income from destination d, divided by province population to yield a per capita measure. The sum (across destinations d) of the ω_{do0} terms gives province o's migrant income per capita from all destinations; dividing by this term makes $Rshock_o$ a weighted average of the $\tilde{\Delta} R_d$ terms.

$Rshock_o$ measures the weighted-average exchange rate shock experienced by a province (with weights reflecting the distribution of the province's migrant income across destinations). However, provinces vary in the magnitude of their aggregate migrant income per capita. The larger a province's migrant income per capita, the larger the likely impact of the exchange rate shock $Rshock_o$ on the dependent variable (e.g., expenditure per capita). A regression equation that captures this difference in exposure would include an interaction term between $Rshock_o$ and pre-shock migrant income per capita (from all destinations), $MigInc_{o0}$. $MigInc_{o0}$ is defined as simply the sum of the ω_{do0} terms across desti-

[10]In practice, we define this as the fractional change between the mean exchange rate during the pre-shock period, July 1996 to June 1997, and the mean exchange rate during the post-shock period, October 1997 to September 1998.

nations d for each province o:

$$MigInc_{o0} = \sum_d \omega_{do0} \tag{2}$$

The interaction of $Rshock_o$ and $MigInc_{o0}$ is our right-hand-side variable of interest. The interaction term $Rshock_o \times MigInc_{o0}$ can also be interpreted as a "shift-share" variable, $Shiftshare_o$:

$$Shiftshare_o = Rshock_o \times MigInc_{o0} = \frac{\sum_d \omega_{do0} \tilde{\Delta} R_d}{\sum_d \omega_{do0}} \times \sum_d \omega_{do0} = \sum_d \omega_{do0} \tilde{\Delta} R_d \tag{3}$$

In this shift-share interpretation of the interaction term, the "shifts" in the shift-share are the destination-d exchange rate shocks $\tilde{\Delta} R_d$. Exchange rate shocks $\tilde{\Delta} R_d$ affect a province-o resident in proportion to the magnitude of migrant income per capita coming from destination d prior to the crisis.

The ω_{do0} term serves as the "share" in the shift-share and captures the average extent to which a province-o resident is exposed to a destination-d exchange rate shock. We refer to the ω_{do0} terms as "exposure weights".[11]

$Shiftshare_o$ is the predicted change in province-o migrant income per capita due to the 1997 exchange rate shocks. In this formulation, each destination-d exchange rate shock $\tilde{\Delta} R_d$ is multiplied by the corresponding exposure weight ω_{do0}, and then summed across destinations d.

$Shiftshare_o$ (equivalent to the interaction term $Rshock_o \times MigInc_{o0}$) will be our right-hand-side (causal) variable of interest. In Appendix C.2, we derive this shift-share variable from a simple theoretical model of migration, which we then use to quantify mechanisms and gauge the plausibility of effect magnitudes.

We estimate the following two-way fixed effects regression equation:

$$\begin{aligned} y_{ot} = \alpha_o + \gamma_t + \beta_1 Shiftshare_o \times Post_t \\ + \boldsymbol{\lambda}' MigInc_{o0} \times \mathbf{D}_t + \boldsymbol{\phi}' Rshock_o \times \mathbf{D}_t + \boldsymbol{\delta}' \mathbf{X}_{o0} \times Post_t + \varepsilon_{ot} \end{aligned} \tag{4}$$

y_{ot} is a dependent variable of interest (such as domestic income per capita) for province o in period t. Province fixed effects α_o capture time-invariant characteris-

[11] Borusyak et al. (2022) call these terms "exposure shares", but we also interchangeably refer to them as "exposure weights" since they are not shares in our application. Because the sum of our ω_{do0} across destinations (within origins) is not one, we are in the "incomplete shares" case.

tics of provinces that affect the dependent variable. Period fixed effects γ_t account for effects common to all provinces in the same time period. We also include $\mathbf{X}_{o0} \times Post_t$, a vector of pre-shock province-level characteristics interacted with the post-shock indicator; this captures any post-shock effects that are predictable by a province's pre-shock (baseline) characteristics.

$Shiftshare_o$ is interacted with $Post_t$, an indicator for periods after 1997, because the exchange rate shocks embodied in $Rshock_o$ occurred in 1997. This is the key independent variable of interest. It measures the predicted change in a province's migrant income per capita due to the 1997 Asian Financial Crisis exchange rate shocks.

As is standard practice (Brambor et al., 2006; Angrist and Pischke, 2009), changes over time associated with the interaction term components ($Rshock_o$ and $MigInc_{o0}$) must also be controlled for in the regression to ensure proper interpretation of the interaction term coefficient (reflecting the additional interaction effect over and above any direct effects). We flexibly account for time effects associated with $MigInc_{o0}$ and $Rshock_o$ by interacting each with the full vector of period fixed effects $\mathbf{D}_t$. (This set of terms absorbs interactions of $Rshock_o$ and $MigInc_{o0}$ with $Post_t$).[12] Inclusion in the regression of $MigInc_{o0} \times \mathbf{D}_t$ and $Rshock_o \times \mathbf{D}_t$ accounts for changes from before to after the shock related to $MigInc_{o0}$ and $Rshock_o$. Identification of β_1 therefore derives solely from the interaction between $MigInc_{o0}$ and $Rshock_o$ embodied in $Shiftshare_o \times Post_t$.

4.2 Causal Identification

In taking this shift-share analytical approach, we follow the frontier of the relevant econometric literature, in particular the "exogenous shares" shift-share framework of Goldsmith-Pinkham et al. (2020).

4.2.1 Identifying Variation

Our identification strategy relies on the exogeneity of pre-1997 provincial migrant destination exposure shares (ω_{do0}, a.k.a. exposure weights). These shares

[12] It is essential to interact the sum of exposure weights ("sum of exposure shares" in Borusyak et al. (2022)) $MigInc_{o0}$ with period indicators in shift-share designs with incomplete shares and panel data. Time period fixed effects (the vector $\mathbf{D}_t$) alone will not isolate variation in the shock within periods. $MigInc_{o0} \times \mathbf{D}_t$ accounts for any time-period effects that vary according to $MigInc_{o0}$. We do the same with $Rshock_o$, interacting it with each time period fixed effect.

determine each province's exposure to destination-specific exchange rate shocks during the Asian Financial Crisis. In our panel data context, exogeneity of the exposure shares involves a parallel trend assumption analogous to one common in difference-in-difference analyses (Borusyak et al., 2024): if not for the 1997 exchange rate shocks, changes over time in dependent variables would have been similar for provinces with different levels of ω_{do0} and consequently $Shiftshare_o$.

Several features of our empirical setting support the exogeneity of these exposure shares. First, unlike "generic" shares such as industrial composition, which could capture exposure to numerous economic forces beyond our treatment of interest, our migration shares are specifically "tailored" to migrant income shocks, making them suitable for gaining identifying variation.

Second, we empirically assess parallel trends. For key domestic outcomes, we have many years of panel data with which to conduct tests of parallel trends in the pre-shock period, up to 12 years prior to 1997. These tests (detailed in Section 5 below) consistently find no worrying pre-trends in the pre-shock period, providing support for the parallel trend assumption.

Third, we measure the shares using 1995 data, two years before the crisis. Lagging the shares ameliorates concerns about reverse causation. As we discuss in Section 2, the Asian Financial Crisis was very much unanticipated. Therefore, decisions to migrate and earn income in particular destinations in the pre-shock period – and thus the shares (exposure weights) ω_{do0} – would not plausibly have reflected anticipation of future 1997 exchange rate shocks. Our estimates are unlikely to be clouded by households, firms, or officials in Philippine provinces anticipating the shocks. Lagging of the shares, therefore, further supports characterization of the shares as "tailored" to the research question.

Fourth, separately from empirical support provided by pre-trend tests, the parallel-trend assumption in our context is also reasonable on an *a priori* basis. The exposure shares capture pre-existing migration networks that formed over many years prior to the Asian Financial Crisis. These networks reflect historical patterns of labor demand in different overseas destinations combined with migration costs that vary by origin-destination pairs due to geographic, linguistic, and cultural proximity. For example, areas in the Philippines with historical ties to Japan developed migration networks that lowered the costs for subsequent migrants to follow similar pathways, leading to persistent patterns in migration destinations across provinces. These previously-established migration patterns would not plausibly have anticipated the future 1997 exchange rate shocks.

We thus consider the set of exposure shares to be "as-good-as-randomly" assigned to provinces, conditional on the set of controls. We make the parallel trend assumption: if not for the exchange rate shocks, changes over time in dependent variables would have been similar for provinces with different values of $Shiftshare_o$. We also assume that, conditional on all our controls (e.g., trade exposure), $Shiftshare_o$ only affects outcomes via changing migrant income prospects.

4.2.2 Key Control Variables

Even with our tailored exposure shares, share exogeneity requires careful consideration of potential confounders that might be correlated with both initial migration patterns and provincial economic trajectories. We thus sequentially include a comprehensive set of controls designed to isolate variation in the composition of migrant income across destinations from other provincial characteristics.

Most importantly, to reiterate, it is crucial to control for total migrant income per capita in province *o* at baseline, $MigInc_{o0}$, which is the sum of the ω_{do0} terms across destinations d for each province. When controlling for $MigInc_{o0}$, our shift-share only leverages variation in the *composition* of migrant overseas income sources across provinces, avoiding comparisons between provinces with high and low total migrant income. Because we conduct panel analyses, we interact $MigInc_{o0}$ with time period fixed effects to account flexibly for time effects associated with provinces' baseline total migrant income per capita.

In panel research designs like ours, we also want to account for time-varying effects associated with baseline characteristics of the units of analysis. We therefore include in regression equation (4) a vector of controls for a variety of baseline provincial characteristics, interacted with an indicator for the post-shock period ($\mathbf{X}_{o0} \times Post_t$). These terms capture any differential changes (from before to after 1997) associated with these provincial characteristics.

We organize these province-level control variables into four groups, and add them sequentially to demonstrate the robustness of our key coefficient estimate (β_1 on $Shiftshare_o \times Post_t$) to increasingly stringent identification assumptions.

The first group of controls captures characteristics of the province's migrant flow (measured in 1995). Controlling for these factors helps ensure that our estimates do not reflect differential trends among provinces with more migrants in high-income versus low-income destinations, or provinces with more highly-skilled migrants. To account for the broad regional mix of migrant destinations, we include the province's share of migrants going to the Middle East and North Africa, going to East Asia, and going to OECD countries. In addition, we control for a province's migrant-destination-country characteristics.[13] The destination-country migrant characteristics are as follows. Mean annual income per Philippine migrant in the destination accounts for the skill level of migrants. We capture occupational-sector mix with the share of Philippine migrants to the destination working in professional occupations (the highest-skilled occupation group), and separately, the share of Philippine migrants to the destination working in manufacturing occupations (the intermediate-skilled group). In addition, we include the share of all Philippine migrants going to the destination; this accounts for differences related to the aggregate size of the country as a migration destination.

The second set of control variables captures pre-shock province development status: share of households that are rural, household asset index, domestic income per capita, and expenditure per capita. These variables account for the possibility that initially more developed provinces both had different migration patterns and were on different economic trajectories, regardless of migration.

The third set of controls pertains to baseline province industrial structure (from the 1990 Census): share of workforce separately in the primary, the manufacturing, and the service sector, and the share of workforce in financial and business services. These variables address concerns that industrial composition could influence both migration patterns and economic growth trajectories.

Finally, the fourth set of controls comprises analogous shift-share variables related to imports and exports, to account for any exchange rate shocks operating via international goods trade. We discuss these variables in Section 4.3.1.

4.2.3 Shares that Matter Most for Estimates

Following Goldsmith-Pinkham et al. (2020), we compute Rotemberg weights to characterize which shares matter most for our estimates. These weights reveal which destination-specific shifts are driving our results and provide guidance on

[13] These destination characteristics are aggregated to the province level using the province-specific exposure weights ω_{do0}, following Borusyak et al. (2022).

which shares should be the focus of balance tests (tests of pre-trends). Five destinations collectively account for 75% of the weights: Saudi Arabia (0.20), Japan (0.19), the United States (0.18), Taiwan (0.10), and Hong Kong (0.08). See Appendix Section B.1 for additional details.

4.3 Additional Threats to Identification

4.3.1 Impacts Thorough Trade

A potential omitted-variable concern is that exchange rate shocks can also affect trade. If migrant income shocks are correlated with trade shocks, β_1 would be jointly capturing the impacts of trade shocks and migrant income shocks, complicating the interpretation of β_1. We therefore construct import and export shift-share exposure measures to assess the stability of our results to their inclusion.

The import and export shift-share variables are in the same spirit as our migrant income shift-share variable. They exploit variation in exchange rate shocks in import and export partners, in combination with baseline import and export values in different industries, and province-level employment shares in import and export industries. Our goal is to measure the labor market exposure to changes in import and export competition due to relative exchange rate changes between the Philippines and its trade partners.

First, we compute the baseline (1990-1996) value of imports and exports between the Philippines and each partner country (destination) for each Standard International Trade Classification (SITC) good using COMTRADE data. We aggregate the SITC goods to 36 ISIC industries to compute industry-level imports and exports between the Philippines and each partner country (destination).[14] We multiply the baseline industry-level trade values with the relative exchange rate shock of the trading partner to measure the industry-destination specific shock. Then, using the 1990 Population Census, we apportion the total industry-destination level import and export shocks to each province according to that province's share of national industry employment. Summing up across industries yields the province-destination level import/export shock. We divide this measure by province population to get a proxy for per capita import/export shock

[14] We match COMTRADE SITC data with ISIC revision 2 data using a crosswalk from the World Integrated Trade Solution by the World Bank. Because the crosswalk is not complete, we manually match all remaining SITC products.

exposure. Finally, we add up over all trading partners to get province-level measures. Formally:

$$Shiftshare_o^m = \sum_d \frac{1}{Pop_o} \sum_j \frac{L_{jo}}{L_j} M_{jd}^m \tilde{\Delta} R_d \,, \tag{5}$$

where $m \in \{import, export\}$ specifies the trade shock, o is province, d is destination (partner) country, and j is industry. M_{jd}^m is the total baseline value of industry j imports or exports between the Philippines and country d. L is the number of workers and Pop denotes population. $\tilde{\Delta} R_d$ is the exchange rate shock as before.

To build intuition, suppose the Philippines imports a high value of electronics from country j at baseline. This suggests that M_{jd}^{import} will be high. If the country d's currency appreciates, provinces with larger baseline employment shares in electronics can face lower import competition than before, changing the income potential of the region. Our measure is intended to approximate exactly this shock to (in this example) import competition by apportioning each baseline shock to industry-country imports ($M_{jd}^{import} \times \Delta R_d$) to Philippine provinces using share of national sector employment at baseline. We then simply add up this measure across all industries and trading partners to get a province-level export and import shock measure. This is conceptually parallel to the "China shock" measure of Autor et al. (2013), but summed up across all baseline trading partners and separately calculated for both imports and exports.

We demonstrate the stability of our β_1 estimates to the inclusion of these import and export shift-share variables in the control vector $\mathbf{X}_{o0}$ in panel D of all regression result tables. Appendix Table A5 demonstrates that this stability is plausible. The import and export shift-share variables are not correlated with the migrant income shock after controlling for the baseline control variables included in the main analyses (i.e., the variation relevant to our estimation). This suggests that we should not expect that inclusion of the import and export shift-share variables would affect coefficient estimates on the migrant income shift-share variable. We formally test this in Panel D of our regression tables.

We provide additional evidence in Section 5.4 that manufacturing exports and FDI do not respond to the shocks, and do not appear to be relevant mechanisms.

4.3.2 SUTVA Violations and Internal Migration

We consider potential violations of the Stable Unit Treatment Value Assumption (SUTVA), which requires that treatment of one unit does not affect outcomes in other units. In our context, SUTVA could be violated if migrant income shocks in one province spill over to affect outcomes in neighboring provinces through trade linkages, factor mobility, or other economic channels.

One concern is that migrant income shocks could trigger internal migration flows, which would confound our province-level estimates by changing population composition. We examine the relationship between $Shiftshare_o$ and internal migration rates. Results are in Appendix Table A6. We find no large or statistically significant impact on net internal migration. There is a small negative effect on outmigration of young adults (aged 16-24), that cannot account for the impacts we document in our analyses. The limited internal migration response suggests that labor mobility between provinces is not a major source of SUTVA violations.

More generally, the Philippines' relatively fragmented internal market structure (with over 7,000 islands) likely limits other forms of inter-provincial economic spillovers. To the extent that spillovers do occur, they would likely be positive – provinces experiencing migrant income gains would generate increased demand for goods and services from neighboring provinces, raising incomes in those areas as well. Such positive spillovers would cause our estimates to be attenuated toward zero, making them conservative estimates of the true causal effects. We test for such general spatial spillovers in Section 5.5, where we show that our main estimates are robust to controlling for the $Shiftshare_o$ value in neighboring provinces (specifically, the inverse distance-weighted average migrant income shock in other provinces). While we cannot fully rule out all potential SUTVA violations, the likely direction of spillovers suggests that our estimates are lower bounds of the true impacts.

4.4 Persistence of Shock

We study the impact of changes in migrant income on long-run provincial outcomes, exploiting an exogenous shock measured by our shift-share variable. A key interpretive question is whether the shock is transitory or persistent.

In analyses detailed in Appendix Section B.3, we show that the shift-share variable's components – in equation (5), the exchange rate shocks $\tilde{\Delta} R_d$ (the "shifts") and the exposure weights ω_{do0} (the "shares") – exhibit persistence over two decades post-1997. Because both these components of the shift-share variable show persistence in the long run, the shock to migrant income is also persistent.

Persistence in the exchange rate changes $\tilde{\Delta} R_d$ is an empirical fact, reflecting that exchange rates were previously misaligned. Persistence in exposure weights ω_{dot} can stem from dyad-specific migration costs (equation A7 of our model). While migrants did adjust their post-1997 migration destinations in response to exchange rate changes, adjustment was partial, due to networks facilitating migration (Munshi, 2003; Kleemans and Magruder, 2019; Mahajan and Yang, 2020), and (relatedly) information frictions and high fixed costs for recruitment agencies in the international labor market (Shrestha and Yang, 2019; Shrestha, 2020; Fernando and Singh, 2021; Bazzi et al., 2021).

In sum, destination-level exchange rate shocks and dyadic migrant income per capita are highly persistent over two decades. The long-run impacts that we find result from an exogenous shock to migrant income (measured by the shift-share variable $Shiftshare_o$) that exhibits substantial persistence over time.

5 Empirical Results

We estimate impacts of the migrant income shift-share shock (β_1 in Equation (4)) on a range of primary and secondary outcomes.

5.1 Domestic Income and Expenditure

We first examine impacts on key primary outcomes: province-level means of annual domestic income and expenditure per capita. "Domestic income" includes income from wages, entrepreneurial activity, and other sources, such as dividends, interest, and the imputed rental value of owned housing. We intend this outcome to capture household earnings in the *domestic* Philippine economy. This variable, therefore, does *not* include international migrant income (which in any case is not recorded in the survey), remittances, or other international income. We calculate international migrant income using the migrant contract data and examine it in the next subsection.[15] To avoid double-counting of earnings in the population, our measure of domestic income also excludes transfers from domestic sources and gifts from other households. For expenditure per capita, we use the Philippine Statistical Authority's definition of "family expenditures": expenses or disbursements purely for personal consumption. This includes food, clothing, education, transport, communications, health, and utilities; consumption from own production; and money payments made during the annual reference period for durable goods, furniture, and household repairs and maintenance.

Results are in Table 1, columns 1-2. Each cell displays the coefficient β_1 on $Shiftshare_o \times Post_t$. We present estimates from regressions with different pre-shock controls interacted with $Post_t$: destination controls only (Panel A), with additional province development status controls (Panel B), with additional province industrial structure controls (Panel C), and with additional import and export shift-share controls (Panel D). All regression results tables have this structure.

The shock has positive effects on both domestic income and expenditure per capita. Coefficient estimates on both the domestic income (column 1) and consumption (column 2) regressions are stable across panels, and in Panel D the coefficients are statistically significantly different from zero at the 1% level.

The effects are meaningful in magnitude. A one-standard-deviation shock (0.093) increases domestic income per capita by PhP1,200 (0.13 standard deviation), and expenditure per capita by PhP1,159 (0.13 standard deviation).

We also present event study diagrams illustrating the dynamics of impacts, and testing for pre-trends. We estimate a modified Equation (4), which includes the partially-treated year 1997 in the sample, and interacts $Shiftshare_o$ with indicators for each time period. The 1994 interaction term is omitted as the reference point. We plot point estimates and 95% confidence intervals on $Shiftshare_o$ interacted with each period indicator. Results are presented in Figure 2a for expenditure and Figure 2b for domestic income. We do not observe differential positive pre-trends: for expenditure, pre-1997 coefficients are small and show no obvious trajectory. For domestic income, there is a statistically insignificant negative trend from 1985-1991 and no trend in 1991-1994. There is also no large or statistically

[15] By excluding international income sources from "domestic income", we are also excluding migrant remittances (which are included in "overseas income"). Migrant remittances may be under-reported in the FIES, because of the rise in electronic banking. Since 2000, international migrants have been increasingly depositing earnings directly into origin-household bank accounts. A comparison of remittance data from the World Bank, the Philippine Central Bank, and the FIES suggests that households responding to the FIES may not consider such deposits as remittances (Ducanes, 2010).

Table 1: Effects of Migrant Income Shock on Global Income, Domestic Income, Migrant Income, and Expenditure per Capita

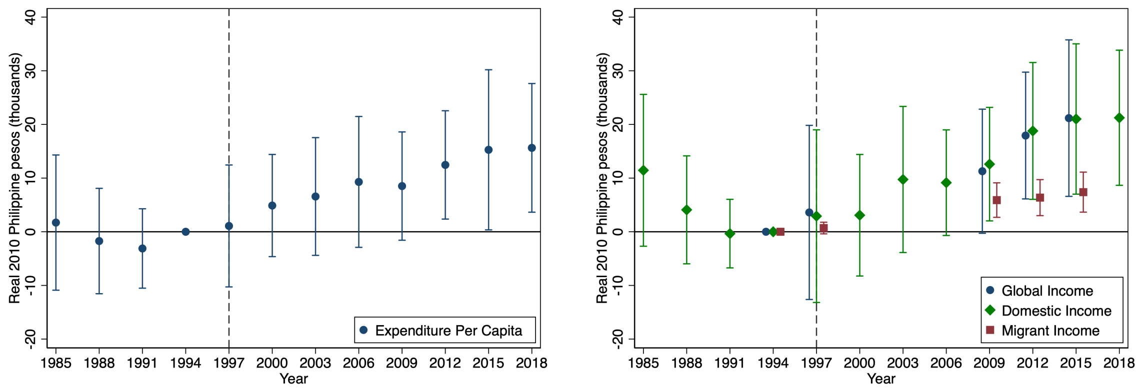
	Triennial: 1985 - 2018		1994, 2009, 2012, and 2015			
	(1) Domestic Income Per Capita	(2) Expenditure Per Capita	(3) Global Income Per Capita	(4) Domestic Income Per Capita	(5) Migrant Income Per Capita	(6) Expenditure Per Capita
Panel A. Destination controls only						
$Shiftshare_o$ × Post	12.761	10.472	31.049	24.599	6.449	19.099
	(8.646)	(7.570)	(9.346)***	(8.500)***	(2.026)***	(8.737)**
Panel B. Additional province development status controls						
$Shiftshare_o$ × Post	9.662	10.029	24.489	18.123	6.366	13.513
	(6.093)	(4.952)**	(6.143)***	(6.040)***	(1.715)***	(5.214)**
Panel C. Additional province industrial structure controls						
$Shiftshare_o$ × Post	13.206	12.651	24.799	18.347	6.452	14.036
	(4.760)***	(4.522)***	(6.044)***	(5.936)***	(1.643)***	(5.426)**
Panel D. Additional import and export shift-share variables						
$Shiftshare_o$ × Post	12.904	12.458	24.484	18.022	6.463	13.801
	(3.982)***	(3.782)***	(5.604)***	(5.531)***	(1.723)***	(4.602)***
Obs.	813	813	296	296	296	296
Baseline DV Mean	26.102	24.497	30.189	26.102	4.087	24.497
Baseline DV St. Dev.	9.406	8.734	11.400	9.406	2.993	8.734

Note: Unit of observation is the province-year. Domestic income and expenditure per capita are from Family Income and Expenditure Survey (FIES). Migrant income per capita is calculated from POEA/OWWA and Philippine Census data. Global income per capita is migrant income per capita plus domestic income per capita. Income and expenditure are in thousands of real 2010 Philippine pesos (17.8 PhP per PPP US$ in 2010). The year 1997 is dropped from the analysis as the exchange rate shock takes place in 1997. Outcome data are not available for one province (Rizal) in 1988 due to a fire that destroyed survey records. Destination pre-shock controls are (all for 1995): GDP per capita of the destination; mean annual income per Philippine migrant in the destination; share of Philippine migrants to the destination working in professional occupations (highest-skilled general occupational category); share of Philippine migrants to the destination working in manufacturing occupations (intermediate-skilled general occupational category; the lowest skilled general occupational category, services, is the omitted category); share of all Philippine migrants going to the destination; share of baseline migrant from province going to Middle East and North Africa; share of baseline migrant from province going to East Asia; share of baseline migrant from province going to Middle East and OECD countries. Destination country-level controls are aggregated to the province level using Borusyak et al. (2022) weights (province's pre-shock aggregate migrant income in the destination). Province development status pre-shock controls are as follows: share of households that are rural and household asset index (from 1990 Census); domestic income per capita and expenditure per capita (average across 1988/1991/1994 FIES). Province industrial structure pre-shock controls are as follows: share of workforce in primary sector, share of workforce in manufacturing, share of workforce in service sector, share of workforce in financial and business services (from 1990 Census). Baseline dependent variable mean and standard deviation calculated based on data from the pre-shock year nearest to the crisis. All regressions include province and year fixed effects. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.10.

significant effect in 1997 for either outcome. For both outcomes, coefficients are positive and increase in magnitude over time after 1997. This increase in the post-shock period is consistent with the gradual accumulation of human and physical capital over time, resulting in increases in domestic income per capita.

