

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

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Abstract

How does income from international migrant labor affect the long-run development of migrant-origin areas? We leverage the 1997 Asian Financial Crisis to identify exogenous and persistent changes in international migrant income across regions of the Philippines, derived from spatial variation in exposure to exchange rate shocks. The initial shock to migrant income is magnified in the long run, leading to substantial increases in income in the *domestic* economy in migrant-origin areas; increases in population education; better-educated migrants; and increased migration in high-skilled jobs. 77.3% of long-run income gains are actually from domestic (rather than international migrant) income. A simple model yields insights on mechanisms and magnitudes, in particular that 23.2% of long-run income gains are due to increased educational investments in origin areas. Improved income prospects from international labor migration not only benefit migrants themselves, but also foster long-run economic development in migrant-origin areas.

JEL codes: F22, J24, O15, O16

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1 Introduction

Moving from a developing to a developed country for work leads to income gains that are larger than the impacts of any known economic development program (Clemens et al., 2019; Pritchett and Hani, 2020). International migrants from developing countries sent home \$605 billion in remittances in 2021, an amount as large as all foreign direct investment, and more than three times larger than foreign aid flows to the developing world (World Bank, 2022).¹ Motivated by these economic gains, most developing-country governments have policies facilitating international migrant labor (United Nations, 2019b).

There is ample evidence that international migration raises incomes for the migrants themselves. However, evidence is scarce on how international migrant income affects broader economic development in migrant-origin *areas*. Positive shocks to the income of international migrants could loosen liquidity constraints on human capital and entrepreneurial investments in origin areas. In addition, higher *potential* income in the international labor market could have effects even in households initially without migrants, by raising the returns to migration. As a result, migration rates could rise. Furthermore, households could invest more in education, because education raises the likelihood of securing an overseas job, and also has returns in overseas work. Increases in such investments in migrant-origin areas should raise longer-run economic growth. Evidence of such development impacts would suggest that international migration policies could play a more prominent role in efforts to reduce global poverty (Nunn, 2019).

We ask how persistent increases in international migrant income affect long-run economic development in migrant-origin areas. We exploit a large-scale natural experiment: changes in international migrant incomes across Philippine migrant-origin areas driven by the 1997 Asian Financial Crisis. Philippine provinces varied prior to 1997 in the amount of migrant income earned by their citizens in many different countries. The vast majority of these migrant workers were overseas on temporary labor contracts (returning eventually to their origin areas). Overseas migrant income sources then experienced exogenous – and heterogeneous – exchange rate shocks in 1997. To undertake our analyses, we obtained

¹International migration also involves large numbers of people. 210 million people from developing countries were international migrants in 2019 (United Nations, 2019a), a magnitude similar to the number of microcredit clients, 140 million (Convergences, 2019), or conditional cash transfer (CCT) program beneficiaries, 185 million (World Bank, 2018b).

unusual Philippine government administrative data on migrant worker contracts, with information on migrant incomes, origin provinces, and overseas destinations. The combination of the natural experiment and these unique data makes possible a shift-share identification strategy. We examine aggregate impacts on 74 Philippine provinces up to two decades later.

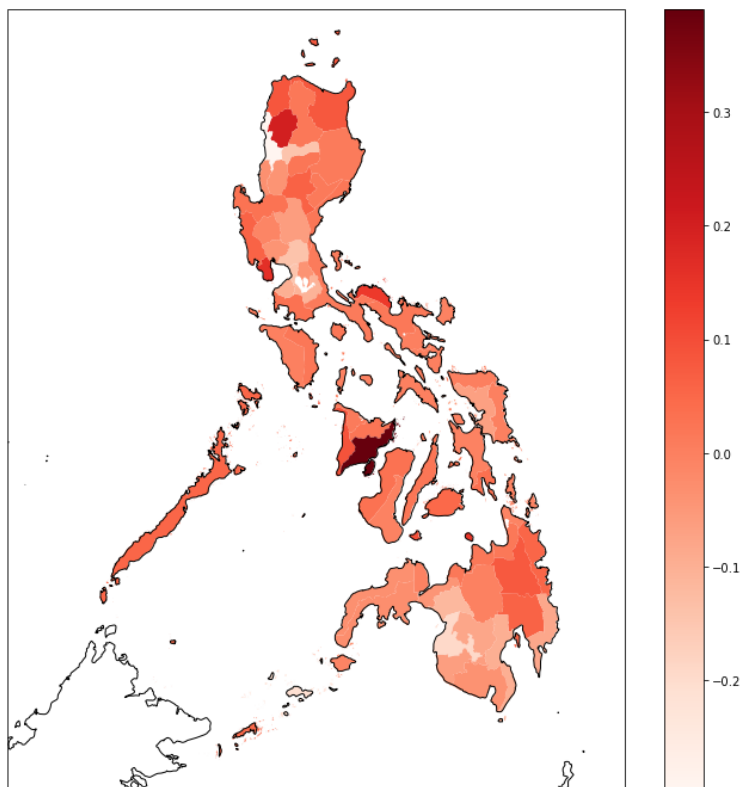
Our empirical analyses implement frontier methods for identification and inference in shift-share research designs, following [Borusyak et al. \(2022\)](#). Each province's exposure "shares" are pre-shock levels of migrant income per capita from each international migrant destination (which we call "exposure weights"). These exposure weights vary greatly across origin provinces and overseas destinations. For example, 1995 migrant income emanating from Japan is 10.7 times higher on a per capita basis for Bulacan province (PhP 3,540 per provincial resident) than for Leyte (PhP 332 per provincial resident).² Japan's exchange rate shock should therefore have 10.7 times greater impact on population-level mean outcomes in Bulacan than in Leyte.