We confirm the absence of pre-trends with "placebo" regressions estimating equation (4), but for data in the pre-period (1985-1997). We replace the indicator for the post-period, $Post_t$, with an indicator for a placebo post-period, 1994 and

Figure 2: Event Studies for Expenditure and Income per Capita



(a) Expenditure

(b) Global, Domestic, and Migrant Income

Note: Regressions modify Equation (4) to include interactions between $Shiftshare_o$ and indicator variables for each pre- and post-shock year. The 1994 interaction term is omitted as reference point. Specification corresponds to that of Table 1, Panel D (including province fixed effects, year fixed effects, and controls for differential trends with respect to pre-shock province characteristics, destination characteristics, and province import and export shift-share variables). Expenditure per capita includes food, education, durable goods, and housing, among other categories. Domestic income per capita includes earned income from wage and entrepreneurial activities, along with income from all other sources excluding transfers from abroad and domestic sources. Migrant income per capita is the sum of all income earned outside the Philippines by a province's migrants. Global income per capita is the sum of domestic and migrant income per capita. Outcomes are in real 2010 PhP (PhP17.8/US$ PPP). Observations are at the province-period level, and include each triennial period between 1985 and 2018 inclusive (when available); unlike in Table 1, we now include partially-treated year 1997 in the sample. 95% confidence intervals shown. Standard errors are clustered at the province level.

1997. The placebo pre-period is 1985, 1988, and 1991. Results are in the top panel of Appendix Table A4, columns 1 and 2. The coefficients on $Shiftshare_o \times Post_t$ are small in magnitude, and none are statistically different from zero.

5.2 Global, Domestic, and Migrant Income per Capita

We examine impacts on migrant income alongside impacts on domestic income. Migrant income is the sum of all income earned outside the Philippines by a province's international migrants. Domestic income is defined as in the above analysis; importantly, it excludes income from international sources. We also define "global income" as the sum of migrant income and domestic income.

Our focus on migrant *income*, rather than remittances (or, relatedly, migrant overseas savings which may eventually be repatriated) deserves a brief discussion. Remittances or overseas savings, of course, are derived from migrant income. Focusing on migrant income is conceptually attractive as it represents the full amount of resources that migrants gain access to when they go overseas for work, and captures their income and material well-being. Migrants make decisions about how much to consume overseas, send home as remittances, save, and invest. In our view, migration decisions should be thought of as motivated by the prospects for earning the full amount of migrant income, not just the amounts they may then remit (or save overseas). In other words, migrant income prospects may also be attractive to individuals due to their potential use for personal consumption or other purposes separate from remittances or other savings or investments for their families.

Regression results for global, domestic, and migrant income per capita are in columns 3-5 of Table 1. Within each Panel, the coefficient in column 3 is the sum of the corresponding coefficients in columns 4 and 5 (since global income is the sum of domestic and migrant income). The shock has positive and statistically significant effects on global, domestic, and migrant income per capita. Coefficient estimates are stable across regressions in Panels A, B, C, and D.

Impacts are large in magnitude. The coefficient estimate in column 3, Panel D, indicates that each one-standard-deviation shock increases global income per capita by 2,277 pesos in 2009-2015 (0.2 standard deviation, or 7.5% of the baseline mean). Corresponding effect sizes for domestic income and migrant income per capita are 1,676 (0.18 standard deviations, or 6.4% of the baseline mean) and 601 pesos (0.2 standard deviations, or 14.7% of the baseline mean).

The coefficient estimate on migrant income (6.463) indicates that the initial shock to migrant income is magnified over time: for each unit migrant income per capita shock (measured by our shift-share variable), migrant income per capita is over six units higher by 2009-2015.[16] We will shortly turn to the mechanisms behind this magnification of the migrant income shock, examining the role of increases in migration rates, educational investments, and migrant skill levels.

To show the robustness of impacts on expenditure per capita, we also present regression estimates for this outcome in the restricted set of periods (1994, 2009, 2012, and 2015), in column 6. Point estimates and significance levels are very similar to the estimates of column 2 (which uses data from 1985-2018).

Figure 2b shows event study diagrams for migrant and global income per capita. There are no apparent pre-trends in 1994-1997. The effects are positive in

[16]To be sure, there is some uncertainty around this estimate: its 95% confidence interval ranges from 3.09 to 9.84 (with the lower bound being less than half as large as the point estimate).

the 2009-2015 post-periods; point estimates for migrant income are stable, while global income point estimates are increasing. Tests showing absence of pre-trends are in the bottom panel of Appendix Table A4, columns 1 and 2. Pre-trend coefficients are small in magnitude and statistically insignificant.

5.3 Diagnostics for Exogenous Shares Identification

Having established our main income and consumption results, following Goldsmith-Pinkham et al. (2020) we conduct diagnostics focused on high-Rotemberg-weight destination shares. First, we examine whether these shares exhibit any pre-trends in our key domestic outcomes prior to the 1997 shock. Second, we present estimates using these shares individually as instruments for $Shiftshare_o$ to assess drivers of our identifying variation. Further, to test the sensitivity of our results to different combinations of exposure shares. We examine specifications using only the top 5, 10, 15, or 20 destinations by Rotemberg weight in constructing our shocks. The results are reassuring, supporting the parallel trend assumption and our interpretation of the coefficient on $Shiftshare_o$ as causal. For details, see Appendix Section B.2.

5.4 Ruling Out Trade and FDI as Confounders

The stability of our estimates with the inclusion of import and export shift-share variables strongly suggests that the coefficient β_1 does not reflect the impacts of changes in trade flows. Here, we provide additional evidence that suggests trade is not driving the impacts we document. Further, we examine another potential mechanism, foreign direct investment (FDI), by testing whether aggregate FDI flows are affected by the same exchange rate shocks.

Lack of correlation between shocks. First, we show in Appendix Table A5 that the migrant income shock is not correlated with the import and export shift-share variables. This lack of association suggests trade is unlikely to drive our estimated impact of the migrant income shock.

Lack of impact on manufacturing exports. We estimate impacts of $Shiftshare_o$ on trade outcomes, starting with manufactured exports per capita.[17] We estimate

[17] We construct this outcome variable at the province-year level by aggregating firm survey microdata. These data are

equation (4) where the dependent variable is in thousands of pesos (PhP) per capita. We examine samples including all years (column 1), as well as a restricted set of periods for "long run" results corresponding to our global income analysis period (1994-1996 vs. 2009-2015, column 2). Results are in Appendix Table A7. We find no large or statistically significant impact on manufactured exports.

Note that even if we found impacts on manufactured exports, this would not necessarily mean our estimates are confounded by the impacts of exchange rate shocks on trade flows. An increase in origin development due to migrant income shocks can, in principle, lead to increased exports. However, the lack of an impact strongly suggests that shocks to exports are not a first-order driver of our results. We further discuss potential reasons behind this lack of impact on manufacturing exports in Section 5.6.4, where we discuss sector-specific local effects.

Lack of impact on agricultural income. It is also of interest to examine agricultural exports, but no corresponding data exists for this outcome. Instead, we examine agricultural income per capita, which should encompass any increase in agricultural exports. In Section 5.6.4 below (on structural change), we present regression estimates of equation (4) where the dependent variables are agricultural income per capita at the province-year level. There is no statistically discernible impact on agricultural income and domestic income impacts are effectively entirely driven by non-agricultural income. This indicates that increases in agricultural export income are unlikely to be driving the effects on domestic income.

Imports and local prices. Another trade-related point is that regions that consume more imports can face changing prices in their consumption basket due to the exchange rate shock. If this exposure through imports is correlated with the shock to migrant income opportunities, our expenditure results may need to be reinterpreted in real terms. While we lack the data to study where imports are consumed, we acquired data on province-year level consumer price index from 1994-2017. If imports are a meaningful share of the consumption basket and import prices are changing, this would be reflected in the CPI. Appendix Table A9 columns 1 and 2 show results from estimating equation (4) with CPI as the outcome. Column 3 regresses the CPI inflation on the migrant income shock. In all specifications, there is no evidence for a positive or significant relationship. For

available in 1994, 1996, 1998, 1999, 2006, 2009, 2010, 2012, 2013, 2014, and 2015 (see Appendix A.8).

example, column 2 suggests each one-standard-deviation shock leads to a 4.1 decrease (p-value = 0.25) in CPI by 2015, when the average CPI is 245. More broadly, this finding highlights that our domestic income and consumption results reflect real changes and not just changes in local price levels.

FDI is not responsive to exchange rate shocks. Finally, we examine foreign direct investment (FDI) as a potential mechanism. Data on inward FDI from specific countries are not available at the province level, only at the national (Philippine) level by year. We therefore run panel regressions where the outcome variable is annual FDI flows to the Philippines from a particular country in a given year.

The right-hand-side variable of interest is the exchange rate shock, $\tilde{\Delta} R_d$, interacted with a dummy for the post-shock period. The regression includes year and country fixed effects. We examine the full set of years (1996-2018, column 1), the "long run" (comparing 1996 with 2009-2015, column 2), as well as robustness to controls for overseas country characteristics (the same included in Table 1) in Panels A and B. We test whether the overseas-country-specific exchange rate shocks affect FDI flows to the Philippines *as a whole*. If no such relationship exists, it would be unlikely that FDI flows to specific provinces are related to the migrant income shift-share. Results in Appendix Table A8 show no large or statistically significant relationship between FDI flows and the exchange rate shocks.[18]

Robustness To baseline trade-related controls. We further provide evidence for the stability of our results when we control for baseline exposure to either tradable sectors or manufacturing exports directly (interacted with time fixed effects). First, we control for baseline manufacturing exports to allow for differential trends based on baseline manufacturing. We control for both per capita and total manufacturing exports, along with the IHS transformations, to allow for some flexibility on the functional form. Second, we control for the time-varying versions of these manufacturing export variables. Third, we jointly control for the 1995 baseline share of the population working in 12 disaggregated tradable manufacturing industries. Fourth, we jointly control for the 1995 baseline share of the population working in 11 disaggregated primary sectors. Even under the demanding cases where we include over 10 additional controls, our results do not meaningfully

[18] The standard deviation of the exchange rate shock, $\tilde{\Delta} R_d$, is 0.040. Appendix Table A8's coefficients indicate that a shock of this magnitude would have very small effects relative to the mean or standard deviation of the outcome variable.

change, which suggests that trends or shocks correlated to baseline manufacturing exports or tradable industry structure are not driving our results. These results are presented in Appendix Figure A3, discussed further in Section 5.5.

Overall, these analyses provide no indication that trade or FDI are important mechanisms driving the causal effects emphasized in this paper.

5.5 Additional Robustness

Appendix Figure A3 presents additional robustness checks for our main income and consumption results. Details of additional control variables are in Appendix Section A.7.3. The robustness checks can be grouped as:

Standard Errors. We present results with (1) "exposure-robust" standard errors (Borusyak et al., 2022) that account for correlations between destinations exposed to similar destination countries and (2) spatially clustered standard errors following Conley (1999), allowing for up to 200 kilometers around the centroid of the province and for auto correlation of order 10 years. The precision of our estimates does not meaningfully change.

Outliers. Among top migrant destinations, Malaysia and South Korea have outlier exchange rate shocks, as is apparent in Table A1. We present results in which our migrant income shock measure excludes Malaysia and South Korea, by setting their "shares" to zero. Regression estimates when excluding Malaysia and South Korea in this way are nearly identical to our main results. We also show that no individual province drives our results by excluding provinces one at a time, as shown in Appendix Figure A4.

Additional Trade Related Controls. The four sets of trade-related controls were introduced and discussed at the end of Section 5.4 on trade confounders.

Geographic Spillovers. To assess bias due to geographical spillovers from nearby provinces, we generate the inverse distance weighted average migrant income shock to all other provinces. Controlling for the inverse distance weighted shock (interacted with year fixed effects) does not impact our estimates.

Tourism controls. We also show robustness to controlling for the baseline share of workers employed in "tourism" industries (as defined by the Philippine Statistical Authority), interacted with year fixed effects. The estimates are stable, suggesting that income from tourism is not confounding our estimates.

5.6 Mechanisms

We now examine potential mechanisms through which these substantial increases in income take place: education, migration rates, migrant skill levels and occupations, domestic wage and entrepreneurial income, and structural change.

5.6.1 Education

Relaxation of household liquidity constraints has been shown to lead to higher educational investments, in the long run (Agte et al., 2022). Positive migrant income shocks could loosen such constraints on educational investments (Yang, 2008b; Gibson et al., 2011, 2014; Clemens and Tiongson, 2017; Theoharides, 2018), and also change the expected return to education in the broader population.[19]

In Table 2, we present results from estimating regression equation (4) where the dependent variables are the share of the population having reached key threshold levels of education: primary (6 years of completed schooling), secondary (10 years), and college (14 years). Dependent variables are from the Philippine Census (pre-shock periods 1990 and 1995; post-shock periods 2000, 2007, 2010, and 2015). The positive shock to migrant income has positive and statistically significant effects on secondary and college (but not primary) completion rates.

Coefficient estimates in columns 2 and 3 indicate that a one-standard-deviation migrant income shock causes 0.59 percentage points higher secondary completion, and 0.43 percentage points higher college completion. Point estimates are relatively stable across sets of controls and statistically significantly different from zero at the 5% level and 1% level respectively in Panel D.[20]

[19] Positive migrant income shocks could raise schooling investments overall if the return to education is perceived to rise (Batista et al., 2012; Docquier and Rapoport, 2012; Clemens and Tiongson, 2017; Shrestha, 2017; Theoharides, 2018; Chand and Clemens, 2023; Khanna and Morales, 2023; Abarcar and Theoharides, 2022), but could reduce schooling investments if returns to education are seen to fall (McKenzie and Rapoport, 2011; de Brauw and Giles, 2017; Tang et al., 2022).

[20] Falsification tests in Appendix Table A4 (middle panel, columns 1-3) and event-study graphs of lead and lag coefficients of $Shiftshare_o$ in Appendix Figure A11b confirm the absence of positive pre-trends for these outcomes. There is evidence for *negative* pre-trends, particularly for primary and secondary schooling. We note that the trends are most precisely estimated for primary schooling, an outcome for which we do not have positive impacts. If these negative trends had continued in the absence of the migrant shock, our results should be considered biased downward.

Table 2: Effects of Migrant Income Shock on Education

	Share Completed:		
	(1) Primary School	(2) Secondary School	(3) College
Panel A. Destination controls only			
$Shiftshare_o \times$ Post	-0.003	0.086	0.037
	(0.029)	(0.034)**	(0.016)**
Panel B. Additional province development status controls			
$Shiftshare_o \times$ Post	-0.009	0.053	0.051
	(0.036)	(0.029)*	(0.018)***
Panel C. Additional province industrial structure controls			
$Shiftshare_o \times$ Post	0.004	0.062	0.046
	(0.034)	(0.028)**	(0.016)***
Panel D. Additional import and export shift-share variables			
$Shiftshare_o \times$ Post	0.003	0.063	0.046
	(0.025)	(0.028)**	(0.015)***
Obs.	444	444	444
Baseline DV Mean	0.763	0.419	0.122
Baseline DV St. Dev.	0.104	0.114	0.039

Note: Unit of observation is the province-year. Analysis uses Census data; periods are 1990, 1995, 2000, 2007, 2010, and 2015. Dependent variables are share of population (aged 20-64) who have completed primary, secondary (high school), and college education. Primary school, secondary school, and college completion is defined as having completed at least 6, 10, and 14 years of schooling respectively. For list of destination and provincial controls, see Table 1. Baseline dependent variable mean and standard deviation calculated based on data from nearest pre-shock year. All regressions include province and year fixed effects. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.10.

These educational responses are plausible in magnitude. We gauge magnitude plausibility by examining the extent to which increases in education are associated with increases in household income, as loosened financing constraints are likely a key reason behind education increases. Our regression results, comparing Panel D of Table 1 (col 3) with Table 2 (col 3) indicate that about 5,322 pesos higher global income is associated with 0.01 higher college completion.[21]

How does this relationship between increased income and increased education compare to relationships seen in cross-sectional data in the pre-period? The cross-sectional relationship between global income and share skilled in the population in the pre-period (1994 for income and 1995 for education) indicates that each 0.01 higher college completion is associated with about 3,500 pesos more in provincial global income per capita. While this is not a causal effect, it is a reasonable point of comparison. The education response we estimate is relatively smaller: 5,322 PhP is "needed" to generate the same increase in college completion.

[21]Note of course that the increase in education investments due to the shock could also be driven in part by perceived changes in the return to education, not only by loosened financing constraints.

5.6.2 Migration Rate, Migrant Salaries, and Migrant Skills and Occupations

Next, we examine the mechanisms underlying the long-run impact on provincial migrant income per capita. Migrant income can increase for two reasons. First, the provincial migration rate may be higher. We use Census data to analyze provincial migration rates. Second, migrants may be earning more, especially given the increase in education rates. We use Census data to explore the education levels of migrants, and contract data to study impacts on average salary and occupations in which migrants work.

In column 1 of Table 3, we report results from estimating equation (4), where the dependent variable is the migration rate (the share of individuals in the province aged 20-64 who are international migrant workers). The coefficient is positive, stable, and statistically significantly different from zero at the 1% level in all panels. A one-standard-deviation larger shock increases the migration rate by 0.18 percentage points (0.22 standard deviations).

Column 2 presents results from regressions where the dependent variable is the share of international migrants who are skilled, defined as having at least college (14 years) education. These coefficients are also positive, stable, and statistically significantly different from zero at the 1% level. A one-standard-deviation higher shock leads to 1.7 percentage points higher share of migrants who are skilled (0.19 standard deviations).[22]

Is the increase in migrant educational levels associated with higher wages, and working in higher-skilled jobs? We use migrant contract data, so the years in the regression are 1994, 2009, 2012, and 2015 (as in Table 1, columns 3-6).

In column 3, we find positive effects on annual salary per migrant. Coefficients are positive and stable, but somewhat imprecise. In Panel D (with all controls added), the coefficient is statistically significant at the 10%; the coefficient in that regression indicates that a one standard deviation shock increases average migrant salaries by 23,703 PhP, or 0.16 standard deviations.[23]

In columns 4-7, the dependent variables are migrant contracts per 10,000 working-age (ages 20-64) population in different contract categories. We estimate equation (4) for migrant contracts in four quartiles of occupations, ordered from

[22] For the outcomes in columns 1-2, there is no evidence of pre-trends in Appendix Table A4 (middle panel, columns 4-5) or in Appendix Figures A11c and A11d.

[23] There is no evidence of pre-trends for this outcome. See Table A4 (bottom panel, column 3) and Figure A11e.

Table 3: Effects on Migration Rate, Migrant Skill, and Contract Type

	Census			Contracts per 10,000 Working Age People			
	(1) Migrant Share Age 20 - 64	(2) Share Skilled Migrants	(3) Average Mig. Salary	(4) 1st Qtile Education	(5) 2nd Qtile Education	(6) 3rd Qtile Education	(7) 4th Qtile Education
Panel A. Destination controls only							
$Shiftshare_o \times$ Post	0.018	0.168	161.309	57.222	4.066	74.116	51.898
	(0.006)***	(0.047)***	(157.003)	(73.710)	(6.769)	(29.949)**	(35.292)
Panel B. Additional province development status controls							
$Shiftshare_o \times$ Post	0.018	0.208	239.679	36.217	-0.302	55.406	18.680
	(0.007)***	(0.058)***	(154.239)	(63.723)	(6.077)	(22.788)**	(24.174)
Panel C. Additional province industrial structure controls							
$Shiftshare_o \times$ Post	0.019	0.184	252.645	34.952	-0.825	49.953	16.018
	(0.006)***	(0.052)***	(151.930)	(61.164)	(5.659)	(18.212)***	(21.415)
Panel D. Additional import and export shift-share variables							
$Shiftshare_o \times$ Post	0.019	0.184	254.873	35.067	-0.995	49.948	15.893
	(0.006)***	(0.053)***	(139.900)*	(60.853)	(6.071)	(18.546)***	(22.005)
Obs.	444	444	296	296	296	296	296
Dep. Var. Mean	0.011	0.300	431.718	52.103	6.468	18.324	18.664
Dep. Var. St. Dev.	0.008	0.089	145.806	45.834	7.934	28.371	24.710

Note: Unit of observation is the province-year. Migrant share in the population and share of migrant workers who are skilled is from the Census (periods are 1990, 1995, 2000, 2007, 2010, and 2015). Skilled is defined as completing 14 years of education, which corresponds to finishing a college degree. Migrant contract variables are calculated from POEA/OWWA data (periods are 1994, 2009, 2012, and 2015). Outcome variable in column 3 is average annual migrant salary and columns 4-7 are the migrant contracts (per 10,000 working age population) in occupations in the 1st (lowest) through 4th (highest) quartiles of migrant years of education. Average annual migrant salary is in thousands of real 2010 Philippine pesos (17.8 PhP per PPP US$ in 2010). For list of destination and provincial controls, see Table 1. Baseline dependent variable mean and standard deviation calculated based on data from nearest pre-shock year. All regressions include province and year fixed effects. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.10.

lowest (1st quartile) to highest (4th quartile) education levels.[24] Results are in columns 2-5 of Table 3. There are positive effects on new international migration in the two highest-education quartiles of occupations, but not for the bottom two quartiles. The coefficient is largest and statistically significant in Panel D for the 3rd (second-highest) quartile, while that on the 4th (top) quartile is also positive but not significantly different from zero.

In sum, migrant income shocks increase the migration rate, the share of migrant workers who are skilled, average salary per migrant, and migrant flows in higher-education occupations. A combination of these effects may drive the substantial gains in income we document over the long run.

[24]The 4th (top) quartile (mean 14.4 years of schooling) includes engineers, medical professionals, and teachers. The 3rd quartile (mean 12.9 years of schooling) includes caregivers, restaurant workers, and performing artists. The 2nd quartile (mean 12.7 years of schooling) includes laborers and production workers. The 1st (bottom) quartile (mean 12.3 years of schooling) includes household workers (maids) and construction workers. We calculate mean years of education in 80 detailed migrant occupations in the 1992-2003 Survey of Overseas Filipinos (SOF). We then assign the mean years of education for the occupation from the SOF to each migrant working in the occupation in the contract data. Then, we calculate mean migrant education within quartiles of the contract data.

5.6.3 Entrepreneurial, Wage, and Other Domestic Income Sources

We now examine impacts on types of domestic income. Table 4 presents regression results from Equation (4) where dependent variables are domestic wage income, entrepreneurial and rental income, and other income per capita. Wage income is compensation (cash or in-kind) from regular or seasonal work. Entrepreneurial and rental income is from any entrepreneurial activity (such as poultry/livestock raising, retail, transportation, and rental of land/property). Other income includes pensions, interest, dividends, and other sources.

Table 4: Effects of Migrant Income Shock on Components of Domestic Income

	Domestic Income Components:		
	(1) Wage Income	(2) Entrepreneurial and Rental Income	(3) Other Income
Panel A. Destination controls only			
$Shiftshare_o$ × Post	13.045	9.728	1.827
	(5.217)**	(4.163)**	(1.853)
Panel B. Additional province development status controls			
$Shiftshare_o$ × Post	11.058	7.236	-0.172
	(4.368)**	(3.690)*	(2.273)
Panel C. Additional province industrial structure controls			
$Shiftshare_o$ × Post	10.714	7.198	0.435
	(3.909)***	(3.780)*	(2.102)
Panel D. Additional import and export shift-share variables			
$Shiftshare_o$ × Post	10.549	7.102	0.371
	(4.009)**	(3.467)**	(2.090)
Obs.	296	296	296
Baseline DV Mean	11.759	9.987	4.355
Baseline DV St. Dev.	6.789	3.109	2.002

Note: Unit of observation is the province-year. Data from the Family Income and Expenditure Survey (FIES); periods are 1994, 2009, 2012, and 2015. For list of destination and provincial controls, see Table 1. Baseline dependent variable mean and standard deviation calculated based on data from nearest pre-shock year. All regressions include province and year fixed effects. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.10.

The shock led to increases in both wages, and entrepreneurial and rental income. Coefficient estimates for both outcomes are robust to controls, statistically significantly different from zero at conventional levels in Panel D, and similar to one another in magnitude. By contrast, there is no robust evidence that "other" income is a major part of the increase in domestic income. The positive impact on wage income and on entrepreneurial and rental income likely reflects higher education levels, and increased enterprise investment (both household and external). We explore this further in Section 6 below.

5.6.4 Sectoral Structural Change

Finally, we examine impacts on structural change. We do so by studying both income from different sectors (using FIES data) and employment shares (using Census data). We are interested in (1) whether there is broad structural change away from primary sectors and (2) whether the structure of the economy moved towards tradable (primary and manufacturing) or non-tradable sectors.[25]

In columns 1-2 of Table 5, we report results from estimating equation (4) where the dependent variables are agricultural and non-agricultural domestic income. The results indicate that the increase in domestic income is almost entirely driven by an increase in non-agricultural income.