Each destination's "shift" is its exchange rate shock. [Table 1](#) displays the exchange rate shock for the top 20 migrant destinations in the immediate post-shock year (1997-1998). These exchange rate movements were persistent over the next two decades, as we discuss further in [Section 4.4](#). The shocks range from a 4% depreciation against the Philippine peso for Korea to a 57% appreciation for Libya. Other important destinations such as Japan and Taiwan fall in between (32% and 26% appreciations, respectively). The identification assumption is that these exchange rate shocks are as-good-as-randomly assigned. Balance tests with respect to pre-shock characteristics support this identification assumption.

We present the resulting variation in the shift-share variable across provinces in [Figure 1](#). The shift-share variable is interpreted as a shock to migrant income per capita (i.e., per provincial resident). We estimate the impacts of this shock on long-run provincial outcomes. Impacts could be due to the positive income shock experienced by migrants who were overseas when the shock occurred. Households initially without migrants at the time of the shock could also change their migration decisions and education investments in response to the increase in the return to migration. Standard errors account for correlation of shocks across provinces with similar exposure weights ([Borusyak et al., 2022](#)).

²All Philippine peso (PhP) amounts in this paper are in real 2010 pesos (PPP exchange rate 17.8 PhP/USD).

Figure 1: Spatial Distribution of Shift-Share Variable (Migrant Income Shock) Across Philippine Provinces



Notes: 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 B.2 for details.

We find, first, that the initial shock to migrant income (measured by our shift-share variable) is magnified over time. Each unit short-run (1997-1998) positive shock to migrant income is increased more than five-fold in the longer run (through 2009-2015). Below, we explore the mechanisms behind this substantial magnification in the context of a structural model.

Second, we find that the positive migrant income shocks lead to substantial increases in *domestic* Philippine income per capita (not including migrant income or remittances) in migrants' origin provinces. A province's "global income" per capita is the sum of its domestic income and (international) migrant income per capita. 77.3% of the long-run increase in global income per capita is from the increase in domestic income, and 22.7% is from migrant income. We also see corresponding increases in household expenditure per capita. These gains emerge

over roughly two decades after the 1997 shocks, reflecting persistence in the exchange rate changes and in the overseas sources of migrant income for particular Philippine provinces. The magnitude of the gains is nontrivial. A one-standard-deviation shock raises global income per capita 12-18 years later by 2,275 Philippine pesos (PhP) (0.18 standard deviation).

We address potential threats to causal identification. First, we find no evidence that changes in any outcome variables in the pre-shock period (“pre-trends”) are correlated with the future value of the shift-share variable. Second, we consider potential omitted variables at the origin-province or migrant-destination level. Our estimates are not sensitive to controls accounting for ongoing trends or heterogeneity in exposure to the Asian Financial Crisis-induced downturn related to baseline province characteristics such as industrial structure and development status. Third, we show that other alternate mechanisms through which our shift-share measure could affect outcomes, in particular exports and foreign direct investment (FDI), are unlikely to be operative: neither exports nor FDI are responsive to the shocks of interest. This helps confirm that the shift-share variable operates as a shock to migrant income, rather than exports or FDI.

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

Given the central role of skill in the model, we empirically estimate impacts on educational investments. We find large positive effects: a one-standard-deviation migrant income shock increases the share of the population with a college education by 0.50 percentage points (0.11 standard deviation). We also show that these increases in skill in the population are accompanied by increases in the share of migrants who are college-educated, and in new labor migration in highly-skilled occupations overseas.

We estimate that educational investments account for 23.2% of the increase in global income per capita. Furthermore, the model fully explains the over-five-fold

magnification of the effect of the shift-share shock on migrant income, derived from increases in educational investments in the population, increasing migrant skill levels, and changes in migration patterns across destinations.

We also provide a stylized framework to understand the plausibility of our estimated effects on domestic income. We make assumptions regarding the share of migrant income returned to origin economies, the aggregate demand multiplier, and the return on entrepreneurial investments. A reasonable set of such assumptions yields the observed long-run increase in domestic income.

Our study is made possible by two unusual elements. First, the natural experiment of the 1997 Asian Financial Crisis generates the exogenous exchange rate variation central to our shift-share identification strategy.³ Second, we obtained unusual Philippine government administrative data on migrant worker contracts. Without these data, provincial exposure weights (“shares” in the shift-share) would have been unobservable, making the shift-share strategy impossible.

This paper contributes to research on the economic impacts of international migration on developing-country populations. Prior research has established causal impacts of migrant economic conditions or migration opportunities on migrants’ origin *households*.⁴ Our work is related to a small body of recent research on economic impacts of international migration on migrant-origin *areas*, that emphasizes causal identification. [Theoharides \(2020\)](#) finds that closing a prior migration opportunity reduces income and raises child labor in Philippine origin areas. [Dinkelman and Mariotti \(2016\)](#) and [Dinkelman et al. \(2020\)](#) examine long-run impacts of migrant work in South Africa on Malawian origin-area education and development. [Caballero et al. \(2021\)](#) study short-run effects of migrant exposure to Great Recession shocks on Mexican origin areas.⁵

An important feature of our paper is our focus on impacts of increased international income from formal, legal migrant labor. Unlike undocumented and unregulated migrant flows across borders, migration that is facilitated and regulated by governments is highly policy-relevant, and most developing country govern-

³Prior 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., 2021](#)).

⁴Such 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. \(2018\)](#), and [Bossavie et al. \(2021\)](#).

⁵In studies of *internal* (within-country) migration, [Kinnan et al. \(2019\)](#) examine impacts of Chinese migration on origin areas using an instrument based on shocks in domestic migrant destinations, and [Akram et al. \(2017\)](#) examine Bangladeshi village-level impacts of randomly inducing rural-urban migration.

ments are taking concrete steps towards promoting it (as we discuss in Section 2). Credible evidence on the impacts of legal, regulated international migrant labor flows on origin-area economic development is of interest to development policy-makers.

This paper has several additional 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. \(2020\)](#) also estimate long-run effects. Those studies differ in estimating long-run impacts of a brief historical episode of migrant work that did not persist. We study a shock to migrant income with long-run persistence, and a migrant flow that also persists. This allows us to examine how resulting investments in education initiate a virtuous migration cycle, by enabling high-skilled future migration, with subsequent increases in future migrant income.

By exploiting persistent exogenous variation in migrant income opportunities, we are able to answer a fundamental question in the economics of migration: do origin areas with greater access to high-income migration opportunities develop faster than origin areas with less attractive migration opportunities? We are able to plausibly identify the causal impact of persistently higher migrant income opportunities, and thus reveal whether migration policy can be used effectively as a part of economic development policy.

In addition, our work is distinct in simultaneously examining impacts on migrant, domestic, and global income, due to our novel data on migrant income. We can therefore examine the relative magnitudes of impacts on domestic income and migrant income, and thus conclude that the vast majority of long-run gains are from increases in domestic income. Finally, we complement our reduced-form estimates with a structural approach to provide insights on mechanisms and the long-run magnification of income gains.

Our findings are reminiscent of the recent literature finding positive long-run impacts of asset transfers to catalyze income gains from household entrepreneurial enterprises ([de Mel et al., 2008](#); [Banerjee et al., 2015](#); [Bandiera et al., 2017](#); [Banerjee et al., 2021](#)), and providing evidence of poverty traps ([Balboni et al., 2021](#); [Kaboski et al., 2022](#)). The migrant income shocks we study could have long-run impacts, in part, by enabling escapes from poverty traps. Our finding that a substantial share of gains in domestic income come from household enterprises suggest that

migration policy can be an effective tool in the development anti-poverty toolkit.

This paper also contributes to research on the impacts of migration on skill composition at origin. Our conclusions concord with prior findings that migration leads to “brain gain,” stimulating educational investments, and raising general skill levels back home (Stark et al., 1997; Mountford, 1997).⁶ These findings contrast with studies finding that migration leads to a net loss of skilled individuals from the population (“brain drain”), in part via reductions in schooling investments (McKenzie and Rapoport, 2011; de Brauw and Giles, 2017; Tang et al., 2022).⁷ We add to this literature by finding that increases in education may generate a virtuous cycle, leading to higher-skilled future migration, which in turn raises incomes and education levels.

2 Context: International Labor Migration

210 million individuals from developing countries were international migrants in 2019. 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. (2018), and Gaikwad et al. (2022) find that random assignment to international migrant work opportunities leads to improved migrant income, and better outcomes for migrants and their origin households.⁸ Income gains from increased international migration flows 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 incomes in the domestic economy of 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%

⁶Such studies include Batista et al. (2012), Docquier and Rapoport (2012), Clemens and Tiongson (2017), Shrestha (2017), Theoharides (2018), Chand and Clemens (2019), Khanna and Morales (2019), and Abarcar and Theoharides (2022).

⁷Evidence on reductions in education investment due to factory openings in Mexico (Atkin, 2016) is also relevant.

⁸Moreover, many prior studies have established positive correlations between international migration and economic development outcomes in origin areas (e.g., Lopez-Cordoba (2005), Acosta et al. (2008), Orrenius et al. (2010)).

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.