While it is not possible to further disaggregate total domestic income to different economic sectors, FIES does allow for entrepreneurial income to be further disaggregated. Accordingly, we broadly group entrepreneurial income into income from primary sectors, manufacturing, and non-tradable goods and service sectors.[26] Columns 3-5 of Table 5 show results indicating that entrepreneurial income from service sectors is the biggest contributor to entrepreneurial income. Looking at Panel D, about 55% of the increase in entrepreneurial income is driven by the service sector. Further, the impact on service sector income is two to three times as large as the impact on manufacturing or primary income per capita (which are both insignificant at 10% level).

To assess whether these income patterns indicate broader structural change in the economy, we use Census data to analyze the impact of the migrant income shock on employment shares in broad sectors. We can observe employment shares in two census rounds before (1990, 1995) and two after (2000, 2010) the 1997 Asian financial crisis. Columns 6-8 of Table 5 present the results from estimating equation (4) for employment share outcomes. The migrant income shock leads to a fall in primary sector employment shares. Focusing on Panel D, a one-standard-deviation higher shock results in a 1.2 percentage point decrease in the share of primary sector employment (0.06 standard deviation). Over 70% of the observed decline in primary sector employment is offset by a corresponding increase in non-tradable goods and service sector employment. We find a smaller

[25]For each outcome considered in this section, we document the absence of significant pre-trends in Appendix Table A4 (top panel columns 6-10 and middle panel columns 5-7) and in Appendix Figures A11g and A11h.

[26]Non-tradable goods and services include all service sectors along with "Electricity, gas, water and waste management" and "Construction". This sector is titled "Service" in Table 5 for brevity.

(statistically significant at 10%) increase in the manufacturing labor force share.

Table 5: Effects of Migrant Income Shock on Structural Change

	Overall Income (FIES)		Entrepreneurial Income (FIES)			Employment Share (Census)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agricultural	Non Agricultural	Primary	Manufacturing	Services	Primary	Manufacturing	Services
Panel A. Destination controls only								
$Shiftshare_o \times$ Post	0.426	24.173	1.550	1.778	5.800	-0.137	0.063	0.074
	(2.540)	(8.574)***	(2.747)	(0.883)**	(2.472)**	(0.045)***	(0.029)**	(0.048)
Panel B. Additional province development status controls								
$Shiftshare_o \times$ Post	3.015	15.108	1.372	1.411	3.950	-0.130	0.067	0.064
	(2.838)	(5.457)***	(3.063)	(0.874)	(1.809)**	(0.045)***	(0.030)**	(0.053)
Panel C. Additional province industrial structure controls								
$Shiftshare_o \times$ Post	2.461	15.886	1.691	1.299	3.695	-0.122	0.036	0.086
	(2.705)	(5.444)***	(2.984)	(0.839)	(1.712)**	(0.046)***	(0.021)*	(0.040)**
Panel D. Additional import and export shift-share variables								
$Shiftshare_o \times$ Post	2.477	15.545	1.677	1.288	3.621	-0.123	0.036	0.087
	(2.733)	(4.987)***	(2.848)	(0.831)	(1.914)*	(0.047)**	(0.021)*	(0.039)**
Obs.	296	296	296	296	296	296	296	296
Baseline DV Mean	3.202	22.900	5.712	0.550	3.561	0.559	0.051	0.390
Baseline DV St. Dev.	1.269	9.771	2.826	0.556	2.059	0.185	0.051	0.141

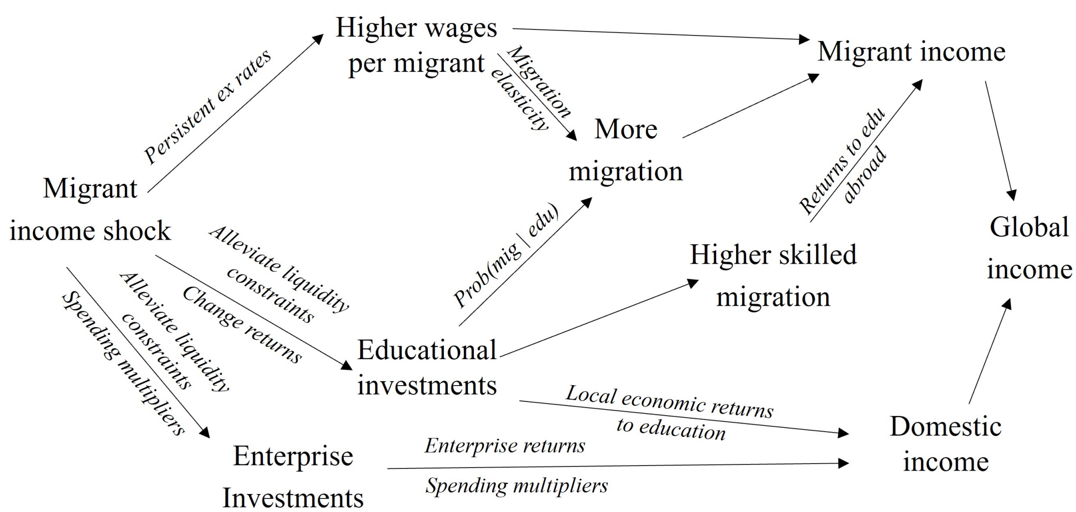
Note: Unit of observation is the province-year. Data from the Family Income and Expenditure Survey (FIES) and Census. FIES analysis includes years 1994, 2009, 2012, and 2015. Census analysis includes years 1990, 1995, 2000, 2010. Services are broadly defined to include the non-tradable utilities and construction sectors. For list of destination and provincial controls, see Table 1. Baseline dependent variable mean and standard deviation calculated based on data from nearest pre-shock year. All regressions include province and year fixed effects. Standard errors are clustered at the province level. All regressions include province and year fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Overall, the persistent increase in migrant income opportunities facilitated the structural change of labor markets away from primary sectors and mainly towards non-tradable goods and service sectors. Beyond its inherent importance in documenting how migrant income can facilitate a process critical to economic development, this has a few important implications for interpreting our results. First, the increase in education documented in Section 5.6.1 can in part be driven by changing local returns to education due to structural change of the local economy. Second, the null impacts of our shock on manufacturing exports, documented in Section 5.4, are consistent with the shift of local economic activity primarily towards the non-tradable service sector, rather than manufacturing. Finally, the concentration of impacts on non-tradable sectors suggests that income originating from abroad likely increases demand for locally produced services. Therefore, higher migrant income flowing to a province would stimulate the local economy, consistent with the impacts on province-level domestic income.

6 Model-Based Quantification and Discussion of Magnitudes

We now provide further insight into the mechanisms and magnitudes of the results thus far. First, we outline a theoretical framework to examine long-run effects on global, migrant, and domestic income. We take a simple model-based approach to quantify how educational investments contribute to income gains. The theoretical framework derives changes in skill shares, migration flows, migrant income, and domestic income as a function of the shift-share variable. The model also reveals whether the magnitude of the effect on migrant income per capita in the long run is explicable. We summarize this model-based quantification here. Appendix Section C contains the full details, derivations, and calculations underlying the model. It also presents validation tests that show our tractable framework closely predicts changes in various income sources.

Figure 3: Stylized Overview of Possible Channels



Note: Overview of modelled channels via which the migrant income shock affects global income. Details in Appendix C.

In Figure 3, we present a stylized diagram illustrating channels through which a migrant income shock affects global income. The persistent shock to migrant income prospects raises wages per migrant, potentially increasing migration and migrant income. The initial shock may also be invested in education, leading to more migration (as the skilled are more likely to migrate) in better-paying skilled jobs, again raising migrant income. The investments in education also raise domestic earnings back home. If this overall persistently high migrant income funds domestic enterprises or stimulates local expenditures, it may also raise domestic earnings. We provide details of the model in Appendix Section C.

6.1 Contribution of the Education Channel

The long-run impact of improved migrant income prospects may be partly due to increased educational investments. First, skilled workers earn more. Furthermore, better-educated individuals have higher migration rates and work in higher-skilled jobs overseas. We quantify the contribution of educational investments to long-run changes in migrant and domestic income.

The college completion regression in Table 2 estimates the education response to the shock. To assess the contribution of educational investments to the income gains, we first multiply each province's specific value of the shift-share variable by the regression coefficient (0.046) in Panel D, column 3 of Table 2 to estimate the change in the province's population share skilled. Then we estimate how migration (to each destination, or remaining at origin) responds to this change in the skill composition, presuming the same pre-shock (1995) dyadic migration probabilities by skill (the probability someone with skill s migrates from origin o to destination d). That is, to estimate the changes in migration flows to each destination, we take the baseline difference between skill groups in the proclivity to migrate to each destination, and scale this by the change in the share skilled.

Then, we calculate how both migrant and domestic income would change in response to such migration changes, assuming the same dyadic skill premium (difference in skilled vs. unskilled income, in origin-destination dyads) from the pre-shock period. That is, we take the baseline skill premia, both for domestic and for migrant income, and multiply it by the change in share skilled to predict the education-driven change in incomes.

This calculation provides estimates of the change in migrant and domestic income per capita resulting from the education channel in Appendix Table A12. The education channel explains 17.8% of the increase in migrant income, and 20.2% of the increase in domestic income. The implied share of global income (the sum of migrant and domestic income) explained by increased education is 19.55%. In sum, the increases in education induced by changes in migrant income opportunities account for roughly one-fifth of long-run income gains.

6.2 Explaining Impact on Migrant Income

We also use the model to explain the increase in migrant income (coefficient 6.463 in Table 1's migrant income regression). As discussed above, educational attainment explains 17.8% of this increase. We seek to explain the remainder of the migrant income increase. Additional mechanisms include the exchange rate shocks themselves, as well as changes in migration flows across destinations.

We first estimate changes in migration flows. Destination exchange rate shocks can alter migration decisions, ultimately leading to changes in long-run migrant income. Our model derives a gravity equation, with a parameter θ that is the elasticity of migrant flows (from origin-o to destination-d) with respect to destination wages. This determines subsequent location choices and migrant income. Higher θ means that migration flows, and thereby migrant income, respond more to exchange rate shocks. We use the exchange rate shocks to estimate θ in Appendix C.4 using a Poisson pseudo-maximum likelihood (PPML) estimator (as many origin-destination dyads have zero flows). This yields an estimate of 3.42, which we use along with the actual exchange rate shocks to predict changes in migration in origin-destination dyads.

We then calculate the change in total migrant income resulting from all dyadic (origin-destination) changes in migration flows, by skill, and changes in exchange rates. We hold fixed skill-specific migrant wages (in destination currency) in each destination at pre-shock levels, so changes in migrant income reflect only exchange rate shocks and altered migration flows. We estimate that these factors explain an additional 64.6% of the change in migrant income. This is on top of the 17.8% attributed to education investments. The modeled components, therefore, explain 82.3% of the increase in migrant income.

The persistence of favorable exchange rates is a crucial driver of the 'exchange rate channel' in Appendix Table A12. Indeed, this differentiates our analysis from studies that focus on one-time cash transfers, or short-run access to higher income. Many parts of the world benefit from persistent access to profitable migrant opportunities, and our variation recreates such an experiment.

In sum, the model accounts for the majority of the magnitude of the effect on migrant income. The six-fold magnification of the initial migrant income shock is mostly explained by the combination of increased education, persistent exchange rate shocks, and changes in migration across destinations.

6.3 Explaining Impact on Domestic Income

We investigate the assumptions needed to explain the magnitude of the impact on domestic income. The coefficient in the domestic income per capita regression of Table 1, Panel D, column 4 indicates that a PhP 1 migrant income shock leads to a PhP 18.02 increase in long-run domestic income. 20.2% of this increase is attributable to the increases in education investments (see Subsection 6.1). This leaves PhP 14.4 to be explained. We consider two mechanisms that could explain this: a demand multiplier, and investments in domestic enterprises.

Recent studies have estimated large demand multipliers in low-income contexts. Egger et al. (2022) estimate a multiplier of 2.5 in response to cash transfers in Kenya. The multiplier due to a credit supply shock in India is 2.9 (Breza and Kinnan, 2021). Gerard et al. (2024) and Mendes et al. (2023) estimate transfer multipliers for Brazil's Bolsa Familia program that range from 2.2 to 7.16 in reduced form and 2.62 under structural assumptions. Multipliers are likely to be larger for relatively closed economies, like Philippine island provinces. Furthermore, as we show in Section 5.6.4, much of the impacts were on non-tradable goods and services, with income gains on local entrepreneurial incomes. We consider how much of our effect on domestic income could be explained by such multipliers.

In our context, multipliers operate on the portion of migrant income sent back to origin provinces. The coefficient estimate in the migrant income regression of Table 1, Panel D, indicates that the multiplier would operate on the portion of the 6.46 increase in migrant income per capita that is sent back to origin provinces. Assuming 64% of the migrant income returns to the local economy, that coefficient and a multiplier of 2.9 implies an increase in domestic income per capita of 12.0 PhP ($6.46 \times 0.64 \times 2.9$). A simple demand multiplier thus explains 83.3% of the remaining (non-education related) 14.4 PhP.[27]

We now consider an additional contributor to the increase in domestic income: previous migrant income could alleviate constraints on investments and lead to higher capital today. The migrant income shock was not a one-time windfall, but was sustained and grew, and so likely led to sustained increases in capital accumulation. While most work on multipliers focuses on short-term shocks, in our

[27]There is no comprehensive data on the share of migrant income returned to the Philippines. We estimate $\alpha = 0.64$ indirectly by combining data from KNOMAD/ILO Migrant Cost Surveys, Survey on Overseas Filipinos, and the POEA/OWWA contract data. Details are at the end of Appendix Section C.7.1.

context, the income gains in previous years may have been invested, leading to higher sustained income gains. It is widely recognized that household enterprises and firms face binding constraints on capital investment (Karlan and Morduch, 2010), and that when constraints are loosened, firms have high rates of return on investment. de Mel et al. (2008) estimate a rate of return to Sri Lankan microenterprise investments from randomly-assigned capital investments of 5% per month (80% per year).[28] Such returns likely explain part of the increases in wage and entrepreneurial incomes seen in Table 4.

We examine whether our domestic income results can be generated in a stylized framework in which a portion of the exogenous increase in migrant income is devoted to capital accumulation, and in which a demand multiplier also operates. We summarize the framework here; details are in Appendix Section C.7.1. We trace the dynamics of domestic income per capita following the initial migrant income shift-share shock. Shock-induced migrant income per capita grows over time, reaching the amounts reflected in the event-study coefficients for migrant income per capita in Figure 2. In each post-shock year, a portion of shock-induced higher migrant income returns to origin provinces. Migrant income returned to origin economies generates an aggregate demand multiplier. In every period, households save a portion of shock-induced higher incomes, investing them in enterprises and firms.[29] We assume relatively high initial rates of return on investment (but not as high as the findings of de Mel et al. (2008)), which decline over time as the initial low-hanging investment fruits are exhausted. Higher incomes induced by these capital investments also generate a multiplier.

In Appendix Figure A10a, we display the shock-induced domestic income of the model between 1998 and 2015, for three values of the share of migrant income spent at origin, α. With α=0.64, a PhP 1 initial migrant income shock becomes PhP 18.88 of domestic income by the year 2015 (around 25% larger than the 14.4 impact we set out to explain). In Appendix Figure A10b, we set α=0.64, vary the initial rate of return on investment, and trace the shock-induced domestic income in 2015. Our estimates range from 15.0 for an initial rate of return of 0.05, to 23.5 for an initial return at 0.8 (the estimate of de Mel et al. (2008)).[30]

[28]Similarly high returns are found by Banerjee and Duflo (2014), Hussam et al. (2022), and Cai and Szeidl (2022). In the Philippines, Edmonds and Theoharides (2020) find a rate of return of 27%, 18 months after a productive asset transfer (although Karlan and Zinman (2018) find limited savings constraints in the Philippines).

[29]We set the savings rate to 0.35 (or a Keynesian multiplier of 2.86 comparable to 2.9 in Breza and Kinnan (2021)).

[30]If we were to ignore the investment channel, our estimates would suggest a multiplier of about 14.4/(0.64×6.463) =

We view this calculation as a sanity check, demonstrating that a set of reasonable assumptions generates the observed long-run impact on domestic income per capita. The framework is agnostic about the possible channels through which the effect on domestic income may arise. Importantly, we do not model potential escapes from poverty traps (Ghatak, 2015; Balboni et al., 2021; Kaboski et al., 2022), or returns to foreign experience for return migrants (Batista et al., 2025). Some of these channels likely contribute to domestic income increases at the origin.

7 Conclusion

We study the long-run consequences of persistent increases in international migrant income prospects for migrant-origin regions. We find that the vast majority of income gains are from *domestic* (origin-area) sources. Gains in international migrant income also increase substantially and play a crucial role in driving overall gains. Model-based estimates suggest that about one-fifth of the income gains (both domestic and international) are due to increased educational investments.

Our findings suggest that migration policy should be an important part of the development policy toolkit. Our results shed light on the impacts of policies – in both origin and destination countries – that affect current international migrant income as well as opportunities to earn such income in the future. Origin-country policies include efforts to facilitate international labor migration, regulate the market power of intermediaries, and educational investments that raise skills and make citizens more competitive for international jobs. Destination country policies include those related to legal immigration opportunities as well as enforcement against undocumented immigrants.

There are also implications for how we think about overseas development assistance (foreign aid). We find that improvements in migrant income have substantial positive impacts on the development of the *domestic* economy of migrant *origin* areas. Development agencies could consider supplementing traditional foreign aid with programs that facilitate international labor migration (Clemens, 2010; Clemens and Pritchett, 2013; World Bank, 2018; Nunn, 2019).

3.4, which is also within the range of multipliers found in the literature.

References

Abarcar, P. (2019). The return motivations of legal permanent migrants: Evidence from exchange rate shocks and immigrants in Australia. *Journal of Economic Behavior and Organization*.

Abarcar, P. and Theoharides, C. (2022). Medical worker migration and origin-country human capital: Evidence from U.S. visa policy. *Review of Economics and Statistics*.

Agte, P., Bernhardt, A., Field, E., Pande, R., and Rigol, N. (2022). Investing in the next generation: The long-run impacts of a liquidity shock. *NBER Working Paper*, (29816).

Akram, A., Chowdhury, S., and Mobarak, A. (2017). Effects of emigration on rural labor markets. *Working Paper*.

Allen, T., Arkolakis, C., and Takahashi, Y. (2020). Universal Gravity. *Journal of Political Economy*, 128(2):393–433.

Anelli, M., Basso, G., Ippedico, G., and Peri, G. (2023). Emigration and entrepreneurial drain. *American Economic Journal: Applied Economics*, 15(2):218–252.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, Princeton, NJ.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–68.

Balboni, C., Bandiera, O., Burgess, R., Ghatak, M., and Heil, A. (2021). Why do people stay poor? *Quarterly Journal of Economics*.

Bandiera, O., Burgess, R., Das, N., Gulesci, S., Rasul, I., and Sulaiman, M. (2017). Labor markets and poverty in village economies. *Quarterly Journal of Economics*.

Banerjee, A. and Duflo, E. (2014). Do firms want to borrow more? Testing credit constraints using a directed lending program. *Review of Economic Studies*, 81:572–607.

Banerjee, A., Duflo, E., Goldberg, N., Karlan, D., Osei, R., Pariente, W., Shapiro, J., Thuysbaert, B., and Udry, C. (2015). A multifaceted program causes lasting progress for the very poor: Evidence from six countries. *Science*, 348(6236).

Banerjee, A., Duflo, E., and Sharma, G. (2021). Long-term effects of the targeting the ultra poor program. *American Economic Review: Insights*, 4(3):471–486.

Batista, C., Han, D., Haushofer, J., Khanna, G., McKenzie, D., Mobarak, A. M., Theoharides, C., and Yang, D. (2025). Brain drain or brain gain: Effects of high-skilled international emigration on origin countries. *Science*, 388(6749):eadr8861.

Batista, C., Lacuesta, A., and Vicente, P. (2012). Testing the brain gain hypothesis: micro evidence from Cape Verde. *Journal of Development Economics*.

Bazzi, S., Cameron, L., Schaner, S., and Witoelar, F. (2021). Information, intermediaries, and international migration. *NBER Working Paper No. 29588*.

Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share designs. *Review of Economic Studies*, 89(1):181–213.
Borusyak, K., Hull, P., and Jaravel, X. (2024). A practical guide to shift-share instruments. *NBER Working Paper Series*, (33236).
Bossavie, L., Gorlach, J.-S., Ozden, C., and Wang, H. (2021). Temporary migration for long-term investment. *World Bank Policy Research Working Paper*, (9740).
Brambor, T., Clark, W. R., and Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis*, 14(1):63–82.
Breza, E. and Kinnan, C. (2021). Measuring the Equilibrium Impacts of Credit: Evidence from the Indian Microfinance Crisis. *The Quarterly Journal of Economics*, 136(3):1447–1497.
Bryan, G. and Morten, M. (2019). The aggregate productivity effects of internal migration: Evidence from Indonesia. *Journal of Political Economy*.
Bucheli, J. R. and Fontenla, M. (2022). The Impact of Return Migration on Economic Development. *The Review of Economics and Statistics*, pages 1–45.
Caballero, M. E., Cadena, B. C., and Kovak, B. K. (2023). The International Transmission of Local Economic Shocks Through Migrant Networks. *Journal of International Economics*, 145.
Cai, J. and Szeidl, A. (2022). Indirect effects of access to finance. *NBER Working Paper*, (29813).
Chand, S. and Clemens, M. A. (2023). Human capital investment under exit options: Evidence from a natural quasi-experiment. *Journal of Development Economics*, 163:103112.
Clemens, M. (2010). The biggest idea in development that no one really tried. In Chamlee-Wright, E., editor, *The Annual Proceedings of the Wealth and Well-Being of Nations: 2009-2010*, pages 25–50. Beloit College Press, Beloit, WI.
Clemens, M., Montenegro, C., and Pritchett, L. (2019). The place premium: Bounding the price equivalent of migration barriers. *Review of Economics and Statistics*.
Clemens, M. and Pritchett, L. (2013). Time-bound labor access to the United States: A four-way win for the middle class, low-skill workers, border security, and migrants. *Center for Global Development Brief*.
Clemens, M. A. (2011). Economics and emigration: Trillion-dollar bills on the sidewalk? *The Journal of Economic Perspectives*, 25(3):pp. 83–106.
Clemens, M. A. and Tiongson, E. R. (2017). Split decisions: Household finance when a policy discontinuity allocates overseas work. *The Review of Economics and Statistics*, 99(3):531–543.
Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1):1–45.
Cuadros-Menaca, A. and Gaduh, A. (2020). Remittances, child labor, and schooling: Evidence from colombia. *Economic Development and Cultural Change*, 68(4):1257–1293.

de Brauw, A. and Giles, J. (2017). Migrant opportunity and the educational attainment of youth in rural China. *Journal of Human Resources*, 52(1).

de Mel, S., McKenzie, D., and Woodruff, C. (2008). Returns to Capital in Microenterprises: Evidence from a Field Experiment. *The Quarterly Journal of Economics*, 123(4):1329–1372.

Dinkelman, T., Kumchulesi, G., and Mariotti, M. (2024). Labor migration, capital accumulation, and the structure of rural labor markets. *Review of Economics and Statistics*.

Dinkelman, T. and Mariotti, M. (2016). The long run effect of labor migration on human capital formation in communities of origin. *American Economic Journal: Applied Economics*.

Docquier, F. and Rapoport, H. (2012). Globalization, brain drain, and development. *Journal of Economic Literature*.

Ducanes, G. (2010). The case of missing remittances in the FIES: Could it be causing us to mismeasure welfare changes? *University of the Philippines School of Economics Discussion Paper*, (4).

Dustmann, C., Frattini, T., and Rosso, A. (2015). The effect of emigration from poland on polish wages. *The Scandinavian Journal of Economics*, 117(2):522–564.

Dustmann, C. and Kirchkamp, O. (2002). The optimal migration duration and activity choice after re-migration. *Journal of Development Economics*.

Dustmann, C., Ku, H., and Surovtseva, T. (2023). Real Exchange Rates and the Earnings of Immigrants. *The Economic Journal*, 134(657):271–294.

Eaton, J. and Kortum, S. (2002). Technology, geography and trade. *Econometrica*, 70:1741–1779.

Edmonds, E. and Theoharides, C. (2020). The short term impact of a productive asset transfer in families with child labor: Experimental evidence from the Philippines. *Journal of Development Economics*, 146.

Egger, D., Haushofer, J., Miguel, E., Niehaus, P., and Walker, M. W. (2022). General equilibrium effects of cash transfers: Experimental evidence from Kenya. *Econometrica*.

Elsner, B. (2013). Does emigration benefit the stayers? evidence from eu enlargement. *Journal of Population Economics*, 26(2):553.

Fernández Sánchez, M. (2025). Mass emigration and human capital over a century: Evidence from the galician diaspora. *Journal of the European Economic Association*. Forthcoming.

Fernando, A. N. and Singh, N. (2021). Regulation by reputation? quality revelation of labor intermediaries in international migration. *Working Paper*.

Gaikwad, N., Hanson, K., and Toth, A. (2024). Bridging the gulf: How migration fosters tolerance, cosmopolitanism, and support for globalization. *Working Paper*.

Gerard, F., Naritomi, J., and Silva, J. (2024). Cash transfers and the local economy: Evidence from brazil. *Working Paper*.

Ghatak, M. (2015). Theories of poverty traps and anti-poverty policies. *World Bank Economic Review*, 29:S77–S105.

Gibson, J., McKenzie, D., Rohorua, H., and Stillman, S. (2018). The Long-term Impacts of International Migration: Evidence from a Lottery. *World Bank Economic Review*, 32(1):127–47.

Gibson, J., McKenzie, D., and Stillman, S. (2010). How important is selection? experimental vs. non-experimental measures of the income gains from migration. *Journal of the European Economic Association*.

Gibson, J., McKenzie, D., and Stillman, S. (2011). The impacts of international migration on remaining household members: Omnibus result from a migration lottery program. *Review of Economics and Statistics*, 93(4).

Gibson, J., McKenzie, D., and Stillman, S. (2014). The development impact of a best practice seasonal migration policy. *Review of Economics and Statistics*.

Giesing, Y. and Laurentsyeva, N. (2018). Firms left behind: Emigration and firm productivity. CESifo Working Paper Series 6815, CESifo (Center for Economic Studies and Ifo Institute).

Godlonton, S. and Theoharides, C. (2024). Diffusion of reproductive health behavior through international migration: Effects on origin-country fertility. *Working Paper*.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Gröger, A. (2019). Easy come, easy go? Economic shocks, labor migration and the family left behind. *Journal of International Economics*, 128.

Gualavisi, M. and Kleemans, M. (2024). Effects of emigration on labor markets in migrant origin areas: Evidence from internal migration in indonesia. Unpublished manuscript.

Harris, R. D. and Tzavalis, E. (1999). Inference for unit roots in dynamic panels where the time dimension is fixed. *Journal of Econometrics*, 91(2):201–226.

Hussam, R., Rigol, N., and Roth, B. (2022). Targeting high ability entrepreneurs using community information: Mechanism design in the field. *American Economic Review*, 112(3):861–898.

Kaboski, J., Lipscomb, M., Midrigan, V., and Pelnik, C. (2022). How important are investment indivisibilities for investment? empirical evidence from Uganda. *NBER Working Paper*, (29773).

Karlan, D. and Morduch, J. (2010). Access to finance. *Handbook of Development Economics*, 5(1):4703–4784.

Karlan, D. and Zinman, J. (2018). Price and control elasticities of demand for savings. *Journal of Development Economics*, 130.

Khanna, G. and Morales, N. (2023). The IT boom and other unintended consequences of chasing the American dream. Working Paper.

Khanna, G., Murathanoglu, E., Theoharides, C., and Yang, D. (2022). Abundance from abroad: Migrant income and long-run economic development. *NBER Working Paper No. 29862*.

Kinnan, C., Wang, S.-Y., and Wang, Y. (2019). Access to migration for rural households. *American Economic Journal: Applied Economics*.

Kirdar, M. (2009). Labor market outcomes, savings accumulation, and return migration. *Labour Economics*.

Kleemans, M. and Magruder, J. (2019). Labor market changes in response to immigration: Evidence from internal migration driven by weather shocks. *The Economic Journal*.

Lagakos, D., Mobarak, A. M., and Waugh, M. E. (2023). The welfare effects of encouraging rural–urban migration. *Econometrica*, 91(3):803–837.

Llull, J. (2018). Immigration, wages, and education: A labor market equilibrium structural model. *The Review of Economic Studies*, 85(3):1852–1896.

Mahajan, P. and Yang, D. (2020). Taken by storm: Hurricanes, migrant networks, and U.S. immigration. *American Economic Journal: Applied Economics*.

McKenzie, D. and Rapoport, H. (2011). Can migration reduce educational attainment? Evidence from Mexico. *Journal of Population Economics*, 24(4):1331–1358.

Mendes, A. G., Miyamoto, W., Nguyen, T. L., Pennings, S. M., and Feler, L. (2023). The macroeconomic effects of cash transfers: Evidence from brazil. *Working Paper*.

Mendola, M. (2012). Rural Out-migration and economic development at origin: A review of the evidence. *Journal of International Development*, 24:102–122.

Mobarak, A. M., Sharif, I., and Shrestha, M. (2023). Returns to International Migration: Evidence from a Bangladesh Malaysia visa lottery. *American Economic Journal: Applied Economics*, 15(4):353–388.

Mountford, A. (1997). Can a brain drain be good for growth in the source country? *Journal of Development Economics*.

Munshi, K. (2003). Networks in the modern economy: Mexican migrants in the U. S. labor market. *The Quarterly Journal of Economics*, 118(2):pp. 549–599.

Nekoei, A. (2013). Immigrants' labor supply and exchange rate volatility. *American Economic Journal: Applied Economics*, 5(4).

Nunn, N. (2019). Rethinking economic development. *Canadian Journal of Economics*, 54(4):1349–1373.

Park, Y. C. and Lee, J. W. (2002). Financial crisis and recovery: Patterns of adjustment in east asia, 1996-99. *Asian Development Bank*.

Pritchett, L. and Hani, F. (2020). The economics of international wage differentials and migration. *Oxford Research Encyclopedia of Economics and Finance*.

Radelet, S. and Sachs, J. (2000). *The Onset of the East Asian Financial Crisis*, pages 105–153. University of Chicago Press.

Rana, P. (1998). The east asian financial crisis – implications for exchange rate management. *Asian Development Bank*.

Shrestha, M. (2020). Get rich or die tryin': Perceived earnings, perceived mortality rates, and migration decisions of potential work migrants from Nepal. *World Bank Economic Review*, 34(1).

Shrestha, S. (2017). No man left behind: Effects of emigration prospects on educational and labor outcomes of non-migrants. *Economic Journal*.

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

Stark, O., Helmenstein, C., and Prskawetz, A. (1997). A brain gain with a brain drain. *Economic Letters*.

Tang, S. H. K., Wang, Y., and Wang, Y. (2022). Curse of lower-skilled emigration on human capital formation: Evidence from the migration surge of the 2000s. *Working Paper*.

Theoharides, C. (2018). Manila to Malaysia, Quezon to Qatar: International migration and the effects on origin-country human capital. *Journal of Human Resources*.

Theoharides, C. (2020). The unintended consequences of migration policy on origin-country labor market decisions. *Journal of Development Economics*.

Tombe, T. and Zhu, X. (2019). Trade, migration and productivity: A quantitative analysis of China. *American Economic Review*, 109(5):1843–1872.

United Nations, T. (2019a). International migrant stock 2019. Technical report, Department of Economic and Social Affairs, United Nations.

United Nations, T. (2019b). World population policies 2019: International migration policies and programs. Technical report, United Nations.

World Bank, T. (2018). *Moving for Prosperity: Global Migration and Labor Markets*. World Bank Publications, Washington, DC.

Yang, D. (2006). Why do migrants return to poor countries? Evidence from Philippine migrants' responses to exchange rate shocks. *The Review of Economics and Statistics*, 88(4):715–735.

Yang, D. (2008a). Coping with disaster: The impact of hurricanes on international financial flows, 1970-2002. *B.E. Journal of Economic Analysis and Policy (Advances)*, 8(1).

Yang, D. (2008b). International migration, remittances, and household investment: Evidence from Philippine migrants' exchange rate shocks. *Economic Journal*, 118:591–630.

Zheng, X., Fang, Z., Wang, Y., and Fang, X. (2022). When left-behind children become adults and parents: The long-term human capital consequences of parental absence in china. *China Economic Review*, 74:101821.

Online Appendix

A Data Appendix

A.1 Migration Data

Calculation of migrant income per capita of each Philippine province in every overseas destination requires unusual data. We obtained two administrative datasets from Philippine government agencies. The Philippine Overseas Employment Administration's (POEA) migrant contract database contains name, date of birth, sex, marital status, occupation, destination country, employer, recruitment agency, salary, contract duration, and date deployed. The database of the Overseas Worker Welfare Administration (OWWA) includes migrants' names, 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, Theoharides (2018) combined the datasets from POEA and OWWA using fuzzy matching techniques for the years 1992-1997 and 2007-2009. The POEA and OWWA data are matched using first name, middle name, last name, date of birth, destination country, sex, and year of departure. The match rate is 95%. Starting in 2010, data from POEA included wages, destination, and province of origin, so our data from 2010-2015 is from POEA only and does not require matching. Several of the immediate post-shock (post-1997) years have relatively high rates of missing data on migrant origin address. We therefore focus on the years 2007-2015, which have low rates of missing address data, and which also span the 2007, 2010, and 2015 Philippine Censuses.[31] All wages are expressed in thousands of real 2010 Philippine pesos. We winsorize the wages at 99% within each destination-occupation category cell.[32]

We use the 1995 contract data to construct the shift-share variable $Shiftshare_o$. First, we calculate province-level migrant income per capita ($MigInc_{o0}$) in 1995. We calculate province total migrant income by multiplying average migrant income for a province's migrants in 1995 (from the POEA/OWWA contract data) by the number of migrants in a given province (from the 1995 Census). We then divide by 1995 province population, obtaining migrant income per capita. We use an analogous calculation for migrant income per capita in 1994, 2009, 2012, and 2015 (corresponding to triennial FIES years). For each year, we calculate average migrant income from the POEA/OWWA data.[33] We then multiply by the total

[31] In the 1992-2009 contract data, the home address variable in the OWWA data includes municipality, but not province. Out of 1630 municipalities in the Philippines, 332 have names that are duplicated in another 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. For the 2010-2015 data, municipality and province are reported for each contract.

[32] When destination-occupation cells have fewer than 100 observations, we aggregate these cells and winsorize at the occupation level.

[33] For these years, we use the migrant wages from the previous three years of contract data to calculate average income per migrant. For example, 2009 migrant income per capita uses the average of income reported in contracts in 2007, 2008,

number of migrants in the 1995 Census (for 1994 migrant income per capita), 2010 Census (for 2010 and 2012 migrant income per capita), or in the 2015 Census (for 2015 migrant income per capita).

Second, we use the contract data to construct $Rshock_o$, the weighted average exchange rate shock of province o's migrants. Weights are the pre-shock share of migrant income from destination d. For each province o, we calculate these weights directly from the contract data, as the share of total province-level migrant annual income from each destination country in 1995 ($\frac{\omega_{do0}}{\sum_d \omega_{do0}}$). We then multiply each exchange rate change $\tilde{\Delta} R_{d0}$ by the corresponding province-o-specific weights to obtain $Rshock_o$.

A small minority of contracts have missing data on municipality in the OWWA data (14.5% in 1995). A concern is that the exchange rate shock might be correlated with the propensity to be missing municipality data in the pre-period, and thus introduce some chance correlation with province or destination characteristics into $Shiftshare_o$. To test this, we regress the exchange rate shock on the share of destination observations with a missing province on the exchange rate shock, weighting by Borusyak et al. (2022) shares. The coefficient on the share missing is very small in magnitude and not statistically significantly different from zero. A one-standard-deviation increase in the share of contracts missing province data is associated with a 0.007 increase in the exchange rate shock (which has a mean of 0.406 and a standard deviation of 0.138). The regression provides no indication that the propensity for migrant worker contracts for a given migration destination to have missing Philippine location data in the pre-period is correlated with that destination's exchange rate shock.

A.2 Domestic Income and Expenditure

All outcomes in money units in this paper (e.g., income and expenditure) are in 2010 real Philippine pesos (PhP; 17.8 PhP per PPP US$ in 2010).

Data on household income and expenditure are from triennial rounds of the Philippine Family Income and Expenditure Survey (1985, 1988, 1991, 1994, 1997, 2000, 2003, 2006, 2009, 2012, 2015, and 2018). The FIES provides the Philippine government's official income and expenditure statistics. It includes detailed household income and expenditure items. Domestic income and expenditure (as in Table 1), are the aggregation of these detailed items. Domestic income is calculated as total household income minus income from international sources, transfers from domestic sources, and gifts from other households. Income from international sources includes migrant remittances, but also includes pensions, retirement, workmen's compensation, and other benefits; cash gifts, support, relief, etc., from abroad; and dividends from investments abroad. Migrant remittances

and 2009. Migrant contracts have an average contract length of 24 months, so the average wages of the stock of migrants in 2009 would reflect the average wages of migrants departing in 2009 as well as previous years.

are not explicitly reported in the data.

We calculate global 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, we focus on a subset of time periods when both domestic and migrant income data are available. This allows us to examine one pre-shock year and three 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 2009, 2012, and 2015 FIES rounds.

A.3 Census Data

Education. We created a panel of schooling outcomes using the 1990, 1995, 2000, 2007, 2010, and 2015 Philippine Census of Population. In each census round, we calculate the provincial share of individuals with primary (6 or more years of schooling), high school (10 or more years), and college education (14 or more years) for the full population (aged 20-64) as well as for international migrant workers.

Sectoral Employment Share. We create a panel of the sectoral share of workforce using 1990, 1995, 2000, and 2010 Philippine Census of Population (the only years with available variables). In each census round, we calculate the share of employed individuals in primary, manufacturing, and non-tradable goods and services sectors. Primary sectors include agriculture, fishing, forestry, mining, and extraction (broadly corresponding to ISIC codes 1-9). The manufacturing sector includes manufacturing (broadly corresponding to ISIC codes 10-33). Non-tradable goods and services include construction, wholesale/retail trade, transportation, storage, communication, electricity, gas, water, waste, finance, insurance, reals estate, business services, hotels and restaurants, education, health, social work, private household services, public administration, and other services (broadly corresponding to ISIC codes 35-98).

A.4 Labor Force Survey Data

The FIES, which we use for our main income and expenditure outcomes, is implemented as a rider every three years to the government's quarterly Labor Force Surveys (LFS). We use the merged LFS and FIES data to calculate domestic income per capita for skilled and unskilled households (used in the model-based quantification, Appendix Section C). The LFS indicates the education level and the employment status of each member of the household. We define a household as "skilled" if any of the employed members have a college education or above. We then calculate domestic income per capita for skilled and unskilled households using the FIES.

A.5 Province Level Consumer Price Index

We obtained the data series for the 2018-Based Consumer Price Index for All Income Households by Commodity Group covering January 1994 to December 2017 from the Philippine Statistical Authority's (PSA) OpenSTAT portal. We renormalize to set CPI for 1996 to be 100 for each province. To standardize province values back to our 1990 definition, we take a weighted average of component provinces' CPIs, where weights are determined by 2015 population.

A.6 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 carry out the model-based quantifications. We use the 1990 Census to construct the baseline probability of migration by skill group (shares of working-age population who migrated, by skill group). In addition, we use the POEA/OWWA data to construct 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 incomes. We exclude origin-destination-skill-time observations where there were no flows. We winsorize the salary data at the 99th percentile.

A.7 Regression Controls

A.7.1 Destination-Level Controls

The first set of destination controls is the baseline (1995) share of migrants going to three regions: Middle East and North Africa (MENA), East Asia, and OECD countries. MENA countries include Saudi Arabia, United Arab Emirates, Kuwait, Qatar, Oman, Bahrain, Egypt, Iran, Yemen, Syria, Jordan, Israel, and Lebanon. East Asia destinations include Japan, Taiwan, Hong Kong, Malaysia, South Korea, Brunei and Singapore. OECD destinations include Canada, United States, Italy, New Zealand, Australia, Belgium, Netherlands, the UK, France, Hungary, Austria, Sweden, Turkey, Spain, Norway, Germany, Denmark, Finland, Greece, Iceland, and Switzerland.

Remaining destination controls are destination-level controls, aggregated to the province level by taking weighted averages of destination-level variables for each province, weighted by baseline migrant earnings from each destination, following Borusyak et al. (2022). To construct baseline GDP per capita, we used 1995 values in current US dollars from World Development Indicators.[34] The baseline destination contract variables are the following four variables from the 1995

[34] For the following small set of destinations, this variable was not available in the WDI. For Taiwan, we used 1995 GDP per capita values from Taiwan's national statistics https://eng.stat.gov.tw/ct.asp?xItem=37408&CtNode=5347&mp=5. For Guam, Midway Island, and Northern Mariana Islands, we used US baseline values as they are US territories. For British Overseas Territories Cayman Islands and Diego Garcia we use UK baseline values. For Netherlands Antilles, we used Netherlands baseline values. For Palau, we use the closest available year of 2000 GDP per capita. Finally, Netherlands and Myanmar only had 1995 GDP per capita in 2010 US$ and had 1999 GDP per capita in current US$ (the closest year to

POEA/OWWA data: (1) average 1995 salary (in real 2010 Philippine pesos) for each destination's contracts, (2) percent of 1995 contracts in professional occupations, (3) percent of 1995 contracts in production occupations, and (4) percent of all 1995 contracts for Philippine international migrant workers going to the destination.

A.7.2 Province-Level Controls

Baseline share of rural households is from the 1990 census. Baseline asset index is from the 1990 census. This is the first principal component of household-level indicators for ownership of a set of durable goods, utilities access, housing quality, and land and home ownership. We then take the mean of this household-level index within each province. Baseline domestic income and expenditure per capita are the average of domestic income per capita and expenditure for 1988, 1991, and 1994, calculated from FIES microdata. Baseline sector shares are shares of employed individuals in primary, industrial, service, and financial/business services sectors, calculated from the 1990 census.

A.7.3 Controls Included for Additional Robustness Results

Manufacturing export controls include total and per capita exports per province. We jointly include both levels and IHS transformations of these variables. Baseline controls include data from 1994 and 1996. Time-varying manufacturing controls include the same variables, but corresponding to the province-year of observation instead of the baseline. The sources of this export data are described in Section A.8 below.

Baseline share of workforce in disaggregated manufacturing sectors jointly include 12 controls for the 1995 share of workforce in the following 12 manufacturing sectors: food/beverage, tobacco, textile/wearing, paper/printing, petroleum/ chemicals/rubber, non-metallic mineral production, basic or fabricated metal production, wood/work/cane, furniture, machinery, transport equipment, and other manufacturing. Data is from the 1995 Census, and the sectors correspond to the most disaggregated manufacturing sector definitions possible given the available 1995 Census industry codes.

Baseline share of workforce in disaggregated primary sectors include 11 controls for the 1995 share of workforce in the following 11 sectors: palay farming, corn farming, banana farming, coconut farming, sugar cane farming, animal farming, other crops farming, hunting/foraging, fishing, metallic ore mining, non-metallic ore mining. Data is from the 1995 census, and the sectors correspond to the most disaggregated primary sector definitions possible given the available 1995 Census industry codes.

1995). We used the following estimate: $gdppc_{1995}^{currentUS\$} = gdppc_{1995}^{2010US\$} \times \frac{gdppc_{1999}^{currentUS\$}}{gdppc_{1999}^{2010US\$}}$

Tourism sectors are determined based on correspondence with the Philippine Statistical Authority (PSA). We define the tourism sector as "employment in tourism industries," which includes employment in restaurants, hotels, and transport services. Data is from the 1995 Census.

A.8 Exports and Foreign Direct Investment

In Section 5.4, we examine potential other mechanisms for our causal effects: manufactured exports and foreign direct investment (FDI).

Data on manufacturing firm exports are from a set of firm sample surveys of the Philippine Statistics Authority: the Annual Survey of Establishments (1994, 1996, 1997, 1998), Annual Survey of Philippine Business and Industry (2008, 2009, 2010, 2013, 2014, 2015), and Census of Philippine Business and Industry (1999, 2006, 2012). We obtain data for province-year observations that had three or more manufacturing establishments in the sample.[35] We sum exports across firms to the province-year level, then divide by province population to obtain per capita figures. Summed exports within province-year cells account for survey sampling weights when available (2000 and after). (Results are robust to using unweighted sums for all years.) We winsorize province-year observations at 99%.

FDI data for 1996-2002 are available from the PSA's Foreign Investment Reports, which provide the breakdown of total approved foreign investments by origin country. FDI data for 2003 and after are from the PSA's OpenStat platform. Data on FDI is broken down at the country level for major investors. FDI coming from other countries are not broken down by country and are assumed to be zero in the analysis.[36]

B Empirical Appendix

In this section, we provide additional empirical analyses to support the analyses in the main text.

B.1 Rotemberg Weights

Following Goldsmith-Pinkham et al. (2020), we compute Rotemberg weights to characterize which shares matter most for our estimates. These weights reveal which destination-specific shifts are driving our results and provide guidance on which shares should be the focus of balance tests (tests of pre-trends).

Appendix Table A3, Panel A displays summary information on the distribution of shares with positive and negative Rotemberg weights. The weights are

[35] Data are not released for province-year cells with fewer than three firms, for confidentiality reasons. We impute zeros for these province-year observations.

[36] The average share of yearly FDI not broken down by country is 6.9%.

predominantly positive. This suggests our estimates are a convex combination of destination-specific estimates. Panel B of Appendix Table A3 displays the top five destinations by Rotemberg weight, which correspond to the only destinations with shares larger than 5%. Saudi Arabia receives the highest weight (0.20), followed by Japan (0.19), the United States (0.18), Taiwan (0.10), and Hong Kong (0.08). These five destinations collectively account for 75% of the weights.

B.2 Diagnostics for Exogenous Shares Identification

B.2.1 Balance (Parallel Trend) Tests for Important Shares

To further validate our identification strategy, we conduct tests of parallel trends focusing on the exposure shares that carry the highest Rotemberg weights. We examine whether these influential shares exhibit pre-trends in our key outcomes prior to the 1997 Asian Financial Crisis. We test for parallel trends by regressing changes in outcomes between 1985-1994 on province-level exposure shares for high-Rotemberg-weight destinations (Saudi Arabia, Japan, the United States, Taiwan, and Hong Kong). The results – presented in Appendix Figure A2 – indicate no significant pre-trends across key outcomes across provinces with varying levels of exposure to the top Rotemberg-weight destinations. These tests provide further support for our parallel trends assumption.

B.2.2 Instrumenting for $Shiftshare_o$ with Top-Rotemberg-Weight Shares

As a diagnostic of our $Shiftshare_o$ measure, we follow Goldsmith-Pinkham et al. (2020) and present estimates using the high-Rotemberg-weight shares individually as instruments for $Shiftshare_o$ to assess the primary drivers of our identifying variation. The results are in Panel B of Appendix Table A3. For the four destinations with Rotemberg weights over 0.1, the coefficient estimates across our main outcome variables (global income, domestic income, migrant income, and consumption) demonstrate consistent patterns and are largely in line with our main results in Panel D of Table 1.[37]

B.2.3 Sensitivity to How Shares are Combined

To further assess the robustness of our shift-share estimates, we examine their sensitivity to alternative combinations of the exposure shares. We progressively restrict the set of shares used in constructing our shift-share instrument, limiting it to only the top 20, top 15, top 10, and top 5 destinations by Rotemberg weight.

The results of these sensitivity checks are reassuring. Our coefficient estimates for global income, domestic income, and migrant income remain stable across

[37] The exceptions are the results for Hong Kong, which has the smallest Rotemberg weight out of the top five and a first-stage F-statistic of near zero.

these alternative specifications. Results are presented in Appendix Figure A3. The magnitude and statistical significance of the estimates are robust to the subset of shares used to construct the shift-share instrument.[38] Robustness to different share combinations further strengthens the credibility of our research design.

B.3 Persistence of $Shiftshare_o$ Components

We provide here analyses showing the persistence of both components of the shift-share variable: the exchange rate shocks $\tilde{\Delta} R_d$ (the "shifts") and the exposure weights ω_{do0} (the "shares"). We examine persistence over two decades after the 1997 Crisis.

Figure 1a showed the persistence of exchange rate shocks for major destinations, and regression analyses confirm these patterns. We run regressions at the level of 104 destinations, where the dependent variables are the change in the exchange rate from pre-Crisis to a certain post-Crisis year, and the right-hand side variable is the short-run (1997-1998) shock, $\tilde{\Delta} R_d$.[39] We present coefficient estimates on $\tilde{\Delta} R_d$ from seven different regressions, for different post-shock time periods, in Appendix Figure A1a. Higher (more positive) coefficients indicate greater persistence, with a coefficient of 1 indicating complete persistence. Over nearly the entire study period, there is very strong persistence of the exchange rate shock. Point estimates are close to and statistically indistinguishable from 1 in nearly all post-shock periods. The only exceptions are 2009 and 2012, immediately following the 2007-2009 Great Recession, when the coefficients are closer to zero (very slightly negative in 2012), after which the coefficients rebound to levels near 1.[40]

Next, we analyze the persistence of the exposure weights ω_{dot}, migrant income per capita in destination-d/origin-o dyads. We create a dyad-level dataset with 7,696 observations (74 provinces times 104 destinations). For the post-shock periods for which we have migrant income data, we regress dyadic migrant income per capita in a post-shock year t (ω_{dot}) on dyadic migrant income per capita in 1995 (ω_{do0}), the pre-shock year in our shift-share variable. There is partial but substantial persistence over time in dyadic migrant income. Appendix Figure A1b presents coefficients on ω_{do0} in the three regressions (for 2009, 2012, and 2015). The coefficients range in magnitude from 0.4 to 0.6. Each is statistically significantly different from zero (and from 1, indicating partial persistence).

Overall, the components of the $Shiftshare_o$ variable – the exchange rate shocks and exposure shares – are highly persistent over two decades post-1997. The long-

[38] The coefficient estimates using just the "top 5" Rotemberg-weight destinations do tend to be somewhat larger in magnitude. However, they are also more imprecise as we likely discard useful variation, so we cannot reject equality with our main estimates.

[39] Observations are weighted by 1995 migrant income to that destination, following Borusyak et al. (2022) for any destination-level regressions.