Table 1: 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, ΔR_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_{do} , across 74 Philippine provinces o ("shares" of the shift-share variable). See Subsection B.2 and Section 4 for details on exposure weight definition. Columns 5 and 6 present exchange rate changes. Column 5 displays exchange rate shock ΔR_d ("shift" of the shift-share variable). Exchange rate shock is change in Philippine pesos (Php) per local currency unit. Exchange Rate Shock (1997-1998, ΔR_d) is fractional change between July 1996-July 1997 and October 1997- September 1998 (e.g., 10% appreciation 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.

In the Philippines, two government agencies facilitate international labor migration. The Philippine Overseas Employment Administration (POEA) regulates international 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 well-being 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 OFW families in hardship, and facilitates the return and "reintegration" of OFWs to the Philippines. POEA and OWWA

are the sources of the migrant contract data we use in our analyses.⁹

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 2018.¹⁰ 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.

Migrant income in the Philippines comes from numerous overseas destinations, and migrant destinations vary substantially across origin provinces. Table 1 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.

3 Data and Measurement

We summarize data sources here; details are in Appendix A. We examine outcomes of 74 Philippine provinces,¹¹ typically over triennial periods or periods determined by census rounds.

3.1 Construction of Shift-Share Variable

To obtain causal estimates, we exploit the component of changes in provincial migrant income per capita that is due to the 1997 Asian Financial Crisis exchange rate shocks. The shift-share variable that isolates this exogenous variation in provincial migrant income per capita is our causal variable of interest.

$Shiftshare_o$ is the predicted short-run change in migrant income per capita

⁹There are several prominent examples of government agencies facilitating 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 Overseas Workers) play similar roles to the Philippines’ migration agencies.

¹⁰Overseas income is primarily migrant remittances, but also includes sources such as pensions and investment income.

¹¹To 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.

due to the exchange rate shocks. In Appendix B.2 we derive this shift-share variable from a simple theoretical model of migration, which we then use to quantify mechanisms and gauge plausibility of effect magnitudes.

The “exposure weight” ω_{do0} serves as the “share” in the shift-share. ω_{do0} captures the extent to which a typical province- o resident is exposed to a destination- d exchange rate shock. 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 “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; we thus refer to the ω_{do0} terms as “exposure weights”.¹²

To calculate province o ’s shift-share measure, 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 . $Shiftshare_o$ is thus the predicted change in province- o migrant income per capita due to the exchange rate shocks:

$$Shiftshare_o = \sum_d (\omega_{do0} \tilde{\Delta}R_d) \quad (1)$$

Now, multiply and divide $Shiftshare_o$ by the pre-shock sum of migrant income across destinations ($\sum_d \omega_{do0}$, the sum of exposure weights). This yields the following expression, providing a complementary interpretation of our shift-share variable:

$$Shiftshare_o = \underbrace{\sum_d \omega_{do0}}_{MigInc_{o0}} \times \frac{\sum_d (\omega_{do0} \tilde{\Delta}R_d)}{\underbrace{\sum_d \omega_{do0}}_{Rshock_o}} \quad (2)$$

$Shiftshare_o$ is the product of two terms. $MigInc_{o0}$ is pre-shock migrant income per capita in origin province o , across all migrant destinations. Provinces with higher $MigInc_{o0}$ have more migrant income per capita facing exchange rate risk (greater aggregate exposure to exchange rate shocks). $Rshock_o$ is the province- o weighted average exchange rate shock, where the weights are pre-shock shares of migrant income from each destination d . In Section 4 below, we

¹²Borusyak et al. (2022) call these terms “exposure shares”, but we say “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.

emphasize that we derive causal identification solely from $Shiftshare_o$, not either of the component factors $MigInc_o$ and $Rshock_o$ alone.

A key challenge is that the data needed to estimate exposure weights ω_{do} , destination- d pre-shock migrant income per capita of province o , are not available in any Philippine Censuses or surveys. We estimate exposure weights ω_{do} using two datasets 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. We match the two datasets to determine migrant origin province in the POEA database, and can then estimate ω_{do} .¹³

Data for the exchange rate shock \tilde{R}_d in $Shiftshare_o$ comes from Bloomberg LP. As we discuss in Subsection 4.2.1, our shift-share variable uses only the immediate, short-run change in exchange rates. We calculate the short-run exchange rate change, \tilde{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 is 0.1).

3.2 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.¹⁴

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), prevent-

¹³We achieve a match rate of 95%. Further details of the matching process are in Appendix Section A.1.

¹⁴We exclude the partially-treated year 1997 from regression analyses, but include it in event-study analyses.

ing 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 fewer triennial periods: 1994, 1997, 2009, 2012, and 2015. Also in triennial periods, we examine secondary outcomes such as migrant contracts as 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 from six rounds of the Philippine Census of Population (1990, 1995, 2000, 2007, 2010, and 2015).

4 Empirical Approach

We discuss the regression equation, causal identification, and temporal persistence of the shock measured by our shift-share variable.