[40] As complementary support for the persistence of exchange rate movements, a Harris and Tzavalis (1999) test for a unit root in the 1990-2017 exchange rate panel data fails to reject the null of non-stationarity.

run impacts that we document in the main results tables result from an exogenous shock to migrant income ($Shiftshare_o$) that itself exhibits substantial persistence over time.

C Model-Based Quantification: Full Elaboration of Model

We present a theoretical framework relating migrant exchange rate shocks to domestic and migrant income. We use this framework to derive our empirical specification and interpret our findings. We build on recent gravity models (Bryan and Morten, 2019; Tombe and Zhu, 2019) which adapt Eaton and Kortum (2002) to model migration. We endogenize skill investments, and allow for skill-dependent migration and income, to further deepen our understanding of mechanisms and magnitudes. Full derivations of the model equations are in Supplementary Appendix S of our NBER Working Paper, Khanna et al. (2022).

We start by introducing the migration decision, and how the migrant income shock helps us derive the empirical independent variable of interest: the shift-share we use for estimation. Then we study educational investments in the theoretical model, and we estimate our gravity equation to quantify the elasticity of migrant flows with respect to destination wages. With these estimates at hand, we evaluate the effects of the exchange rate shock on origin province migrant flows, migrant income, and domestic income in our model and quantify the importance of the education channel.

Our goal is to quantify the contribution of various channels. In doing so, we make a few assumptions. First, individuals have heterogeneous preferences on where to work (drawn from a Frechet distribution), and ability levels are allowed to vary at the origin-destination-time level. This flexibility allows, for instance, that people from a certain origin may be more productive at a certain destination, and this may change with time. Second, we assume a linear response of education changes to income shocks, but do not impose a specific mechanism behind the education responses (for instance, the alleviation of liquidity constraints.)

Our assumptions allow us to isolate the object of interest, by keeping everything else at the baseline level. For instance, when we identify the contribution of the education channel, we keep the returns to education (and destination wages) fixed at baseline, and the probability of migration to various destinations fixed. These assumptions allow us to isolate the role played by a particular object of interest. We also do not impose a reason why domestic income changes. These could be because of returns to investments, or consumption-driven multipliers.[41]

[41] While the Philippines is a large migrant source country, Filipinos are typically not a substantial fraction of the overall labor force in destinations, and so fluctuations in Filipino migration are unlikely to change destination wages, especially as migrant contracts are pre-determined for 2-3 years.

C.1 Migration Decisions

An individual i's earnings vary across origin province o, destination country d, skill level s, and time t. They depend on destination-specific wage profiles w_{dst} (wages in destination differing by skill) and exchange rates R_{dt}. Additionally, ϵ_{dot} is any unobservable factor that makes migrants from origin o more productive in destination d. Overseas wages w_{dst} and unobservable component ϵ_{dot} are in destination-d currency units. Exchange rates R_{dt} are in Philippine pesos (PhP) per destination-d currency unit. We denote $w_{dost} \equiv w_{dst}\epsilon_{dot}$ as the wage profiles of workers from o in destination d.

Individuals have destination-specific preference draws q_{id}. Workers lose a fraction of their earnings to migration cost $0 \leq \tau_{dot} \leq 1$. Indirect utility from destination choice is:

$$V_{idost} = w_{dst}\epsilon_{dot}R_{dt}(1-\tau_{dot})q_{id} \equiv w_{dost}R_{dt}(1-\tau_{dot})q_{id} \qquad \text{A6}$$

For all o, $\tau_{oo} = 0$ (migration cost is zero if remaining at origin) and $R_{ot} = 1$ (origin earnings are in origin currency). We assume preferences q_{id} are distributed multivariate Fréchet with shape parameter θ, as in Bryan and Morten (2019).[42] This parameter determines the dispersion of preferences across locations. Let π_{dost} be the fraction of people of skill s from origin o choosing to work in d. Through the properties of the Fréchet distribution, this share can be written as:[43]

$$\pi_{dost} = \frac{(w_{dst}R_{dt}(1-\tau_{dot})\epsilon_{dot})^{\theta}}{\sum_k (w_{kst}R_{kt}(1-\tau_{kot})\epsilon_{kot})^{\theta}} \qquad \text{A7}$$

Intuitively, the share of individuals of skill s migrating from origin o to destination d is increasing in the destination wages in Philippine pesos, $w_{dst}R_{dt}$.

C.2 Migrant Income Shock and the Shift-Share Variable

Our model derives the shift-share variable that is our primary independent variable, making our model entirely consistent with our empirical framework.

We assume there are two skill groups in the population: high-skilled h and unskilled u ($s = \{h, u\}$).[44] At baseline ($t = 0$), the share of high-skilled and unskilled workers in province o are denoted, respectively, ℓ_{oh0} and ℓ_{ou0}, with $\ell_{ou0} = 1 - \ell_{oh0}$. Province-level global income per capita Y_{ot} depends on the distribution of worker

[42] Here, θ is the elasticity of migration with respect to the destination wage. In the standard formulation: $F(q_1, ..., q_D) = exp\left\{-\left[\sum_{d=1}^{D} q_d^{-\theta}\right]\right\}$. The Fréchet assumption, while widely used in the migration literature (e.g., Bryan and Morten (2019); Tombe and Zhu (2019)) relies on an IIA assumption. An alternative would be to separate the decision to emigrate from the location choice. In our setting, where international migration is fairly common (7.5% of households had a migrant abroad), and recruitment agencies facilitate migration, we think the Fréchet assumption is a reasonable approximation.

[43] Full derivations are in the Supplementary Appendix of our NBER Working Paper, Khanna et al. (2022).

[44] We micro-found the education decisions in Supplementary Appendix S2 of Khanna et al. (2022).

locations and skill levels:

$$Y_{ot} = \sum_{s=h,u} \left[\ell_{ost} \sum_{d} \left(\pi_{dost} w_{dost} R_{dt} \right) \right] \tag{A8}$$

Our shift-share variable isolates exogenous variation in only the migrant income portion of Y_{ot}. $\tilde{\Delta} R_d$ is the short-run change in destination d exchange rate.[45]

The short-run migrant income change due to exchange rate shocks $\tilde{\Delta} R_d$ in province *o* depends on the share of workers in each destination for each skill level.[46]

$$\tilde{\Delta} Y_o = \sum_{s=h,u} \left[\ell_{os0} \sum_{d} \left(\pi_{dos0} w_{dos0} \tilde{\Delta} R_d \right) \right] \equiv Shiftshare_o \tag{A9}$$

In the pre-shock period ($t = 0$), let total population in an origin be Pop_{o0}, and the number of workers by skill be L_{os0}. Also, let the number of workers going from o to destination d be L_{dos0}, so that $\ell_{os0} \equiv \frac{L_{os0}}{Pop_{o0}}$, and $\pi_{dos0} \equiv \frac{L_{dos0}}{L_{os0}}$. Let w_{dos0} be average pre-shock income in destination d for workers of skill s from origin o.

The "exposure weight" ω_{do0}, serves as the "share" in the shift-share. As in the main paper, we define this as province *o*'s pre-shock aggregate migrant income from destination *d* (summed across skill groups), divided by province population to yield a *per capita* variable: $\omega_{do0} \equiv \frac{\sum_{s=h,u} L_{dos0} w_{dos0}}{Pop_{o0}}$. Now rewrite Equation A9:

$$Shiftshare_o = \sum_{s=h,u} \sum_{d} \frac{L_{os0}}{Pop_{o0}} \frac{L_{dos0}}{L_{os0}} w_{dos0} \tilde{\Delta} R_d = \sum_{d} \left(\omega_{do0} \tilde{\Delta} R_d \right) \tag{A10}$$

This is precisely the independent variable we use in our estimation.

C.3 Education Investments

Migrant income may drive educational investments at home, for instance, by easing liquidity constraints or changing the returns to schooling. In Supplementary Appendix S2 of Khanna et al. (2022), we micro-found changes to human capital under various scenarios, and derive how the change in the share of high-skilled

[45] Let $\tilde{\Delta}$ refer to a short-run change. In practice, we use the short-run 1997-1998 change following the July 1997 crisis to construct the shift-share variable. To signify this captures a short-run change, we include no subscript t in terms involving $\tilde{\Delta}$. Focusing on a shift-share variable capturing a short-run change is desirable because the immediate post-Crisis exchange rate changes are more plausibly exogenous than subsequent, longer-run exchange rate changes that may be endogenous to post-Crisis economic policies in destinations.

[46] The origin as a destination drops out as there are no exchange rate changes for the origin.

workers h in origin o is:

$$\Delta\ell_{oht} = \frac{1}{\Psi}\Delta Y_o = \frac{1}{\Psi}\sum_{s=h,u}\left[\ell_{os0}\sum_d\left(\pi_{dos0}w_{dos0}\tilde{\Delta}R_d\right)\right] = \frac{1}{\Psi}\underbrace{\sum_d \omega_{do0}}_{MigInc_{o0}} \times \underbrace{\frac{\sum_d \omega_{do0}\tilde{\Delta}R_d}{\sum_d \omega_{do0}}}_{Rshock_o}, \tag{A11}$$

where $\frac{1}{\Psi}$ captures the effect of the migrant income shock on skill share.[47] The regression result in column 3 of Table 2 is our quantitative estimate of this skill response. Below, we unpack the implications of these changing skill shares.

C.4 Gravity Estimation of Migration Flows

Accounting for the impact of migrant income shocks first requires an estimate of impacts on migration itself. In our gravity equation, the Frechet parameter θ pins down the elasticity of migrant flows (from o to d) with respect to destination d wages. This determines subsequent location choices and migrant income. Taking logs of the gravity equation A7 yields the estimating equation:

$$\log\ \pi_{dost} = \theta\log\ w_{dst} + \theta\log\ R_{dt} + \theta\log\ (1-\tau_{dot}) - \log\ \left[\sum_k (w_{kst}R_{kt}(1-\tau_{kot})\epsilon_{kot})^{\theta}\right] + \theta\epsilon_{dot} \tag{A12}$$

To estimate θ, we leverage the exogenous exchange rate shocks. The coefficient on $\log R_{dt}$ identifies θ. We implement this at the origin-destination-skill level using a differenced regression.[48]

$$\Delta log\ \pi_{dos} = \gamma_{os} + \theta\Delta log\ R_d + \tilde{\epsilon}_{dos}$$

Here, the Δs are the change between before and after the shock; and so this differenced regression is equivalent to including destination fixed effects. We further include the origin-by-skill fixed effects and cluster our standard errors at the destination level. The results are in Appendix Table A10. We estimate $\theta = 3.42$.

C.5 Change in Migrant Flows: Predictions and Decomposition

Migration flows from origin o to destination d depend on the probability of migrating by skill level, and share of workers who are of each skill level: $\pi_{doht}\ell_{oht} +$

[47] In Supplementary Appendix S2 of Khanna et al. (2022) we derive changes to human capital with liquidity constraints, with no liquidity constraints, or with no borrowing. For certain models, Ψ captures the cost of education. 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, and has little bearing on our quantification.

[48] As is common in such data, a large fraction of these units have no flows, and so we use a Poisson pseudo-maximum likelihood (PPML) estimator.

$\pi_{dout}\ell_{out}$. 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:[49]

$$\Delta\ Flows_{ot} = \underbrace{\Delta\ell_{oht}\sum_{d\neq o}(\pi_{doh0}-\pi_{dou0})}_{\text{Education channel in outflows}} + \underbrace{\theta\sum_{d\neq o}(\ell_{oh0}\pi_{doh0}+\ell_{ou0}\pi_{dou0})\frac{\Delta R_{dt}}{R_{d0}}}_{\text{Exchange rate channel in outflows}} \quad \text{A13}$$
$$-\underbrace{\theta\left(\ell_{oh0}\pi_{ooh0}\frac{\Delta w_{oht}}{w_{oh0}}+\ell_{ou0}\pi_{oou0}\frac{\Delta w_{out}}{w_{ou0}}\right)}_{\text{Domestic income stemming outflows}} - \underbrace{\chi_o}_{\text{Indirect re-sorting}}$$

First, the skilled and unskilled have different migration probabilities. If the skilled are more likely to migrate, then an increase in the fraction skilled will raise migration. If, alternatively, most jobs abroad are unskilled, then migration probabilities may fall. The effect of education on flows is captured by the first term, which is a product of two components: the education response $\Delta\ell_{oht}$, and skill-differential in migration probabilities $\pi_{doht}-\pi_{dout}$. Second, as exchange rates change favorably, there will be a migration response to higher compensation. This depends on θ (the elasticity of migration with respect to destination wages), the shock size ΔR_{dt}, and migration probabilities $\ell_{oht}\pi_{doht}+\ell_{out}\pi_{dout}$. This second term is the "Exchange rate channel in outflows." Finally, the shock can change local earning levels, affecting Δw_{ost}. For instance, earnings from abroad may fund investments in firms and household enterprises at origin locations. Increases in domestic income stem the outflow of migrants, as captured by this last channel, which again depends on the location elasticity with respect to wages θ. These components are each increasing functions of the exchange rate shocks, and suggest (as we test empirically) that the shock may change migrant flows. For instance, the first term ("Education channel in outflows") can be seen from

[49] The derivation is in Supplementary Appendix S4 of our NBER Working Paper, Khanna et al. (2022). The term $\chi_o \equiv \theta\sum_{s=h,u}\ell_{ost}\left[(1-\pi_{oost})\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)-\pi_{oost}\left(\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)\right]$ 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. Since both sets of exchange rates change simultaneously, a portion of the lower Malaysian emigration is redirected to the increase in US emigration. Equation A41 shows a version with these indirect effects.

Equations A11 and A13 to be:

$$\Delta\ell_{oht}\sum_{d\neq o}(\pi_{doh0}-\pi_{dou0})=\frac{1}{\Psi}\underbrace{\sum_{d\neq o}(\pi_{doh0}-\pi_{dou0})}_{\text{Skill bias in outmigration}}\left(\underbrace{\sum_{d}\omega_{do0}}_{MigInc_{o0}}\times\underbrace{\frac{\sum_d\omega_{do0}\tilde{\Delta}R_d}{\sum_d\omega_{do0}}}_{Rshock_o}\right) \tag{A14}$$

We use this framework to quantify the importance of the education and exchange rate channels. To quantify the education channel, we obtain (a) the education response to the income shock $\Delta\ell_{oht}$ from column 3 of Table 2, and obtain (b) the skill-differential in migration probabilities $\pi_{doh0}-\pi_{dou0}$ from the raw data. Figure A5a shows that for every province, the likelihood of 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 role played by the exchange rate and wage channels is jointly determined by simultaneous changes to exchange rates across potential migration destinations (ΔR_{dt}) and increases in domestic wages Δw_{ost}. We obtain the increases in domestic wages for different skill groups from columns 1 and 2 of Appendix Table A11. Migration responses to these, in turn, depend on the Frechet parameter θ, estimated in section C.4. We combine these estimates with measures of the shares of skilled and unskilled at each province, and propensity to migrate abroad by skill group at baseline to calculate the second and third terms in Equation A13.

Together, these channels predict outflows. We validate the structure of our model by comparing model-predicted flows to the OLS prediction from column 4 of Appendix Table A11 in Appendix Figure A6a. The strong upward sloping relationship 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. We calculate the share of the total regression-based predicted flows attributable to the education channel: $\frac{\Delta\ell_{oht}\sum_d(\pi_{doh0}-\pi_{dou0})}{\widehat{Flows}_{ot}^{OLS}}$. Appendix Figure A6b plots the distribution of the contribution of the education channel across provinces. On average about 17.2% of the increase in migrant flows is attributable to the increased education response (Table A12).[50] 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. At the same time, however, improvements in domestic income stem such outflows, canceling out a large component of the gains from migration. On net, changes in relative prices explain about

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

29.7% of the outflows. The remaining half is unexplained. We may not expect to explain the entire flows as we use baseline (1995) shares of migration flows.

C.6 Change in Migrant Income: Predictions and Decomposition

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.

$$\underbrace{\Delta\ell_{oht}\left(\sum_{d\neq o} w_{doh0}\pi_{doh0}R_{d0} - \sum_{d\neq o} w_{dou0}\pi_{dou0}R_{d0}\right)}_{\text{Education channel in migrant income}} + \theta \underbrace{\left(\sum_{s=h,u}\left[\ell_{os0}\sum_{d}\left(\pi_{dos0}w_{dos0}\Delta R_{dt}\right)\right]\right) - \tilde{\chi}_{o2}}_{\text{Exchange rate channel in migrant income}} \tag{A15}$$

Here, we know $\Delta\ell_{ost}$ is a function of the migrant income shock from Equation A11. $\beta^{mig} = \left(\sum_{d\neq o} w_{doh0}\pi_{doh0}R_{d0} - \sum_{d\neq o} w_{dou0}\pi_{dou0}R_{d0}\right)$ is the migrant skill premium. The education channel contribution to the change in income is $\frac{\beta^{mig}}{\Psi}\tilde{\Delta}Y_o$. Similarly, the exchange rate channel is $\theta\tilde{\Delta}Y_o - \tilde{\chi}_{o2}$, and 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 higher flows of migrants (both skilled and unskilled) to places with more positive exchange rate movements.[51] 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. The total change in migrant income per capita $\left(\frac{\beta^{mig}}{\Psi} + \theta\right)\tilde{\Delta}Y_o - \tilde{\chi}_{o2}$ is empirically shown in Table 1 col 5.

To quantify the importance of each component, we decompose the contributions of each channel. For the education channel, we first obtain $\Delta\ell_{ost}$ with the help of linear fit of the regression in column 3 of Table 2. The second component is the probability-weighted skill-premium abroad β^{mig}. We plot the skill premium $(w_{doh0} - w_{dou0})$ at the origin-destination pair in Figure A5b.[52]

For the exchange rate channel, we use our estimate of θ. 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_{os0} and π_{dos0}, and wages w_{dos0} at baseline (1995), and use them as weights for exchange rate changes ΔR_{dt} as in the second term of Equation A15.

Together, the predicted migrant income estimate due to the education channel and the exchange rate channel can be compared to the simple OLS prediction based on the regression from column 5 of Table 1. We plot the relationship be-

[51] As before, the second-order indirect effects of changes in location choice are captured by $\tilde{\chi}_{o2} \equiv \theta\sum_{s=h,u}\sum_{d}\left[\ell_{ost}w_{dst}\pi_{dost}\left(\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right) + \pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)\right]$.

[52] 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.

tween these predicted flows in Figure A7a. As before, we see a strong upward sloping relationship in Figure A7a, 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.

To quantify the role played by each channel, we measure the predicted education channel as a ratio of the predicted increase in migrant incomes (Appendix Figure A7b). We do a similar exercise for the exchange rate channel in migrant income. On average, the education channel explains 17.8% of the increase in migrant income, and the exchange rate channel explains 64.6% (Table A12).

C.7 Change in Domestic Income: Prediction and Decomposition

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, earnings from domestic work (conditional on skill) may also increase as a result of more local investment in enterprises and an increase in aggregate demand (the "Direct wage channel"). While simple to introduce, we do not explicitly model firm production to keep our framework tractable. While the underlying mechanisms are not modeled, our framework captures the ultimate effect of the shock on domestic earnings. Specifically, investments in entrepreneurial capital and aggregate demand will raise domestic income for each skill group Δw_{ost}, and investments in human capital will raise the share high-skilled $\Delta \ell_{oht}$. Together, these increase domestic income per capita:

$$\Delta W_{ot} = \underbrace{\Delta \ell_{oht} \left(\underbrace{w_{oh0}\pi_{ooh0}}_{\text{skilled wage at home}} - \underbrace{w_{ou0}\pi_{oou0}}_{\text{unskilled wage at home}} \right)}_{\text{Education channel in domestic income}} + \underbrace{\sum_{s=h,u} \ell_{os0}\pi_{oos0} \left(\Delta w_{ost} \right) - \tilde{\chi}_{o1}}_{\text{Direct wage (and resorting) channel}} \tag{A16}$$

Here, the domestic "direct wage channel" captures the direct effect of changes in local wages due to, say, expansion of household entrepreneurship (and the indirect effects of staying back/or emigrating given the relative changes in wages at home and abroad).[53] As we do not take a stance on the mechanisms underlying enterprises decisions, we allow Δw_{ost} to be a function of migrant income per capita. As we show in Section C.6, migrant income per capita is a function of the exchange rate shock: $\left(\frac{\beta^{mig}}{\Psi} + \theta \right) \tilde{\Delta} Y_o$. Let ζ be a local multiplier driven by changes to aggregate demand and entrepreneurial investments. In that case, $\Delta w_{ost} \equiv$

[53]The indirect resorting is $\tilde{\chi}_{o1} \equiv \sum_{s=h,u} \ell_{ost}\theta\pi_{oost}w_{ost} \left(\sum_{d\neq o} \left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}} \right) + \pi_{oost}\frac{\Delta w_{ost}}{w_{ost}} \right) - \sum_{s=h,u} \ell_{ost}\pi_{oost}\theta\Delta w_{ost}$

$\zeta\left(\frac{\beta^{mig}}{\Psi}+\theta\right)\tilde{\Delta}Y_o$. We empirically estimate the associated regression:

$$\Delta W_{ot} = \underbrace{\sum_{s=h,u} \ell_{os0}\pi_{oos0}\left(\zeta\left(\frac{\beta^{mig}}{\Psi}+\theta\right)\tilde{\Delta}Y_o\right)}_{\text{Direct wage channel}} + \underbrace{\frac{1}{\Psi}\tilde{\Delta}Y_o\left(w_{oh0}\pi_{ooh0} - w_{ou0}\pi_{oou0}\right)}_{\text{Education channel in domestic income}}$$
$$= \left(\zeta\left(\frac{\beta^{mig}}{\Psi}+\theta\right)+\frac{\beta^{dom}}{\Psi}\right)\underbrace{\sum_d \omega_{do0}}_{MigInc_{o0}} \times \underbrace{\frac{\sum_d \omega_{do0}\tilde{\Delta}R_d}{\sum_d \omega_{do0}}}_{Rshock_o}, \quad \text{A17}$$

where $\beta^{dom} \equiv (w_{oh0}\pi_{ooh0} - w_{ou0}\pi_{oou0})$ are the domestic returns to education. We test for the change in domestic income per capita in Table 1 above.

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 quantifying the education channel. Again, we aggregate predicted domestic income due to the education channel and the direct wage 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 column 4 of Table 1. We plot the relationship between these predicted flows in Appendix Figure A8a. As before, we see a strong upward sloping relationship. The model slightly under-predicts domestic income per capita. Predicted values are distributed around the 45° line.

To quantify the role played by the direct wage channel, we estimate the impact of the migrant income shock on domestic income per worker by skill level in columns 1-2 of Table A11. 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 A16.

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 A8b. We do a similar exercise for the direct wage channel. On average, the education channel explains 20.2% of the increase in domestic income, whereas the direct wage channel explains 69.08% (Table A12). The remaining component is likely driven by other aggregate changes to the income distribution.

C.7.1 Explaining Impacts on Direct Domestic Income

In this section, we investigate the assumptions needed to explain the magnitude of the impact on domestic income per capita. As discussed in Subsection 6.3 of the main text, we need to explain how a 1 PhP migrant income shock leads to a 18.81 PhP increase in long-run domestic income, which is the coefficient estimate on the shift-share variable in the domestic income per capita regression of Table 1, Panel D column 4. 20.2% of the increase in domestic income can be attributed to the increase in education induced by the shock (as discussed in Section 6.1). This leaves the remaining 14.4 PhP increase to be explained. Here, we describe the framework in which we assess whether an effect of this size is reasonable.

We examine whether this remaining 14.4 PhP increase in domestic income per capita can be generated in a stylized framework in which a portion of the exogenous increase in migrant income is devoted to capital accumulation in productive enterprises, and in which a demand multiplier also operates. In every post-shock period t, an origin area enjoys the following increment to income per capita (we suppress origin o subscripts for simplicity):

$y_t = \alpha m_t + r_t S_{t-1}$, where m_t is exogenous migrant income per capita, α is the share of migrant income that is spent in the origin economy, S_t is the induced savings in the economy due to the shock, and r_t is the return to capital.

An exogenous portion s of the additional income is saved (and invested) each period, with shock-induced savings accumulating as: $S_t = S_{t-1} + sy_t$.

The shock-induced increase in domestic income per capita is then simply the shock-induced incremental per period income (y_t) multiplied by the Keynesian multiplier ($\frac{1}{s}$). We set the savings rate to 0.35, which implies a Keynesian multiplier of 2.86 (comparable to the 2.9 estimate in Breza and Kinnan (2021)). For migrant income m_t, given we are interested in the result of a 1 PhP shock, we set the initial shock $m_1 = 1$ and let the shock to evolve according to a function that asymptotically reaches our migrant income coefficient for 2015 ($m_\infty = 7.4$), and passes through our migrant income coefficient for 2009 ($m_{12} = 5.9$) from the event study (Figure 2).

We set the rate of return to initial rate $r_1 = 0.45$; this is high, but not as high as the estimate of de Mel et al. (2008). We then let r_t decline over time, according to a function that asymptotically reaches 0.05. This decline captures that the initial rate of return to capital may be quite high when liquidity constraints on investment are first loosened, but r_t declines over time as the most profitable investment opportunities are taken.[54]

Figures A10a and A10b trace out the shock-induced domestic income generated under these assumptions. The remaining 14.4 PhP increase in migrant income per capita is fully explainable, and is well within plausible assumptions.[55]

Estimating Remittance Share α = 0.64. To the best of our knowledge, there is no comprehensive data on the share of migrant income returned to the Philippines. We estimate this as follows:

[54] The functional forms for the path of migrant income and rate of returns on savings are as follows: $m_t = \frac{7.39t^2 - 1.23t - 2.39}{t^2 + 2.77t}$ and $r_t = \frac{0.05t^2 + 0.85t}{t^2 + t}$. Time t is relative to 1997, where $t = 1$ is for 1998, and so on.