4.1 Regression Equation

We estimate causal effects using the shift-share approach of [Borusyak et al. \(2022\)](#). Our regression equation is:

$$y_{ot} = \alpha_o + \gamma_t + \beta_1(Shiftshare_o \times Post_t) + \lambda'(MigInc_{o0} \times \mathbf{D}_t) + \phi'(Rshock_o \times \mathbf{D}_t) + \delta'(\mathbf{X}_{o0} \times Post_t) + \varepsilon_{ot}, \quad (3)$$

y_{ot} is an outcome of interest for province o in period t . $Shiftshare_o$ is the shift-share variable, which is interacted with $Post_t$, an indicator for periods after 1997.¹⁵ The coefficient β_1 is the coefficient of interest. Causal interpretation of β_1 exploits changes in migrant income per capita driven by the 1997 exchange rate shocks, as discussed in Subsection 4.2.1 below.

$MigInc_{o0}$ is pre-shock migrant income per capita in the province, and $Rshock_o$ is the province- o weighted-average exchange rate shock. Both these variables

¹⁵While in many shift-share research designs the shift-share variable is used as an instrumental variable for a potentially-endogenous right-hand-side variable of interest, in our context we do not do so, and simply examine the “reduced form” impact of the shift-share variable. We take this approach due to likely violations of the IV exclusion restriction. Using $Shiftshare_o$ as an instrument for migrant income per capita, for example, would violate the IV exclusion restriction because the shock’s effects operate not only via migrant income *per se*, but also via increased returns to migration. Perceived returns to education may then rise, driving education investments independently of effects due to migrant income shocks.

are interacted with a vector of period fixed effects \mathbf{D}_t .¹⁶ 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 $Shiftshare_o \times Post_t$. We discuss this further in Subsection 4.2.2.

$\mathbf{X}_{o0} \times Post_t$ is a vector of pre-shock destination characteristics and province-level characteristics interacted with the post-shock dummy. We discuss these further in Subsection 4.2.1. Province fixed effects α_o account for time-invariant differences across provinces. Period fixed effects γ_t account for common time effects. ε_{ot} is a mean-zero error term.

We do not impose the typical assumption of i.i.d. data. Our “shifts”, the destination- d exchange rate shocks $\tilde{\Delta}R_d$, are common to provinces with similar exposure weights ω_{do0} . Borusyak et al. (2022) and Adao et al. (2019) demonstrate that conventional standard errors in shift-share designs are invalid due to likely correlation in residuals across observations with similar shock exposure. We report “exposure-robust” standard errors based on estimation of shock-level regressions following Borusyak et al. (2022).

4.2 Causal Identification

We discuss assumptions required for causal identification, and empirical evidence supporting these assumptions.

4.2.1 Exogeneity of Exchange Rate Shocks

In the Borusyak et al. (2022) shift-share approach, causal identification is based on exogeneity of the shifts (shocks), rather than on exogeneity of the shares. Our shifts are destination- d exchange rate shocks, $\tilde{\Delta}R_d$. The shares are province- o “exposure weights”, ω_{do0} , for each destination.

Our identification assumption is therefore that the exchange rate shocks $\tilde{\Delta}R_d$ are as good as randomly assigned (conditional on destination- d -level controls). The exposure weights (shares) ω_{do0} can actually be endogenous.¹⁷ An example of

¹⁶Following Borusyak et al. (2022), it is essential to interact the sum of exposure weights (which they call “sum of exposure shares”) $MigInc_{o0}$ 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 $MigInc_{o0}$.

¹⁷In the Goldsmith-Pinkham et al. (2020) approach, the shares must be considered exogenous.

a failure of this assumption would be if a destination’s exchange rate shock were correlated with the characteristics of Filipino migrant workers in the destination. For example, it would be a worry if baseline (pre-shock) migrant wages or education levels in a destination were associated with the destination’s exchange rate shock.¹⁸ Our estimate of β_1 in equation (3) could then be biased by any ongoing trends related to migrants’ baseline characteristics.

Define the destination- d exchange rate shock immediately after the crisis as $\tilde{\Delta}R_d = \frac{R_{d,1998} - R_{d,1996}}{R_{d,1996}}$. $R_{d,1996}$ is the destination- d exchange rate (nominal Philippine pesos per destination- d currency unit) in the pre-period (twelve months leading up to June 1997), while $R_{d,1998}$ is the destination- d exchange rate in the immediate post-Crisis period (twelve months through October 1998). The exchange rate shock is thus a fractional change (e.g., a 10% appreciation is 0.1).

All components of the shift-share variable (equation (1)) are from the pre-shock period, except for the post-shock exchange rate $R_{d,1998}$. Identification derives from the change in the destination- d exchange rate relative to its pre-shock level, $R_{d,1996}$.

It is plausible *a priori* that the exchange rate shocks are exogenous. The Asian Financial Crisis was unanticipated by global policy-makers and governments (Radelet and Sachs, 1998), so our estimates are unlikely to be clouded by anticipation of the shocks by households, firms, or officials in Philippine provinces (i.e., there are plausibly no effects of being treated in the future on outcomes in the pre-treatment period). While the real effects of the Crisis were short-lived (Park and Lee (2002) describes the “speedy V-shaped recovery”), the changes in exchange rates were persistent.

Our shift-share variable exploits the fact that the Asian Financial Crisis was a surprise, using only the short-run (1997-1998) change in exchange rates immediately post-Crisis. We do not exploit further (post-1998) changes in exchange rates for identification. The short-run Crisis-induced exchange rate shocks are most plausibly exogenous. In the longer run, by contrast, the evolution of exchange rates may be endogenous to destination-country economic policies.

As it turns out, there is strong persistence of the short-run (1997-1998) exchange rate shocks over our entire two-decade study period. Destination- d 1997-1998 exchange rate shocks have strong predictive power for the long-run exchange

¹⁸Time trends in key outcomes such as migrant wages or employment may differ by baseline (pre-shock) values of the outcomes, for example if there are different growth rates across industries with different skill-intensities in production.

rate up to 2018. We show this empirically in Subsection 4.4 below. By focusing on a shift-share variable defined with only the short-run 1997-1998 shocks, we estimate a reduced-form effect that includes any long-run exchange rate movements that are correlated with the short-run 1997-1998 exchange rate shocks, but that are not endogenous to subsequent destination-level economic policies.

Since exogenous variation in this framework derives from the shifters (Borusyak et al., 2022), we statistically show balance in these destination-specific exchange rate shocks. We run regressions at the level of all 104 migrant destinations. The dependent variable is the exchange rate shock, $\tilde{\Delta}R_d$, and the independent variables are pre-shock destination- d characteristics.¹⁹

The destination characteristics we examine are all pre-shock (1995). GDP per capita accounts for destination development status. Other independent variables are aspects of the destination’s Philippine migrant flow. We account for the skill level of migrants going to particular destinations by, first, examining mean annual income per Philippine migrant in the destination. Second, we examine 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). We omit the lowest-skilled occupation group, services. In addition, we examine 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. We also test the predictability of the exchange rate shocks with a sixth independent variable, the pre-shock (1994-1996) change in the exchange rate.²⁰ In a final regression we include all six independent variables.

Regression results in Appendix Table A1 show no statistically significant relationships between pre-shock destination characteristics and the exchange rate shocks $\tilde{\Delta}R_d$. We reject joint significance of the right-hand-side variables in Column 7. These results provide support for the assumption that destination- d exchange rate shock can be considered as-good-as-randomly assigned.

While $\tilde{\Delta}R_d$ is balanced *vis-a-vis* these destination-level variables, inclusion of these controls can improve precision of estimates by absorbing residual variation.

¹⁹Following Borusyak et al. (2022), observations in these regressions are weighted by the destination’s average exposure weight ω_{d00} across provinces.

²⁰Table 1 shows the change in the exchange rate in the pre-crisis period (1994-1996) alongside the change in the post-crisis period (1997-1998) for the top 20 destinations.

We therefore include these destination-level variables (interacted with the post-shock-period indicator) in the vector of controls \mathbf{X}_{o0} in equation (3) (aggregated to the province level using exposure weights ω_{do0} , following [Borusyak et al. \(2022\)](#)).

4.2.2 Exogeneity of Shift-Share Variable

Exogeneity of the exchange rate shocks should lead to exogeneity of our shift-share variable, $Shiftshare_o$. Concerns about causal identification arise if $Shiftshare_o$ is correlated with baseline (pre-shock) provincial characteristics (conditional on other right-hand-side variables in the regression). For example, provinces with lower baseline development status (income and expenditure per capita, rural share of population, etc.) could be on different time trends than other provinces.²¹ If there are such differential time trends, and $Shiftshare_o$ is correlated with baseline (pre-shock) provincial development status, our estimate of β_1 in equation (3) would be biased. Thus it is important to control for potential differential time trends related to baseline development status of provinces.

As equation (2) shows, $Shiftshare_o$ can be written as the product of two terms. $MigInc_{o0}$ is migrant income per capita in province o in the pre-shock period. $Rshock_o$ is the province- o weighted average exchange rate shock. Table 2 shows $MigInc_{o0}$ has mean PhP 4,044 (standard deviation 2,984), while $Rshock_o$'s mean is 0.415 (standard deviation 0.040).

We take only $Shiftshare_o$ to be exogenous, not its component factors $MigInc_{o0}$ and $Rshock_o$. In regression equation (3), we achieve this by interacting $MigInc_{o0}$ and $Rshock_o$ with period fixed effects, which accounts for any changes over time that are correlated with these variables. Identification therefore comes only from $Shiftshare_o \times Post_t$.

It is important to *not* exploit variation in $MigInc_{o0}$ by itself for identification. The worry is that provinces with different levels of $MigInc_{o0}$ may differ on a host of other dimensions, and thus may be on different time trends from the pre- to post-shock period. In the [Borusyak et al. \(2022\)](#) framework, the fact that $MigInc_{o0}$ varies across provinces makes ours an “incomplete shares” setting. We do not take the shares as exogenous. Controlling for time trends associated with $MigInc_{o0}$

²¹Initially-poorer provinces could be the beneficiaries of national government programs to improve education, promote small enterprises, improve infrastructure, etc., leading them to have more-positive time trends in development outcomes over our study period. The time trend could go in the opposite way, for example if agglomeration economies lead to higher growth rates in initially-richer provinces compared to initially-poorer ones.