[55] If we were to ignore the investment channel, our estimates would suggest a multiplier of about 14.4/(0.64×6.463) = 3.4, which is also within the range of multipliers found in the literature.

1. We use the 2015 and 2016 KNOMAD/ILO Migrant Cost Survey data, which asks 849 Filipino labor migrants in Qatar and UAE across a variety of occupations about their earnings and remittances. The average migrant reports remitting 67% of their income.

2. We use the Survey on Overseas Filipinos (SOF) data, which reports the destination and amount remitted for overseas individuals. However, earnings abroad are not reported, so we cannot calculate what share of overseas income is remitted. We use this data to estimate how much migrants in different destinations remit back home relative to migrants in UAE and Qatar. For example, the average overseas Filipino in Japan remits about twice as much as the average Filipino in the UAE and Qatar, according to the SOF.

3. We use the contract data to estimate the relative salaries in different destinations compared to UAE and Qatar. For example, the average salaries for Filipino workers in Japan are 2.5 times as much as the salaries in UAE and Qatar.

4. We use all of this information to calculate the remittance rate of migrant workers in different destinations. For example, given migrant workers in UAE and Qatar remit 67% of their earnings, and given that migrant workers in Japan remit twice as much while earning 1.5 times more, implies that the remittance rate for migrant workers in Japan is about 53%. We note that the granularity of our destination geography is limited by the geographical granularity of the SOF data. For example, SOF data does not specify whether a migrant is in Germany or Italy, but instead reports they are in "Europe". However, for top migrant destinations, countries are specified.

5. After calculating the destination-specific remittance rates, we take a weighted average across destinations where the weights are determined by the share of total new contract salaries coming from the destination (calculated from the contract data). This leaves us with an estimate of 64%.

C.8 Change in Global Income: Predictions and Decomposition

Together, the longer-term change in the global income of individuals is:[56]

$$\left(\frac{\beta^{mig}+\beta^{dom}}{\Psi}+\theta+\zeta\left(\frac{\beta^{mig}}{\Psi}+\theta\right)\right)\tilde{\Delta}Y_o-\tilde{\chi}_o \qquad \text{A18}$$

There is intuition behind this relationship.[57] First, higher skill-premia (the β terms) imply that as individuals acquire schooling, incomes (both domestic and

[56] The derivation for global income is in Supplementary Appendix S5 of our NBER Working Paper, Khanna et al. (2022).

[57] The total indirect effect on global income due to location resorting is $\tilde{\chi}_o \equiv \theta\sum_{s=h,u}\sum_d\left[\ell_{ost}w_{dst}\pi_{dost}\left(\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)+\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)\right]-\theta\sum_{s=h,u}\left[\ell_{ost}\pi_{oost}\Delta w_{ost}\right]$

international) rise. Second, a higher migration elasticity θ means that migration flows, and thereby migrant incomes, are more responsive to favorable exchange rates. Finally, if incomes rise locally, then that would have a direct impact on income as well. Local incomes may rise through increases in aggregate demand or entrepreneurial investment, for instance.

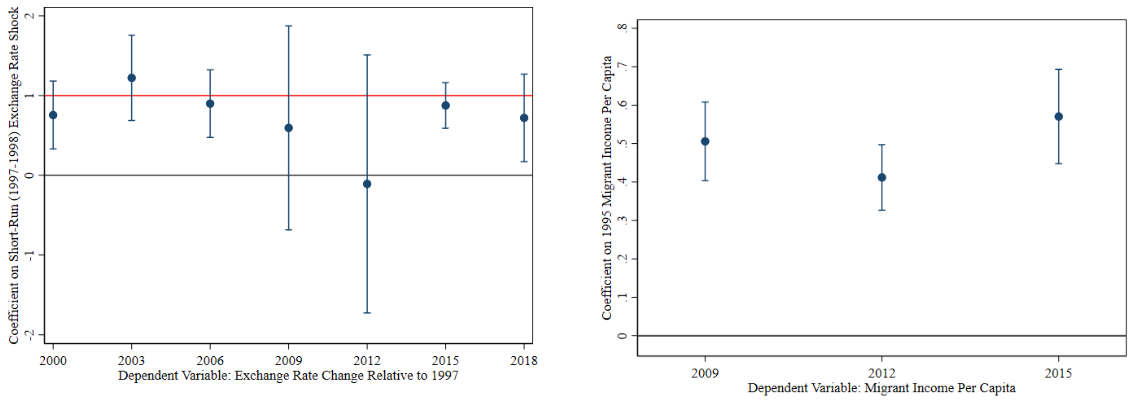
In the long run, global income and household expenditure increase substantially, as we show in column 3 of Table 1. Overall changes in expenditure (column 2 of the same table) reflect changes in welfare. As we show, our theoretical predictions are consistent with our empirical predictions. This allows us to interpret our reduced form estimates, rationalize the magnitudes, and quantify the contribution of each channel discussed.[58]

Together, the changes in migrant income and domestic income allow us to decompose the changes in global income per capita. To test the validity of the model, we again predict the change the global income per capita using the regression estimated in column 3 of Table 1 for global income. Appendix Figure A9a 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 A9b plots the distribution of this contribution across provinces. Table A12 shows that the education channel explains 19.55% of the overall increase in global income, while the changes in earnings potential (both at home and abroad) explain 67.48% of the overall increase in global income. Overall, the model explains 87.8% of the increase in global income.

D Additional Tables and Figures

[58] A short note on the model 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).

Figure A1: Persistence of Exchange Rate Shock and Province-Destination Migrant Income

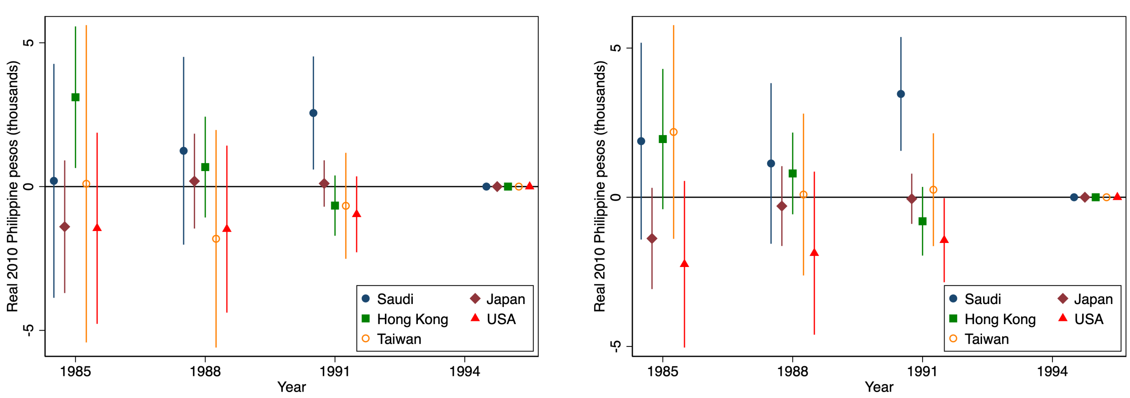


(a) $\tilde{\Delta}R_d$ and Future Exchange Rate Changes

(b) Province-Destination Migrant Income

Notes: (a) Coefficient estimates from regressing destination exchange rate changes relative to 1997 for 2000-2018 triennially on $\tilde{\Delta}R_d$, weighted by 1995 migrant income shares (N = 104). (b) Figure examines persistence from before to after the 1997 Asian Financial Crisis of ω_{dot} (migrant income per capita of province o from destination d). Figure displays coefficient estimates from regressing ω_{dot} for 2009, 2012, and 2015 (respectively) on ω_{do0} (1995 migrant income per capita, or the "exposure weight" used in the shift-share variable.) N = 74 $\times$ 104 = 7696, SEs clustered at province level.

Figure A2: Relationship Between Top Rotemberg Weight Destination Migrant Income Shares and Outcome Trends

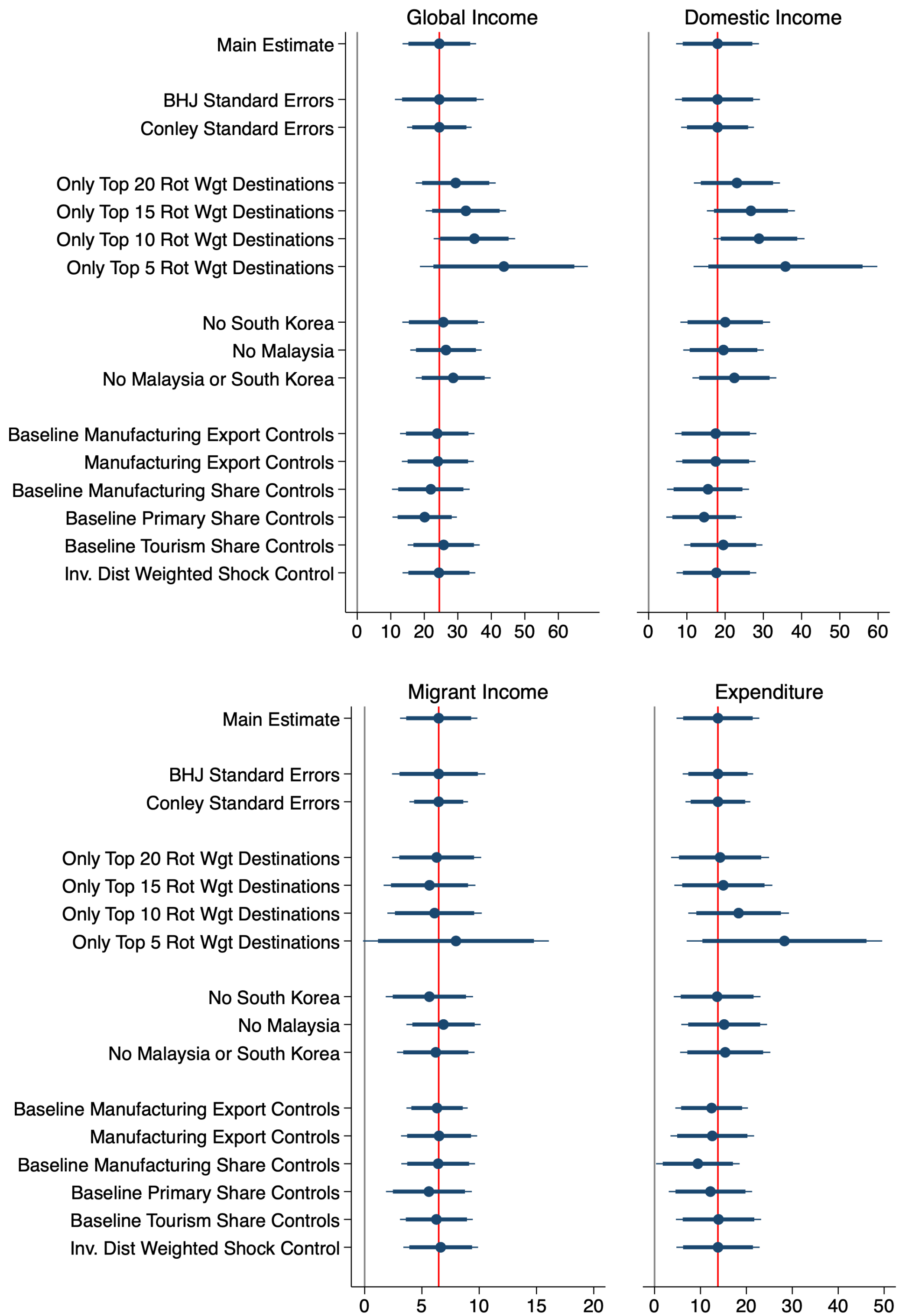


(a) Domestic Income

(b) Consumption

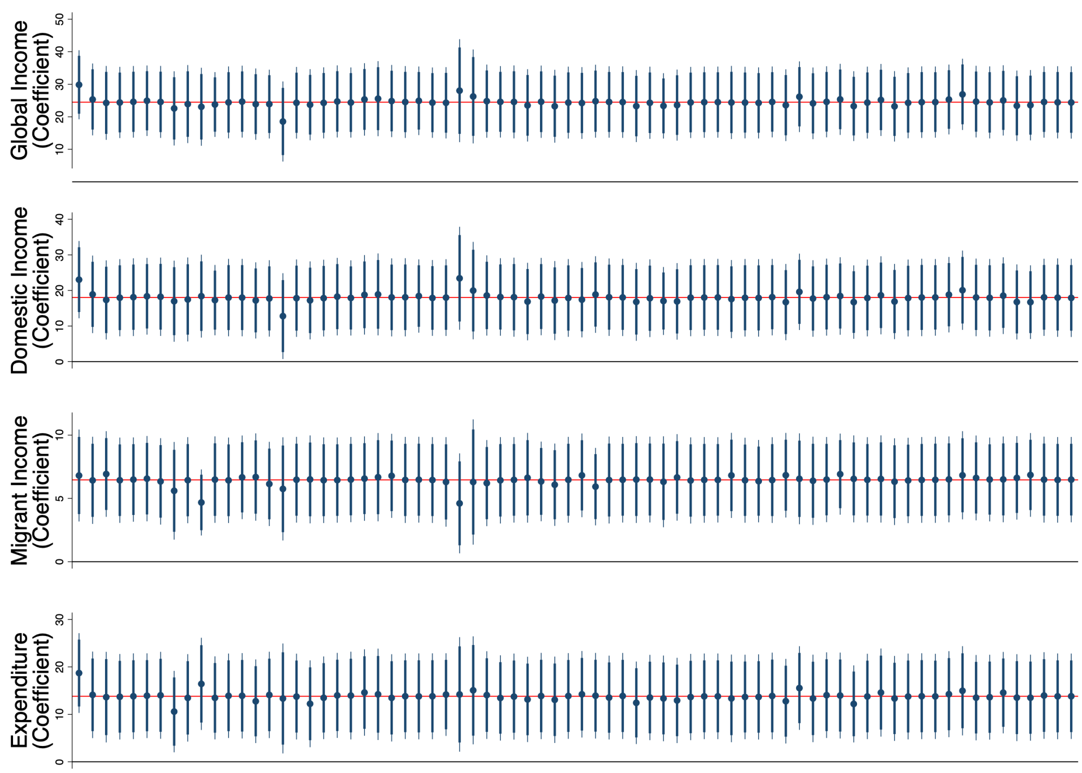
Notes: For each country, the coefficients are from a regression that interacts the migrant income "share" ω_{do0} of the country with indicator variables for each pre-shock year. Five individual regression are run (one for each country) per outcome. All regressions include province fixed effects, year fixed effects, and $MigInc_{o0}$ and $Rshock_o$ interacted with year fixed effects. Outcomes are in real 2010 PhP (PhP17.8/US\$ PPP). Observations are at the province-yrar level. 95% confidence intervals shown. Standard errors are clustered at the province level.

Figure A3: Additional Robustness Results



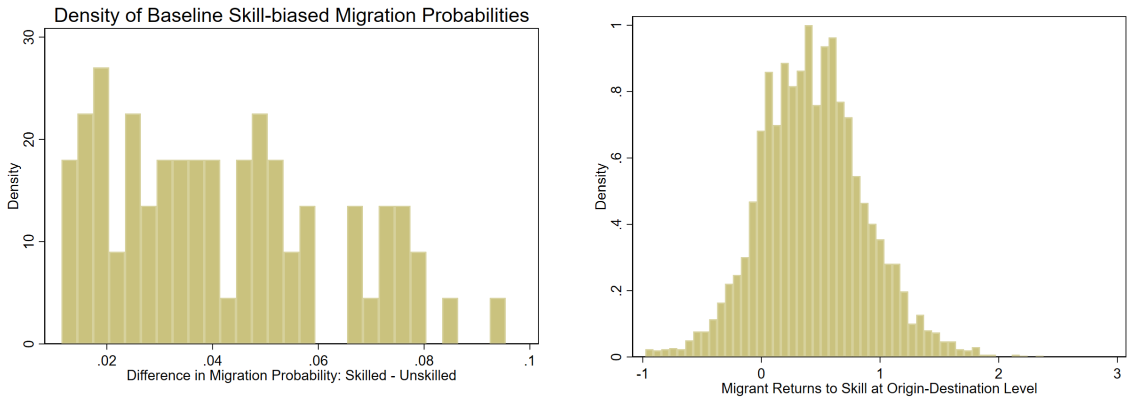
Notes: The figure presents the coefficients of interest on $Shiftshare_o$ from estimating equation (4) for our main income and expenditure results. All regressions include the full set of controls, corresponding to Columns 3-6 Panel D in Table 1. The vertical red lines denotes the coefficient estimates from Table 1. Thick blue lines correspond to 90% confidence interval, thin blue lines correspond to 95% confidence interval. The modifications for each estimate are described in Section 5.5.

Figure A4: Robustness To Dropping Provinces One-By-One



Notes: We present the coefficients of interest on $Shiftshare_o$ from estimating equation (4) for our main income and expenditure results. Each dot corresponds to estimates with one province dropped. All regressions include the full set of controls, corresponding to Columns 3-6 Panel D in Table 1. The red lines denotes the coefficient estimates from Table 1. Thick blue lines correspond to 90% confidence interval, thin blue lines correspond to 95% confidence interval.

Figure A5: Skill Level, Migration Probabilities, and Migrant Wages



(a) Skilled-Unskilled Migration Probabilities

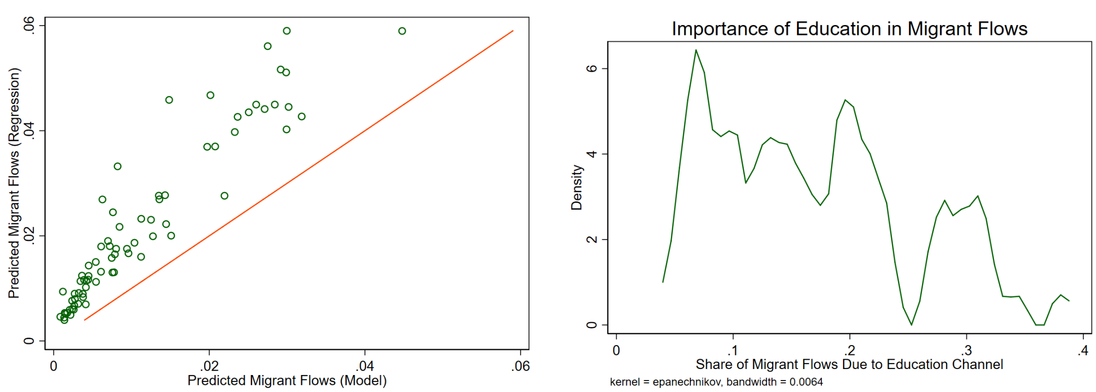
(b) Wage skill-premium among migrants

Notes: (a) 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 $\sum_k (\pi_{kos} - \pi_{kou})$. (b) Figure plots the distribution of $w_{dost} - w_{dout}$ at the origin-destination pair level.

Figure A6: Model Validation & Contribution of Education Channel in Migrant Flows

(a) Validation: Migrant flows

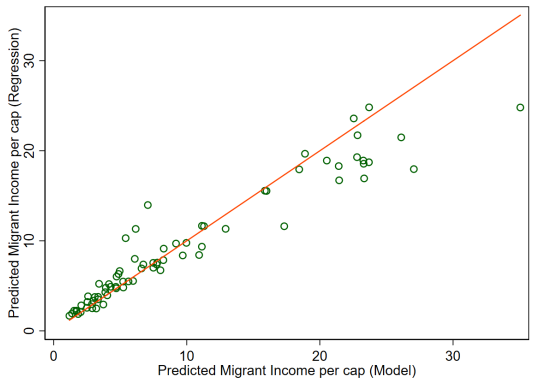
(b) Contribution of Education Channel



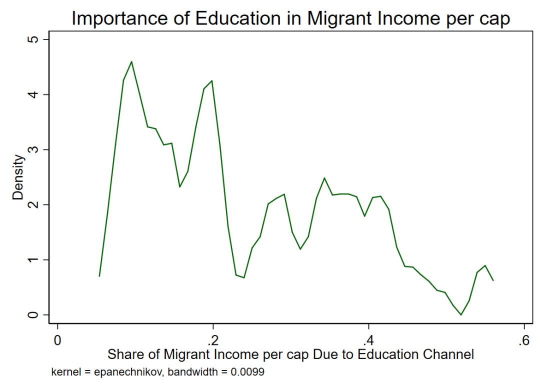
Notes: Figure A6a plots the predicted flows of migrants vs the predicted flows as determined by the components of Equation A13. The red line has an angle of 45 degrees. Each point represents a province. Figure A6b plots the province-level distribution of the contribution of the education channel in predicting migrant flows: $\frac{\Delta \ell_{ost} \sum_k (\pi_{kos0} - \pi_{kou0})}{\widehat{Flows}_{ot}^{OLS}}$

Figure A7: Model Validation & Contribution of Education in Migrant Income

(a) Validation: Migrant Income per capita



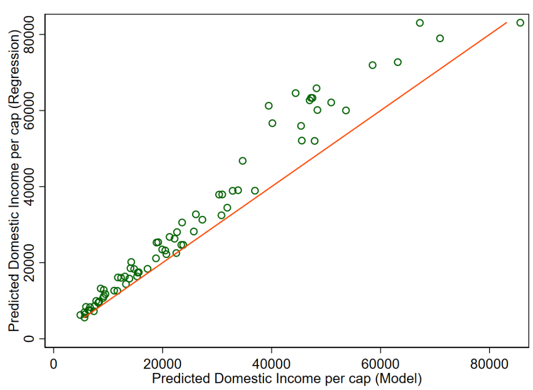
(b) Contribution of Education Channel



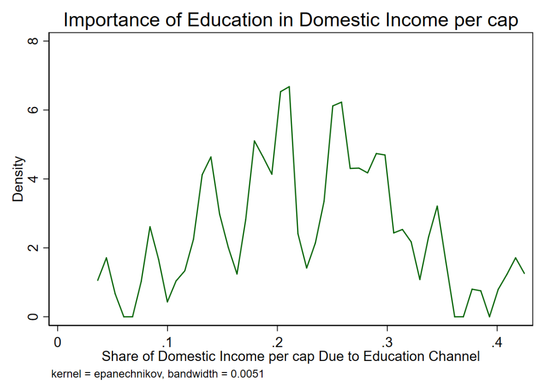
Notes: Figure A7a plots the predicted migrant income per capita from the regressions (vertical axis) vs the predicted migrant income as determined by the education and exchange rate components. The red line has an angle of 45 degrees. Each point represents a province. Figure A7b plots the province-level distribution of the contribution of the education channel in predicting migrant income per capita.

Figure A8: Model Validation & Contribution of Education in Domestic Income

(a) Validation: Domestic Income per capita



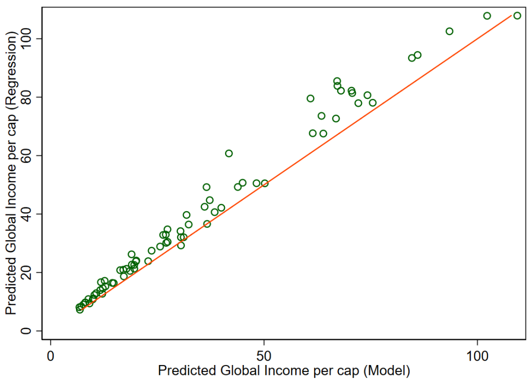
(b) Contribution of Education Channel



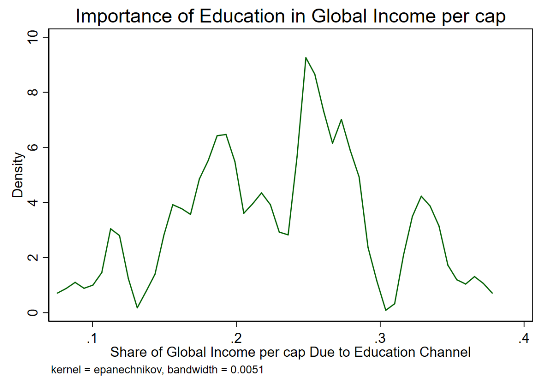
Notes: Figure A8a plots the predicted domestic income per capita from the regressions vs the predicted domestic income per capita as determined by the education and exchange rate components. The red line has an angle of 45 degrees. Each point represents a province. Figure A8b plots the province-level distribution of the contribution of the education channel in predicting domestic income per capita.

Figure A9: Model Validation & Contribution of Education to Global Income

(a) Validation: Global Income per capita

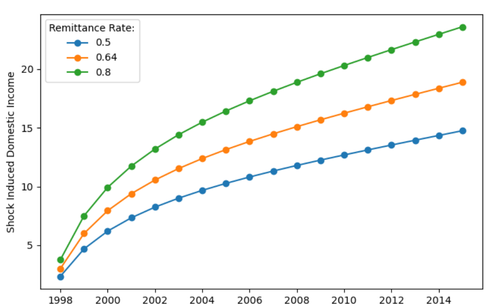


(b) Contribution of Education Channel

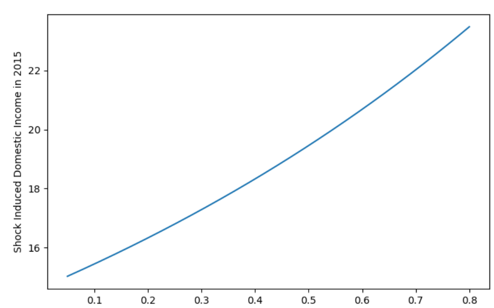


Notes: Figure A9a plots the predicted global income per capita (domestic plus migrant income) from the regressions vs the predicted global income per capita as determined by the education and exchange rate components. The red line has an angle of 45 degrees. Each point represents a province. Figure A9b plots the province-level distribution of the contribution of the education channel in predicting global income per capita.