Table 2: 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
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
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
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								
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 panel. For bottom panel, 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. Expenditure, total income, 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 and total income 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 (periods are 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. 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. Service sector excludes financial services (examined separately). Per capita GDP is from the World Development Indicators, in thousands of 1995 USD. Destination level contract controls are calculated from POEA/OWWA dataset.

(the “sum of exposure shares”) is therefore necessary. In our panel regression, this involves controlling for $MigInc_{o0}$ interacted with period indicators.

The concern with exploiting variation in $MigInc_{o0}$ for identification becomes apparent when examining its correlation with pre-shock province covariates. We regress a set of provincial pre-shock development measures on $MigInc_{o0}$. Results are in Appendix Table A2, Panel A. Provinces with higher $MigInc_{o0}$ are more developed along all dimensions: they have lower rural share, and higher asset indices, domestic income per capita, expenditure per capita, and shares of employment in industry, services, and financial sectors.

A similar concern applies to identifying off variation in $Rshock_o$, because it is also imbalanced with respect to pre-shock province characteristics. In Appendix Table A2, Panel B, we examine the correlation of $Rshock_o$ with pre-shock province covariates. Provinces with higher $Rshock_o$ appear less developed: they have higher share of rural households, and lower asset indices, domestic income per capita, expenditure per capita, and shares of employment in the modern (non-primary) sectors. These patterns raise concerns that ongoing trends in development outcomes may be correlated with $Rshock_o$. Therefore we do not identify causal effects off variation in $Rshock_o$.

By contrast, the shift-share variable $Shiftshare_o$ is uncorrelated with pre-shock province characteristics, once $MigInc_{o0}$ and $Rshock_o$ are controlled for. This is apparent in Appendix Table A2, Panel C. There is no statistically significant relationship between $Shiftshare_o$ and pre-shock measures of provincial development. These results bolster confidence in the exogeneity of $Shiftshare_o$ (after conditioning on $MigInc_{o0}$ and $Rshock_o$).

Because we only consider $Shiftshare_o$ exogenous when conditioning on $MigInc_{o0}$ and $Rshock_o$, we report in Table 2 the residualized $Shiftshare_o$ after partialling-out $MigInc_{o0}$ and $Rshock_o$. It has a mean of 0 and a standard deviation of 0.093. We will use this standard deviation of 0.093 in all discussions of magnitudes of effects below.

Figure 1 displays the spatial distribution of residualized $Shiftshare_o$ across provinces. The shock appears to be evenly distributed across the Philippines. All regions contain provinces with a range of shock values.

The pre-shock province-level characteristics examined in Appendix Table A2 are also included in the control vector \mathbf{X}_{o0} of regression equation (3). These con-

trols capture changes over time that may be related to provincial pre-shock development. Inclusion of these controls can help improve precision by absorbing residual variation.

4.2.3 Falsification Tests

Following [Borusyak et al. \(2022\)](#), we conduct a variety of falsification tests of the key assumption that the destination- d -level exchange rate shocks $\tilde{\Delta}R_d$ are as-good-as-random. Above, we showed that $\tilde{\Delta}R_d$ is uncorrelated with a variety of pre-shock destination characteristics (Section [4.2.1](#)), and that the resulting shift-share variable $Shiftshare_o$ is conditionally uncorrelated with a set of pre-shock province characteristics (Section [4.2.2](#)).

In addition, [Borusyak et al. \(2022\)](#) also recommend conducting “pre-trend” analyses, testing whether changes in the outcome variable in the pre-shock period are correlated with the future value of shift-share variable. This is analogous to tests of parallel trends in difference-in-difference research designs. We present these in Section [5](#) (Appendix Table [A3](#)) below. We find no evidence of that changes in any of our primary or secondary outcome variables in the pre-shock period are correlated with (future) $Shiftshare_o$. We also show event-study graphs of lead and lag coefficients of $Shiftshare_o$, building on regression equation [\(3\)](#) (Figure [3](#) and Appendix Figure [A8](#)). These figures confirm the conclusion that pre-trends are uncorrelated with the future value of the shift-share variable.

4.3 Additional Threats to Identification

We account for additional potential threats to identification. We rule out the possibility that the causal effects of the shift-share variable operate via changes in exports or FDI. These analyses, presented in Subsection [5.3](#) below, show that exports and FDI do not respond to the shocks of interest, and so do not appear to be mechanisms driving our findings.

We also address the possibility of confounding changes in population composition. We examine the relationship between $Shiftshare_o$ and internal migration rates. Results are in Appendix Table [A4](#). We find no large or statistically significant impact on net internal migration. There is a small negative effect on outmigration, driven by young adults (aged 16-24), that cannot account for the

impacts we document in our analyses. Changes in population composition due to internal migration appear to be a minor concern.