Figure A10: Explaining Effect on Domestic Income: Sensitivity to Key Assumptions

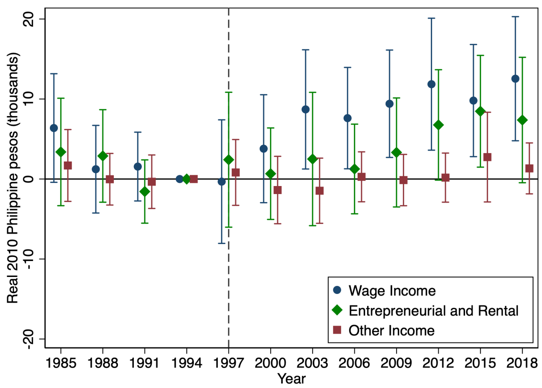


(a) Domestic Income Effects by Share of Migrant Income Spent at Origin (α)

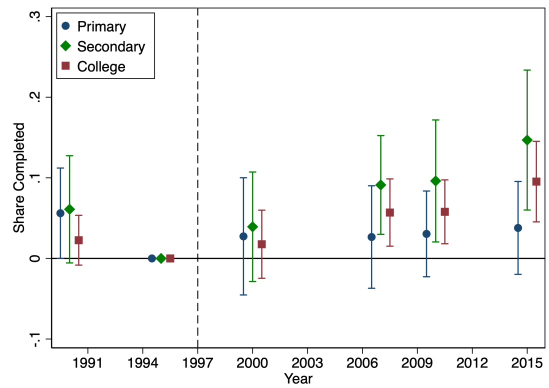


(b) Impact on Domestic Income by 2015, by Initial Rate of Return to Capital

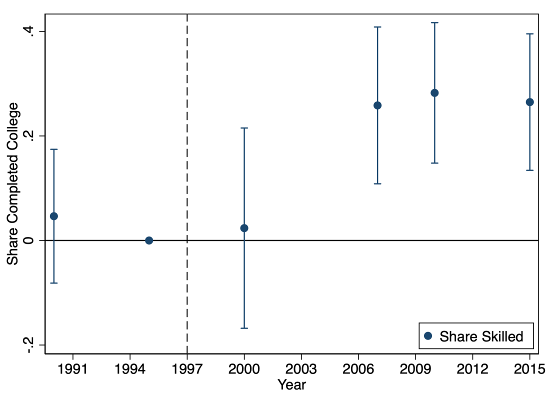
Figure A11: Event Studies for Other Outcomes



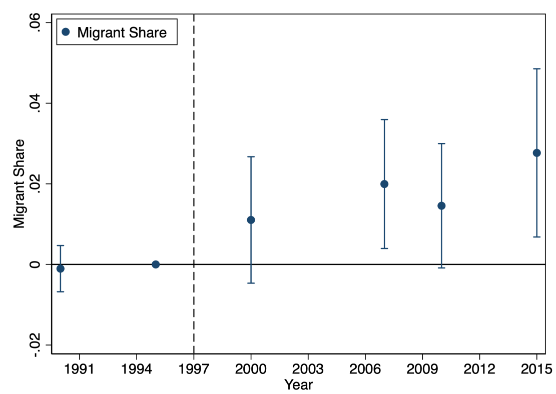
(a) Domestic Income Subcomponents



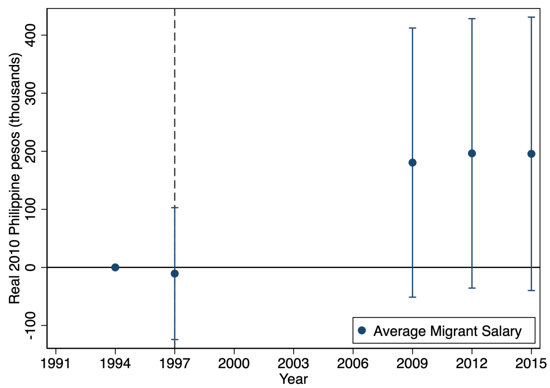
(b) Educational Attainment



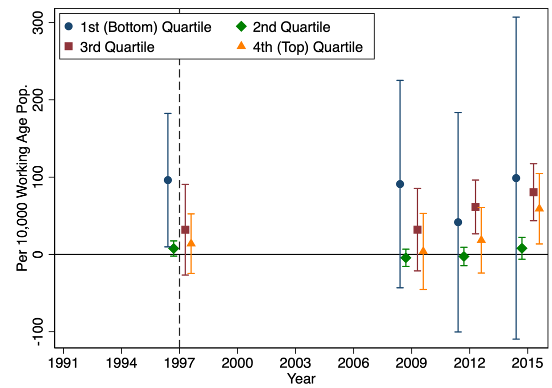
(c) Share of Migrant Workers Skilled



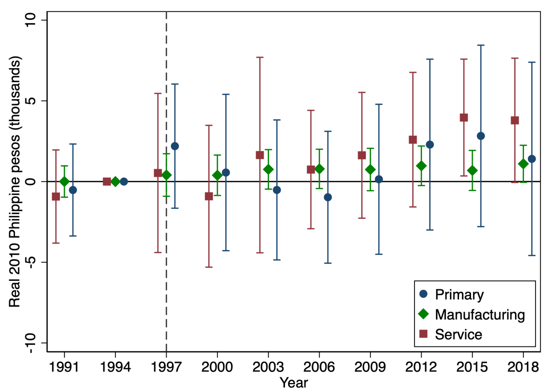
(d) Migrant Share



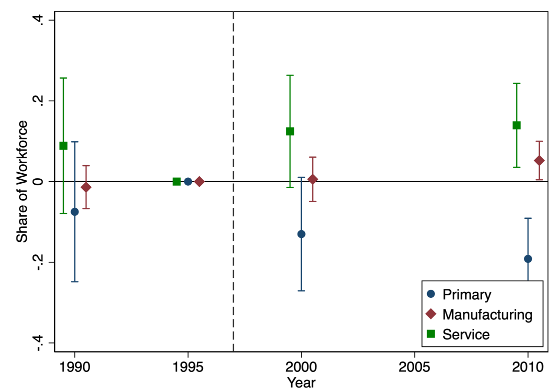
(e) Average Migrant Salary



(f) Migrant Occupations by Education Qtile



(g) Entrepreneurial Income Sector



(h) Share of Labor Force

Note: Regressions modify Equation (4) to include interactions between $Shiftshare_o$ and indicator variables for each pre- and post-shock year. Panel (a) corresponds to outcomes in Table 4, panel (b) corresponds to outcomes in Table 2, panels (c) - (f) corresponds to outcomes in Table 3, and panels (e) and (f) corresponds to outcomes in Table 5. The 1994 or 1995 interaction term, for contract/FIES or census outcomes respectively, is omitted as the reference point. Monetary outcomes are in real 2010 PhP (PhP17.8/US$ PPP). Observations are at the province-period level. We include the partially-treated year 1997 in event study samples. 95% confidence intervals shown. Standard errors are clustered at the province level.

Table A1: Exposure Weights and Exchange Rate Shocks in Top 20 Destinations of Filipino Migrants

Destination	Mean Exposure Weight	Std. Dev. of Exposure Weight	10th Percentile Exposure Weight	90th Percentile Exposure Weight	Exchange Rate Shock (1997-1998, $\tilde{\Delta}R_d$)	Exchange Rate Change, 1994 - 1996 (pre-shock)
Japan	792.10	1130.49	81.69	2326.40	0.32	−0.07
Taiwan	709.79	804.84	63.41	1872.03	0.26	−0.04
Saudi Arabia	670.42	583.41	196.61	1635.78	0.52	−0.01
Hong Kong	576.08	787.50	37.90	1640.57	0.52	−0.01
United States	452.86	509.16	48.32	1045.28	0.52	−0.01
United Arab Emirates	126.23	132.14	21.35	236.41	0.52	−0.01
Malaysia	74.56	85.63	5.30	172.55	−0.01	0.04
Kuwait	72.27	218.87	0.00	77.34	0.50	−0.02
Qatar	66.98	91.55	0.74	142.48	0.52	−0.01
South Korea	54.51	108.20	0.00	103.49	−0.04	−0.01
Brunei Darussalam	50.87	43.54	8.47	108.42	0.30	0.08
Oman	47.40	319.45	0.00	21.25	0.52	−0.01
Libya	40.85	38.73	2.64	83.48	0.57	−0.21
Guam	38.10	90.22	0.00	89.82	0.52	−0.01
Italy	30.43	55.54	0.00	100.28	0.38	0.04
Canada	29.91	44.13	0.00	84.75	0.42	−0.01
Northern Mariana Islands	28.17	40.10	0.00	73.16	0.52	−0.01
Bahrain	25.67	43.89	0.00	49.30	0.52	−0.01
Singapore	25.18	24.68	0.00	72.84	0.29	0.08
Israel	17.12	94.28	0.00	16.59	0.38	−0.06

Notes: Table displays 20 destinations d with the highest mean exposure weight (across provinces o). Columns 1-4 present summary statistics for exposure weights ω_{do0}, across 74 Philippine provinces o ("shares" of the shift-share variable). See Subsection C.2 and Section 4 for details on exposure weight definition. Columns 5 and 6 present exchange rate changes. Column 5 displays exchange rate shock $\tilde{\Delta}R_d$ ("shift" of the shift-share variable). Exchange rate shock is change in Philippine pesos (PhP) per foreign currency unit. Exchange Rate Shock (1997-1998, $\tilde{\Delta}R_d$) is fractional change between July 1996-June 1997 and October 1997- September 1998 (e.g., 10% appreciation of the foreign currency against the Philippine peso is 0.1). Column 6 (Exchange rate change 1994-1996) is corresponding fractional change in exchange rate between 1996 and 1994, before July 1997 Asian Financial Crisis. 84 additional destinations not shown.

Table A2: Summary Statistics

	Mean	SD	10th P.	25th P.	Median	75th P.	90th P.	Obs.
Shock Variables								
Residualized $Shiftshare_o$	0.000	0.093	-0.105	-0.040	0.002	0.031	0.084	74
$MigInc_{o0}$	4.044	2.984	0.967	1.684	3.072	5.974	8.616	74
$Rshock_o$	0.415	0.040	0.371	0.389	0.412	0.436	0.454	74
Import Shock	10.673	9.180	2.766	4.148	7.661	12.864	24.678	74
Export Shock	10.432	10.057	2.786	4.626	6.801	12.739	21.966	74
Expenditure and Income								
Expenditure per Capita	29.074	10.525	18.220	22.041	26.939	33.557	42.329	887
Global Income per Capita	35.305	12.468	22.427	26.652	32.484	41.215	52.412	296
Domestic Income per Capita	30.699	10.618	20.007	23.453	28.570	35.151	44.949	296
Migrant Income per Capita	4.606	2.924	1.537	2.310	3.746	6.608	8.812	296
Average Migrant Salary	319.519	104.876	232.558	253.662	293.700	345.532	433.095	296
Education and Migration								
Share Primary School	0.789	0.114	0.638	0.719	0.799	0.880	0.927	444
Share Secondary School	0.486	0.146	0.291	0.374	0.490	0.580	0.689	444
Share College	0.133	0.046	0.082	0.098	0.126	0.158	0.191	444
Share College: Migrants	0.338	0.135	0.174	0.236	0.336	0.433	0.530	444
Migrant Share	0.013	0.009	0.003	0.006	0.011	0.018	0.025	444
Sectoral Share of Workforce								
Share in Primary Sector	0.530	0.185	0.232	0.435	0.563	0.667	0.733	296
Share in Manufacturing	0.063	0.056	0.016	0.025	0.043	0.074	0.139	296
Share in Service Sector	0.407	0.147	0.243	0.301	0.377	0.499	0.627	296
Migrant Contracts								
(per 10,000 working age people)								
1st Quartile Education Occupations	94.191	71.725	22.301	44.736	82.824	120.183	178.979	296
2nd Quartile Education Occupations	8.694	6.616	1.730	3.760	6.886	12.455	16.924	296
3rd Quartile Education Occupations	24.690	19.297	5.942	12.679	19.967	34.584	47.180	296
4th Quartile Education Occupations	43.096	32.762	7.236	17.110	35.481	62.302	87.562	296
Baseline Province Controls								
Baseline Share Rural	0.643	0.193	0.337	0.564	0.696	0.761	0.819	74
Baseline Asset Index	-0.636	1.023	-1.576	-1.321	-0.966	-0.169	1.069	74
Baseline Total Income per Capita	29.914	10.333	20.504	23.191	27.803	32.582	46.112	74
Baseline Expenditure per Capita	24.368	7.891	16.416	19.454	22.683	26.817	35.265	74
Share of Workforce in Primary Sector	0.567	0.175	0.282	0.491	0.596	0.692	0.760	74
Share of Workforce in Industry	0.121	0.082	0.042	0.066	0.095	0.150	0.256	74
Share of Workforce in Service Sector	0.299	0.095	0.194	0.234	0.287	0.348	0.421	74
Share of Workforce in Financial Services	0.013	0.013	0.004	0.006	0.009	0.015	0.026	74
Baseline Destination Controls								
Share of Migrant Workers in MENA	0.442	0.204	0.234	0.317	0.413	0.509	0.720	74
Share of Migrant Workers in OECD	0.057	0.051	0.011	0.024	0.044	0.070	0.106	74
Share of Migrant Workers in East Asia	0.459	0.197	0.203	0.359	0.455	0.595	0.724	74
1995 GDP Per Capita	21.721	13.245	7.691	12.565	23.497	28.691	43.429	104
Average Contract Salary	329.291	258.947	108.387	108.387	166.838	669.068	708.831	104
Share of Contracts Professional	0.351	0.429	0.002	0.012	0.154	0.962	0.994	104
Share of Contracts Manufacturing	0.285	0.305	0.001	0.001	0.179	0.477	0.716	104
Share of all 1995 Contracts	0.126	0.098	0.011	0.024	0.108	0.192	0.299	104

Note: Unit of observation is 74 provinces (times periods as relevant) in all cases except bottom five rows. For bottom rows, unit of observation is 104 migrant destination countries. Shock variables are constructed from POEA/OWWA dataset and other sources (see text). $MigInc_{o0}$ denotes pre-shock (1995) migrant income per capita. $Rshock_o$ denotes weighted-average exchange rate shock. Import and export shocks are as described in Section 4.3.1. Expenditure and domestic income data are from FIES. Migrant income is constructed from POEA/OWWA dataset and Philippine Census. Income and expenditure variables are in thousands of real 2010 Philippine pesos (17.8 PhP per PPP US$ in 2010). Periods for expenditure are triennial, from 1985 to 2018 inclusive. (One observation, Rizal province in 1988, is missing due to loss of FIES data in a fire.) Periods for global, domestic, and migrant income data are 1994, 2009, 2012, and 2015. Shares of population by education level and share of population migrants are from Census (1990, 1995, 2000, 2007, 2010, 2015). Shares of population with primary, secondary, and college education are for those aged 20-64. "Share College: Migrants" is share of migrants reported in Census who have college or more education. Sectoral share of workforce variables from Census (1990, 1995, 2000, 2010). Migrant contracts are from the POEA/OWWA dataset (periods are 1994, 2009, 2012, and 2015); working age defined as 20-64. Baseline province controls are from Census for share rural and asset index; and from FIES for total income and expenditure. Baseline service sector excludes financial services (examined separately). Per capita GDP is from the World Development Indicators, in thousands of 1995 USD. Other destination level contract controls are calculated from POEA/OWWA dataset.

Table A3: Rotemberg Weights

Panel A. Positive and negative weights	**Sum**	**Mean**	**Share**				
$\hat{\alpha} > 0$	1.004	0.012	0.996				
$\hat{\alpha} \leq 0$	-0.004	-0.000	0.004				
Panel B. Top 5 Destinations	**Rot Wgt.**	**F-Stat**	$\hat{\beta}_k^{Global}$	$\hat{\beta}_k^{Domestic}$	$\hat{\beta}_k^{Migrant}$	$\hat{\beta}_k^{Consumption}$	
Saudi Arabia	0.20	27.0	39.4***	31.9***	7.5***	22.6***	
Japan	0.19	9.5	31.0***	27.6***	3.4	9.1	
United States	0.18	22.0	30.8**	29.1*	1.7	6.7	
Taiwan	0.10	22.9	35.8***	28.0***	7.9***	18.9**	
Hong Kong	0.08	0.9	-20.0	-12.7	-7.3	-38.4	

Note: The table presents diagnostic results for the shift-share following the approach suggested by Goldsmith-Pinkham et al. (2020). Panel A provides the sum, mean, and distribution of negative and positive Rotemberg weights $\hat{\alpha}$. Panel B displays the 5 destinations with largest Rotemberg weights. It presents the Rotemberg weights assigned to each destination when used collectively. Additionally, it reports the second stage coefficients for income $\hat{\beta}_k$ and F-statistics when each destination share is used individually as an instrument for the overall shift-share measure. The coefficients are provided for each main outcome presented in Table 1, corresponding to panel D, columns 3-6. *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Placebo Regressions

Variables Constructed from FIES Data
Pre Period: 1985, 1988, 1991; Post Period: 1994, 1997

			Domestic Income Subcomponents			Entrepreneurial Income Sectors				
	(1) Domestic Income Per Cap.	(2) Expenditure Per Cap.	(3) Wage	(4) Entrepreneurial and Rental	(5) Other	(6) Primary	(7) Manu.	(8) Service	(9) Agr. Income	(10) Non Agr. Income
$Shiftshare_o$ × Post	-2.527	2.248	-2.510	-0.205	0.188	1.589	0.159	1.272	-0.160	-2.367
	(5.501)	(4.714)	(2.905)	(1.959)	(1.592)	(1.407)	(0.499)	(1.315)	(0.684)	(5.785)
Obs.	369	369	369	369	369	222	222	222	369	369
Baseline DV Mean	26.962	25.372	11.585	10.843	4.534	6.038	0.623	4.170	2.682	24.280
Baseline DV St. Dev.	10.150	8.951	6.879	3.620	2.217	3.252	0.556	2.635	1.515	10.133

Variables Constructed from Census Data
Pre Period: 1990; Post Period: 1995

	Share Aged 20-64 Completed:					Share of Workforce in Sector:		
	(1) Primary School	(2) Secondary School	(3) College	(4) Migrant Share Age 20 - 64	(5) Share Skilled Migrants	(6) Primary	(7) Manufacturing	(8) Service
$Shiftshare_o$ × Post	-0.058	-0.061	-0.022	0.001	-0.045	0.066	0.010	-0.076
	(0.027)**	(0.032)*	(0.015)	(0.003)	(0.062)	(0.095)	(0.023)	(0.093)
Obs.	148	148	148	148	148	148	148	148
Baseline DV Mean	0.734	0.383	0.112	0.009	0.301	0.560	0.073	0.367
Baseline DV St. Dev.	0.114	0.117	0.038	0.007	0.095	0.180	0.063	0.134

Variables Constructed from Contract Data
Pre Period: 1994; Post Period: 1997

				Contracts per 10,000 Working Age People			
	(1) Global Income Per Capita	(2) Migrant Income Per Capita	(3) Average Mig. Salary	(4) 1st Qtile Edu.	(5) 2nd Qtile Edu.	(6) 3rd Qtile Edu.	(7) 4th Qtile Edu.
$Shiftshare_o$ × Post	4.693	0.579	-19.168	94.758	7.695	29.691	12.897
	(8.684)	(0.646)	(61.048)	(42.742)**	(4.795)	(29.219)	(18.924)
Obs.	148	148	148	148	148	148	148
Baseline DV Mean	33.485	3.893	405.084	45.449	6.000	18.254	19.579
Baseline DV St. Dev.	13.519	2.874	123.997	41.849	7.522	24.503	23.314

Note: Table presents coefficients on $Shiftshare_o \times Post_t$ in placebo regressions with false "post" periods. For definitions of outcomes, see: Table 1 (global, domestic, and income; and domestic income subcomponents), Table 2 (education outcomes), and Table 3 (share skilled migrants; migrant occupation outcomes). Compared to these other tables, $Post_t$ is redefined to refer to periods no later than 1997. All regressions include province fixed effects, year fixed effects, and $MigInc_{o0}$ and $Rshock_o$ interacted with year fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Table A5: Import and Export Shift-Share Variables Do Not Predict the Migrant Income Shift-Share Variable

	Migrant Income Shift-Share Variable ($Shiftshare_o$)			
	(1)	(2)	(3)	(4)
Panel A. Import and Export Shocks Jointly				
Import Shift-share ($Shiftshare_o^{import}$)	0.000742	0.00106	-0.000121	-0.000121
	(0.00173)	(0.00160)	(0.00132)	(0.00143)
Export Shift-share ($Shiftshare_o^{export}$)	0.0000892	0.000110	-0.0000904	0.000149
	(0.00133)	(0.00165)	(0.00159)	(0.00165)
Panel B. Import Shock Only				
Import Shift-share ($Shiftshare_o^{import}$)	0.000807	0.00114	-0.000177	-0.0000250
	(0.00168)	(0.00188)	(0.00142)	(0.00152)
Panel C. Export Shock Only				
Export Shift-share ($Shiftshare_o^{export}$)	0.000547	0.000781	-0.0000904	0.0000926
	(0.00145)	(0.00191)	(0.00159)	(0.00158)
Obs.	74	74	74	74
Controls	None	Panel A	Panel B	Panel C

Note: Unit of observation is province. The outcome variable is the migrant income shift-share variable, $Shiftshare_o$. All columns control for $MigInc_{o0}$ and $Rshock_o$. "Controls" row in table indicates set of additional control variables included in the regression, with panels corresponding to the structure of our main effect tables. Panel A includes destination controls only. Panel B additionally includes province development status controls. Panel C additionally includes province industrial structure controls. For list of destination and provincial controls, see Table 1. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Effects of Migrant Income Shock on Internal Migration

	Census: 1990, 2000, 2010					
	Age: 25 - 64			**Age: 16 - 24**		
	(1) In Migration Rate	(2) Out Migration Rate	(3) Net Migration Rate	(4) In Migration Rate	(5) Out Migration Rate	(6) Net Migration Rate
Panel A. Destination controls only						
$Shiftshare_o$ × Post	-0.010	-0.016	-0.006	-0.011	-0.038	-0.027
	(0.024)	(0.009)*	(0.026)	(0.029)	(0.018)**	(0.037)
Panel B. Additional province development status controls						
$Shiftshare_o$ × Post	-0.024	-0.015	0.009	-0.026	-0.034	-0.008
	(0.025)	(0.011)	(0.030)	(0.028)	(0.016)**	(0.036)
Panel C. Additional province industrial structure controls						
$Shiftshare_o$ × Post	-0.030	-0.014	0.016	-0.035	-0.036	-0.002
	(0.025)	(0.011)	(0.029)	(0.028)	(0.016)**	(0.035)
Panel D. Additional import and export shift-share variables						
$Shiftshare_o$ × Post	-0.030	-0.014	0.015	-0.034	-0.037	-0.002
	(0.024)	(0.011)	(0.028)	(0.028)	(0.016)**	(0.034)
Obs.	217	217	217	217	217	217
Baseline DV Mean	0.036	0.036	-0.001	0.041	0.056	0.015
Baseline DV St. Dev.	0.024	0.014	0.023	0.030	0.025	0.040

Note: Internal migration data is from 1990, 2010, and 2010 Censuses. Due to missing internal migration data in the 1990 Census, five provinces are dropped at the recommendation of the Philippine Statistical Authority (Camarines Sur, Capiz, Cavite, Mindoro Oriental, and Zamboanga Del Sur). Dependent variables are in-migration rate (individuals reporting having moved into the province within the last five years, as share of provincial population), out-migration rate (analogously, share who moved out of the province in the last five years), and net migration rate (the out-migration rate minus the in-migration rate). For list of destination and provincial controls, see Table 1. Baseline dependent variable mean and standard deviation calculated based on data from nearest pre-shock year. All regressions include province and year fixed effects. Standard errors are clustered at the province level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A7: Effects of Migrant Income Shock on Manufactured Exports

	Manufactured Exports per Capita	
	Full Period	Long Run
	(1)	(2)
Panel A. Destination controls only		
$Shiftshare_o \times$ Post	4.335	5.526
	(9.034)	(13.551)
Panel B. Additional province development status controls		
$Shiftshare_o \times$ Post	6.206	4.734
	(9.686)	(14.817)
Panel C. Additional province industrial structure controls		
$Shiftshare_o \times$ Post	3.442	-1.029
	(7.617)	(11.057)
Panel D. Additional import and export shift-share variables		
$Shiftshare_o \times$ Post	3.541	-0.873
	(7.676)	(11.287)
Obs.	888	370
Baseline DV Mean	3.195	3.195
Baseline DV St. Dev.	8.091	8.091

Note: Unit of observation is the province-year. Dependent variable is total value of manufactured exports, in thousands of real 2010 Philippine pesos (PhP), divided by province population. Dependent variable winsorized at 99%. Manufactured exports data are from Annual Survey of Philippine Business and Industry (ASPBI), Annual Survey of Establishments (ASE) and Census of Philippine Business and Industry (CPBI) (depending on year). Full period includes all years with export data available, except the year 1997 (1994, 1996, 1998, 1999, 2006, 2008, 2009, 2010, 2012, 2013, 2014, and 2015). Long run includes years 1994, 1996, 2009, 2012, and 2015. For list of destination and provincial controls, see Table 1. Baseline dependent variable mean and standard deviation calculated based on data from nearest pre-shock year. All regressions include province and year fixed effects. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Exchange Rates and Foreign Direct Investment to Philippines

	FDI	
	Full Period	Long Run
	(1)	(2)
Panel A. No Controls		
$\tilde{\Delta} R_d \times$ Post	-0.888	-1.007
	(1.780)	(1.791)
Panel B. Destination Controls		
$\tilde{\Delta} R_d \times$ Post	-1.037	-1.512
	(3.327)	(3.667)
Obs.	4,378	995
Dep. Var. Mean	0.747	0.845
Dep. Std. Dev.	5.107	6.156

Note: Unit of observation is country-year. Countries are weighted by the baseline migrant income in each destination. FDI data are from the PSA's Foreign Investment Reports for 1996-2002 and from PSA's OpenStat platform for after 2002. Yearly FDI are in billions of real 2010 PhPs. Full period includes years from 1996 to 2018. 1997 is dropped from the analysis due to partial treatment. Long run includes years 1996, 2009, 2012, 2015, and 2018. For list of destination controls, see Table 1. All regressions include province and year fixed effects. Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.10.

Table A9: Migrant Income Shock and Price Levels

	Consumer Price Index (1996 = 100)		Inflation
	(1) Full Period	(2) Long Run	(3) $\frac{CPI_{2017}-CPI_{1996}}{CPI_{1996}}$
Panel A. Destination controls only			
$Shiftshare_o$ × Post	-29.521	-43.376	-0.352
	(24.003)	(33.729)	(0.392)
Panel B. Additional province development status controls			
$Shiftshare_o$ × Post	-28.315	-42.553	-0.241
	(27.839)	(38.041)	(0.454)
Panel C. Additional province industrial structure controls			
$Shiftshare_o$ × Post	-28.533	-43.258	-0.263
	(27.142)	(37.444)	(0.454)
Panel D. Additional import and export shift-share variables			
$Shiftshare_o$ × Post	-28.912	-43.628	-0.271
	(27.125)	(37.847)	(0.466)
Obs.	1,702	296	74
Baseline DV Mean	100	100	1.553
Baseline DV St. Dev.	0	0	0.263

Note: For columns 1 and 2 unit of observation is the province-year and the dependent variable is province CPI. "Full period" includes 1994-2017, with 1997 excluded. "Long run" includes years included in our Global Income analysis in Table 1: 1994, 2009, 2012, and 2015. Regressions in columns 1 and 2 include province and year fixed effects. Standard errors are clustered at the province level. For column 3 the unit of observation is the province, and the dependent variable is the percent change in CPI from 1996 to 2017. $Shiftshare_o$ is not interacted with a post indicator for this cross-sectional specification. For list of destination and provincial controls, see Table 1. Baseline dependent variable mean and standard deviation calculated based on data from nearest pre-shock year (1996). *** p<0.01, ** p<0.05, * p<0.10.

Table A10: Estimating θ using Poisson Pseudo-maximum Likelihood

	OLS	PPML	PPML
		Change in Migrants	
Log(ΔR_d)	9.374*	3.471**	3.417**
	(5.146)	(1.720)	(1.707)
Observations	26,344	24,788	24,788
Fixed Effects	Origin x Skill	None	Origin x Skill

Note: OLS and PPML estimates of θ using the migration response to a destination shock, at the origin-destination-skill level. Standard errors clustered at the destination level. ΔR_d is the change in exchange rates across destinations d over the course of the Asian Financial Crisis. 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 A11: Impacts on Domestic Income by Skill

	1994, 2009, 2012, and 2015	
	(1) Domestic Income Per Capita Skilled	(2) Domestic Income Per Capita Unkilled
Panel A. Destination controls only		
$Shiftshare_o$ × Post	59.180	15.152
	(26.991)**	(5.193)***
Panel B. Additional province development status controls		
$Shiftshare_o$ × Post	27.317	11.682
	(19.501)	(4.974)**
Panel C. Additional province industrial structure controls		
$Shiftshare_o$ × Post	28.495	10.775
	(20.104)	(4.573)**
Panel D. Additional import and export shift-share variables		
$Shiftshare_o$ × Post	27.820	10.593
	(19.479)	(4.312)**
Obs.	296	296
Dep. Var. Mean	58.508	21.084
Dep. Var. St. Dev.	17.982	6.955

Note: Unit of observation is the province-year. Domestic income by skill are calculated from merged Family Income and Expenditure Survey (FIES) and Labor Force Survey (LFS) data, where we define a household as skilled if any working member is skilled. For list of destination and provincial controls, see Table 1. Baseline dependent variable mean and standard deviation calculated based on data from nearest pre-shock year. All regressions include province and year fixed effects. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.10.

Table A12: Overall Changes and Model-based Decomposition of Flows and Income

	Domestic Income	Migrant Income	Global Income
Mean	26.102	4.087	30.189
Std. Dev.	(9.405)	(2.993)	(11.340)
Impact of 1-std.-dev. shock	**1.676**	**0.601**	**2.277**
Increase as % of mean	6.4%	14.7%	7.5%
Share of global income increase	73.6%	26.4%	100.0%
Model-based decomposition:			
Education channel	20.2%	17.8%	19.55%
Exchange rate channel	——	64.6%	17.04%
Direct wage channel	69.08%	——	50.84%
Explained by model	89.3%	82.3%	87.8%

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 mean and standard deviation values are for the closest available year before the crisis (1995 for migrant flows and 1994 income). The impact of a 1 std dev shock in migrant income is the coefficient from the regressions multiplied by 0.093 (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.

S Supplementary Appendix: Model Derivations

S1 Deriving share of flows from o to d

Indirect utility of worker i is as defined in the text:

$$V_{idost} = w_{dst} R_{dt} (1 - \tau_{dost}) q_{id} \epsilon_{dot} \equiv \widetilde{w_{dost}} q_{id} \qquad \text{A19}$$

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

$$\begin{aligned} \pi_{1ost} &= Pr\left[\widetilde{w_{1ost}} q_1 > \widetilde{w_{d'ost}} q_{d'}\right] \quad \forall d' \neq 1 \\ &= Pr\left[q_{d'} < \frac{\widetilde{w_{1ost}} q_1}{\widetilde{w_{d'ost}}}\right] \quad \forall d' \neq 1 \\ &= \int \frac{dF}{dq_1} \left(q_1, \alpha_2 q_1, ..., \alpha_D q_1\right) dq_1 \end{aligned} \qquad \text{A20}$$

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:

$$F(q_1, ..., q_D) = exp\left\{-\left[\sum_{d=1}^{D} q_d^{-\theta}\right]\right\} \qquad \text{A21}$$

So the derivative of the CDF is given by:

$$\frac{dF}{dq} = \theta q^{-\theta-1} exp\left\{-\left[\sum_{d=1}^{D} q_d^{-\theta}\right]\right\} \qquad \text{A22}$$

This derivative evaluated at $(q_1, \alpha_2 q_1, ..., \alpha_D q_1)$, allows us to determine the probability of choosing destination 1:

$$\begin{aligned}
\pi_{1ost} &= \int \theta q^{-\theta-1} exp\left\{-\left[\sum_{d=1}^{D}(\alpha_d q)^{-\theta}\right]\right\} dq \\
&= \frac{1}{\sum_{d=1}^{D}\alpha_d^{-\theta}} \int \left(\sum_{d=1}^{D}\alpha_d^{-\theta}\right) q^{-\theta-1} exp\left\{-\left[q^{-\theta}\left(\sum_{d=1}^{D}\alpha_d^{-\theta}\right)\right]\right\} dq \\
&= \frac{1}{\sum_{d=1}^{D}\alpha_d^{-\theta}} \int dF(q) \\
&= \frac{1}{\sum_{d=1}^{D}\alpha_d^{-\theta}}.1 \\
&= \frac{\widetilde{w_{1ost}}^{\theta}}{\sum_{d=1}^{D}\widetilde{w_{dost}}^{\theta}} \qquad \text{A23}
\end{aligned}$$

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 get equation A7:

$$\pi_{dost} = \frac{(w_{dst}R_{dt}(1-\tau_{dot})\epsilon_{dot})^{\theta}}{\sum_k (w_{kst}R_{kt}(1-\tau_{kot})\epsilon_{kot})^{\theta}} \qquad \text{A24}$$

S2 Micro-founding the Education Responses

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

$$c_{1io} = Y_{io} - p_o S_{io} + b_{io} \quad \text{and} \quad c_{2io} = V_{idost} - I_o b_{io}\ , \qquad \text{A25}$$

where w_{idost} is the wage after the location choice.

We may expect that changes in migrant income help drive investments in human capital at home, for instance, by easing liquidity constraints for households or changing the returns to schooling. For instance, under certain assumptions on $u(.)$ and w say, $w_{do}(S)$ linear in S, and log-utility $u(c)$ and for credit constrained households $\bar{b} = 0$, average province-level schooling responds to shocks to migrant income: $\Delta S_{ot} = \frac{1}{2p}\Delta Y_o$. In this case, for $\Psi \equiv (ed_1 - ed_0)2p$, the change in the share of high-skilled workers h in origin o is:

$$\Delta\ell_{oht} = \frac{1}{\Psi}\Delta Y_o = \frac{1}{\Psi}\sum_{s=h,u}\left[\ell_{os0}\sum_d(\pi_{dos0}w_{dos0}\Delta R_{d0})\right] = \frac{1}{\Psi}\underbrace{\sum_d \omega_{do0}}_{MigInc_{o0}} \times \underbrace{\frac{\sum_d \omega_{do0}\tilde{\Delta}R_d}{\sum_d \omega_{do0}}}_{Rshock_o} \quad \text{A11}$$

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 $= p_1 S + p_2 S^2$, the optimal amount of schooling does not depend on Y, but only on the returns to education:

$$S_i^u = \frac{w'(s)_d(1-\tau_{dot})R_{dt}q_{id} - p_1}{2p_2} \quad \text{A26}$$

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:

$$S_{do}^u = \frac{w'(s)_d(1-\tau_{dot})R_{dt}\pi_{dot}^{\frac{-1}{\theta}}\Gamma - p_1}{2p_2} \quad \text{A27}$$

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

$$S_o^u = \sum_d S_{do}\pi_{dot} = \sum_d \frac{w'(s)_d(1-\tau_{dot})R_{dt}\pi_{dot}^{\frac{-1}{\theta}+1}\Gamma - p_1}{2p_2} \quad \text{A28}$$

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

$$\Delta S_o^u = \sum_d \frac{w'(s)_d(1-\tau_{dot})\theta\pi_{dot}\Gamma}{2p_2}\frac{\Delta R_{dt}}{R_{dt}} \quad \text{A29}$$

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 long lasting.

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 A25, 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:

$$pu'(c_1) = w'(S)u'(c_2) \tag{A30}$$

For continuous, increase, and concave utility and earnings functions, using the implicit function theorem, we can show education is an increasing function of income $\frac{\Delta S}{\Delta Y} > 0$.[59] 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

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. Additionally, if period 2 consumption is subjectively discounted, say at rate β, then both the education and skill-share response will be scaled by $\frac{\beta}{1+\beta}$.

S3 Deriving the changes in π_{dost}

Flows from origin o to destination d are given by Equation A24. We define V_{ost} as the denominator of Equation A24. That is, $V_{ost} \equiv \sum_k (w_{kst}R_{dt}(1-\tau_{kot})\epsilon_{kot})^{\theta}$. This comes to represent the option value of working in the various possible destinations. Similarly, let us define the numerator of Equation A24 to be $V_{dost} = (w_{dst}R_{dt}(1-\tau_{dot})\epsilon_{dot})^{\theta}$.

$$\pi_{dost} = \frac{(w_{dst}R_{dt}(1-\tau_{dot})\epsilon_{dot})^{\theta}}{\sum_k (w_{kst}R_{kt}(1-\tau_{kot})\epsilon_{kot})^{\theta}} \equiv \frac{V_{dost}}{V_{ost}} \tag{A24}$$

We can take the total derivative of these flows with respect to changes (derivative) in the exchange rate for one specific destination ΔR_{dt}:[60]

$$\Delta\pi_{dost} = \underbrace{\frac{((1-\tau_{dot})\epsilon_{dot})^{\theta}}{V_{ost}}\left(w_{dst}^{\theta}\theta R_{dt}^{\theta-1}\Delta R_{dt} + R_{dt}^{\theta}\theta w_{dst}^{\theta-1}\Delta w_{dst}\right)}_{\text{from the numerator of Equation A24}} - \underbrace{\frac{V_{dost}}{V_{ost}^2}\Delta V_{ost}}_{\text{from the denominator of Equation A24}} \tag{A31}$$

The above equation is derived using the quotient rule. The first part takes changes in the numerator, where only R_{dt} and w_{dst} change. This captures the

[59] 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 $\frac{\Delta S}{\Delta Y} > 0$.

[60] Here, and elsewhere, we use Δ to denote a derivative, as d is already used for destinations.

effect of the exchange rate shocks to destination d specifically. 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 indirect changes as well? The second part takes the total derivative of the denominator. Now, since $\pi_{dost} \equiv \frac{V_{dost}}{V_{ost}}$, we can simplify this further:

$$\Delta\pi_{dost} = \underbrace{\theta\pi_{dost}\left(\frac{\Delta R_{dt}}{R_{dt}} + \underbrace{\frac{\Delta w_{dst}}{w_{dst}}}_{=0\ if\ o\neq d}\right)}_{\text{from the numerator of Equation A24}} - \underbrace{\frac{\pi_{dost}}{V_{ost}}}_{\text{from denominator of Equation A24}}\Delta V_{dost} \qquad \text{A32}$$

For all $d \neq o$ the shocks do not change destination wages (i.e. Filipino migrants are small enough a group in destinations to affect their equilibrium wages). As such, for such destinations, we know that there is a direct effect, and an indirect effect to go to specific destination d:

$$\Delta\pi_{dost} = \theta\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}} - \frac{\pi_{dost}}{V_{ost}}\left[\sum_{d\neq o}\left(V_{dost}\theta\frac{\Delta R_{dt}}{R_{dt}}\right) + \left(V_{oost}\theta\frac{\Delta w_{ost}}{w_{ost}}\right)\right] \qquad \text{A33}$$

This can be rewritten as:

$$\Delta\pi_{dost} = \theta\pi_{dost}\left[\underbrace{\frac{\Delta R_{dt}}{R_{dt}}}_{\text{Direct effect}} - \left(\underbrace{\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Indirect resorting}} + \underbrace{\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}}_{\text{Domestic earnings stemming flows}}\right)\right] \qquad \text{A34}$$

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 affect flows to the current destination.

We can sum up across destinations, and rewrite this equation

$$\sum_{d\neq o}\Delta\pi_{dost} = \theta\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\left[1 - \sum_{d\neq o}\pi_{dost}\right]\right) - \left(\theta\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\left[\sum_{d\neq o}\pi_{dost}\right]\right) \qquad \text{A35}$$

$$\sum_{d \neq o} \Delta\pi_{dost} = \underbrace{\pi_{oost}\left[\theta \sum_{d \neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)\right]}_{\text{Exchange rates driving outflows*}} - \underbrace{[1-\pi_{oost}]\left(\theta\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)}_{\text{Domestic earnings stemming outflows*}} \qquad \text{A36}$$

Alternatively, we could separate out the indirect sorting effects:

$$\begin{aligned}\sum_{d \neq o} \Delta\pi_{dost} = & \underbrace{\theta \sum_{d \neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right)}_{\text{Exchange rates driving outflows}} - \underbrace{\theta\left(\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)}_{\text{Domestic earnings stemming outflows}} \\ & \underbrace{-\,\theta\left[\sum_{d \neq o}\pi_{dost}\sum_{d \neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right) - \left[1-\sum_{d \neq o}\pi_{dost}\right]\pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right]}_{\text{Indirect resorting}} \qquad \text{A37}\end{aligned}$$

S4 Deriving the changes in total flows

The above derivation is for a specific skill level s. Yet, skill levels may change as a result of the shock, and different skill groups have different propensities to migration. We know that flows from a specific origin to a specific destination can be characterized by:

$$\pi_{doht}\ell_{oht} + \pi_{dout}\ell_{out} \qquad \text{A38}$$

Suppose, only R_{dt} changed for one d, and there were no changes to domestic wages, then the direct effect would come from the first part of Equation A34:

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

The second part above (exchange rate channel in direct flows) comes straight from the first part (direct effect) of Equation A34 replaced into Equation A38.

Equation A36 allows us to derive $\Delta\ Flows_{ot} \equiv \sum_{d\neq o} \Delta\ Flows_{dot}$:

$$\Delta\ Flows_{ot} = \underbrace{\Delta\ell_{oht} \sum_{d\neq o} (\pi_{doht} - \pi_{dout})}_{\text{Education channel in outflows}} + \underbrace{\theta \sum_{d\neq o} (\ell_{oht}\pi_{ooht}\pi_{doht} + \ell_{out}\pi_{oout}\pi_{dout}) \frac{\Delta R_{dt}}{R_{dt}}}_{\text{Exchange rate channel in outflows (from Equation A36 part 1)}} \tag{A40}$$

$$\underbrace{- \theta \left(\ell_{oht} \left[1 - \pi_{ooht}\right] \pi_{ooht} \frac{\Delta w_{oht}}{w_{oht}} + \ell_{out} \left[1 - \pi_{oout}\right] \pi_{oout} \frac{\Delta w_{out}}{w_{out}} \right)}_{\text{Domestic earnings stemming outflows (from Equation A36 part 2)}}$$

We can split up the exchange rate channel by skill group:

$$\Delta\ Flows_{ot} = \underbrace{\Delta\ell_{oht} \sum_{d\neq o} (\pi_{doht} - \pi_{dout})}_{\text{Education channel in outflows}} \tag{A41}$$

$$+ \theta \left[\underbrace{\ell_{oht}\pi_{ooht} \sum_{d\neq o} \left(\pi_{doht} \frac{\Delta R_{dt}}{R_{dt}} \right)}_{\text{Exchange rate driving skilled outflows*}} + \underbrace{\ell_{out}\pi_{oout} \sum_{d\neq o} \left(\pi_{dout} \frac{\Delta R_{dt}}{R_{dt}} \right)}_{\text{Exchange rate driving unskilled outflows*}} \right]$$

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

Here, the channels above include the indirect re-sorting to the alternative destinations. Alternatively, we can keep the indirect re-sorting separate and use Equation A37:

$$\Delta\ Flows_{ot} = \underbrace{\Delta\ell_{oht} \sum_{d\neq o} (\pi_{doht} - \pi_{dout})}_{\text{Education channel in outflows}} - \underbrace{\chi_o}_{\text{Indirect re-sorting}} \tag{A13}$$

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

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

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

S5 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):

$$\sum_{s=h,u} \ell_{ost}\pi_{oost}w_{ost} \tag{A42}$$

The direct effect on the domestic income would exist if wages increased $\Delta w_{ost} \neq 0$. 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.

$$\Delta W_{ot} = \underbrace{\Delta\ell_{oht} \left(\underbrace{w_{oh0}\pi_{ooh0}}_{\text{skilled wage at home}} - \underbrace{w_{ou0}\pi_{oou0}}_{\text{unskilled wage at home}} \right)}_{\text{Education channel in domestic income}} + \underbrace{\sum_{s=h,u} \ell_{os0}\pi_{oos0} (\Delta w_{ost}) - \tilde{\chi}_{o1}}_{\text{Direct wage (and resorting) channel}} \tag{A16}$$

Overall income generated by the individuals that originate from these regions changes by more than simply the direct wage and education channels. This is because the location choices of individuals change as well, in response to lucrative exchange rates, and domestic wage increases. If domestic wages increase, then more people may remain behind locally, and earn at home: $\Delta\pi_{oost}$. We can return to Equation A32, and set $d = o$, and $\Delta R_{ot} = 0$. But this time, $\Delta w_{ost} \neq 0$. So the analogue of Equation A34 is given by:

$$\Delta\pi_{oost} = \theta\pi_{oost}\left[\underbrace{\frac{\Delta w_{ost}}{w_{ost}}}_{\text{Remainers}} - \underbrace{\left(\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right) + \pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)}_{\text{Indirect resorting}}\right] \qquad \text{A43}$$

There is also the indirect effect once again. If wages do not increase at home, more workers may leave if exchange rates abroad become more favorable, reducing domestic income.

How does $\Delta\pi_{oost}$ contribute to domestic earning increases? We can replace the result for $\Delta\pi_{oost}$ above into Equation A42, and derive the indirect resorting $\tilde{\chi}_{o1} \equiv \sum_{s=h,u}\ell_{ost}\theta\pi_{oost}w_{ost}\left(\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right) + \pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right) - \sum_{s=h,u}\ell_{ost}\pi_{oost}\theta\Delta w_{ost}$.

While this captures the domestic income gains, migrant income may change as well. Migrant income is given by:

$$\sum_{s=h,u}\ell_{ost}\sum_{d}\pi_{dost}w_{dost}R_{dt} \qquad \text{A44}$$

Again, changes to ℓ_{ost} (upskilling) will contribute to the education channel, as always:

$$\Delta\ell_{oht}\left(\underbrace{\sum_{d\neq o}w_{doht}\pi_{doht}R_{dt}}_{\text{skilled wage abroad}} - \underbrace{\sum_{d\neq o}w_{dout}\pi_{dout}R_{dt}}_{\text{unskilled wage abroad}}\right) \qquad \text{A45}$$

Now to get at how changes to exchange rates directly (and changes to local wages indirectly) affect flows, and thereby incomes, we need to go back to Equation A34, which described how flows changed. To be specific, the effects on income due to 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:

$$\Delta\pi_{dost} = \theta\pi_{dost}\left[\underbrace{\frac{\Delta R_{dt}}{R_{dt}}}_{\text{Direct effect}} - \underbrace{\left(\sum_{d\neq o}\left(\pi_{dost}\frac{\Delta R_{dt}}{R_{dt}}\right) + \pi_{oost}\frac{\Delta w_{ost}}{w_{ost}}\right)}_{\text{Indirect resorting}}\right] \qquad \text{A34}$$

Again, the indirect resorting channel depends on the relative changes to exchange rates in other destinations. From Equation A44, we can see that the changes to income are driven by (1) $\Delta\ell_{ost}$ (shown in Equation A45), (2) $\Delta\pi_{dost}$ (shown in Equation A34), and (3) just direct changes to ΔR_{dt} (say, in the short run). Since Equation A45 already documents how changes to skill affect income, let us concentrate on (2) and (3) here:

$$\sum_{s=h,u} \ell_{ost} \sum_{d} \Delta\pi_{dost} w_{dost} R_{dt} + \sum_{s=h,u} \ell_{ost} \sum_{d} \pi_{dost} w_{dost} \Delta R_{dt} \qquad \text{A46}$$

Replacing the result from Equation A34 in the first part of the equation above, we know:

$$\sum_{s=h,u} \ell_{ost} \sum_{d} \theta \pi_{dost} \frac{\Delta R_{dt}}{\cancel{R_{dt}}} w_{dost} \cancel{R_{dt}} - \tilde{\chi}_{o2} \; + \; \sum_{s=h,u} \ell_{ost} \sum_{d} \pi_{dost} w_{dost} \Delta R_{dt} \qquad \text{A47}$$

where $\tilde{\chi}_{o2} \equiv \theta \sum_{s=h,u} \sum_{d} \left[\ell_{ost} w_{dost} \pi_{dost} \left(\sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}} \right) + \pi_{oost} \frac{\Delta w_{ost}}{w_{ost}} \right) \right]$ is the indirect resorting (from Equation A34). Rewriting this in terms of the initial shock ΔY_o:

$$\underbrace{\theta \sum_{s=h,u} \ell_{ost} \sum_{d} \pi_{dost} w_{dost} \Delta R_{dt}}_{\Delta Y_o = \text{Migrant Earnings Shock}} + \underbrace{\sum_{s=h,u} \ell_{ost} \sum_{d} \pi_{dost} w_{dost} \Delta R_{dt}}_{\text{Short run } \Delta c_{1o} = \Delta Y_o} - \tilde{\chi}_{o2} \qquad \text{A48}$$

So together the contribution of wages and exchange rate changes (not skill-upgrading) to longer-run changes in global income generated (and consumption Δc_{2o}) by individuals from these regions (whether they are located at home or abroad) is given by:

$$\underbrace{\sum_{s=h,u} \left[\ell_{ost} \pi_{oost} \left(\underbrace{\Delta w_{ost}}_{\text{Direct wage channel}} + \underbrace{\theta \Delta w_{ost}}_{\text{Remainers channel}} \right) \right]}_{\text{Domestic earnings due to firm-side responses}} - \tilde{\chi}_{o2} + \underbrace{\underbrace{\theta \left(\sum_{s=h,u} \ell_{ost} \sum_{d} \pi_{dost} w_{dost} \Delta R_{dt} \right)}_{\Delta Y_o = \text{Migrant Earnings Shock}}}_{\text{Earnings from Abroad: Exchange Rate Channel}} \qquad \text{A49}$$