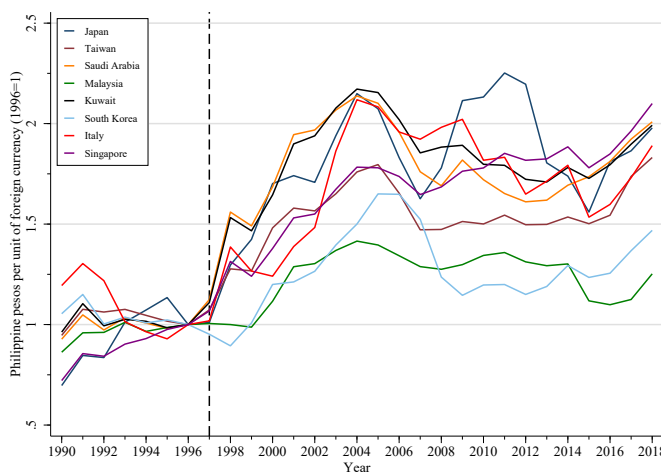
4.4 Persistence of Shock

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.

We examine whether the shift-share variable’s components – in equation (1), the exchange rate shocks $\tilde{\Delta}R_d$ (the “shifts”) and the exposure weights ω_{do0} (the “shares”) – show persistence over two decades post-1997. If both these components of the shift-share variable show persistence in the long run, the shock to migrant income would also be persistent.

We first examine persistence of the exchange rate shocks. Figure 2 shows nominal exchange rates (foreign currency units per PhP, normalized to 1 in 1996) for eight major Philippine migrant destinations. The year of the Asian Financial Crisis, 1997, is denoted by the vertical dashed line. The 1997 exchange rate shocks appear persistent, showing no apparent reversion to pre-shock levels.

Figure 2: Exchange Rate Shocks Due to 1997 Asian Financial Crisis



Notes: Data are from World Development Indicators. Annual average nominal exchange rates are 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 Asian Financial Crisis).

Regression analyses confirm this conclusion. 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, $\tilde{\Delta}R_d$.²² 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 1.²³

Next, we analyze 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).

In our theoretical framework, persistence in exposure weights ω_{dot} can stem from persistent dyad-specific migration costs, τ_{dot} , in equation A5. While migrants adjust their post-1997 migration destinations in response to exchange rate changes, adjustment is only partial, due to networks facilitating migration (Munshi (2003), Kleemans and Magruder (2019), Mahajan and Yang (2020)), and (relatedly) information frictions 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

²²Observations are weighted by 1995 migrant income to that destination, following Borusyak et al. (2022) for any destination-level regressions.

²³As 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.

variable $Shiftshare_o$) that exhibits substantial persistence over time.

5 Empirical Results

We estimate impacts of the shift-share shock (β_1 in Equation (3)) 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. We calculate these province-level outcomes from the FIES survey microdata.

“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.²⁴) 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.

The data are a panel of provinces observed every three years. There are four pre-shock observations (1985, 1988, 1991, and 1994) and seven post-shock observations (2000, 2003, 2006, 2009, 2012, 2015, and 2018) for each province. The 1997

²⁴By excluding international income sources from “domestic income”, we are also excluding migrant remittances (which are not explicitly reported in the data; they are included in “overseas income”). There are concerns that migrant remittances are considerably under-reported in the FIES, because of the rise in electronic banking. Particularly since 2000, international migrants have been increasingly depositing their earnings directly into origin-household bank accounts. Comparison of remittance data from the World Bank, Philippine Central Bank, and the FIES suggests that households responding to the FIES may not consider funds deposited electronically into their bank accounts from overseas as remittances (Ducanes, 2010).

observation is excluded because it is partially treated (the Asian Financial Crisis occurred in July 1997).

Table 3: 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
<i>Panel A. Destination controls only</i>						
<i>Shiftshare_o × Post</i>	12.972 (5.852)**	10.526 (4.045)***	28.101 (5.131)***	23.817 (4.122)***	4.284 (1.916)**	18.056 (4.626)***
<i>Panel B. Additional province development status controls</i>						
<i>Shiftshare_o × Post</i>	12.928 (8.833)	12.603 (4.993)**	24.698 (7.926)***	19.082 (6.423)***	5.616 (2.453)**	14.265 (3.203)***
<i>Panel C. Additional province industrial structure controls</i>						
<i>Shiftshare_o × Post</i>	14.490 (7.394)*	13.159 (4.726)***	24.463 (7.546)***	18.905 (5.982)***	5.558 (2.593)**	14.102 (3.473)***
Obs.	813	813	296	296	296	296
Dep. Var. Mean	29.885	28.975	35.305	30.699	4.606	30.181
Dep. Var. St. Dev.	10.908	10.505	12.468	10.618	2.924	10.623

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. Destination 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. From 1990 Census: share of households that are rural, and household asset index. Average across 1988/1991/1994 FIES: total income per capita, and expenditure per capita. Province industrial structure pre-shock controls are as follows. From 1990 Census: 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. All regressions include province and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions ([Borusyak et al., 2022](#)). *** p<0.01, ** p<0.05, * p<0.10.

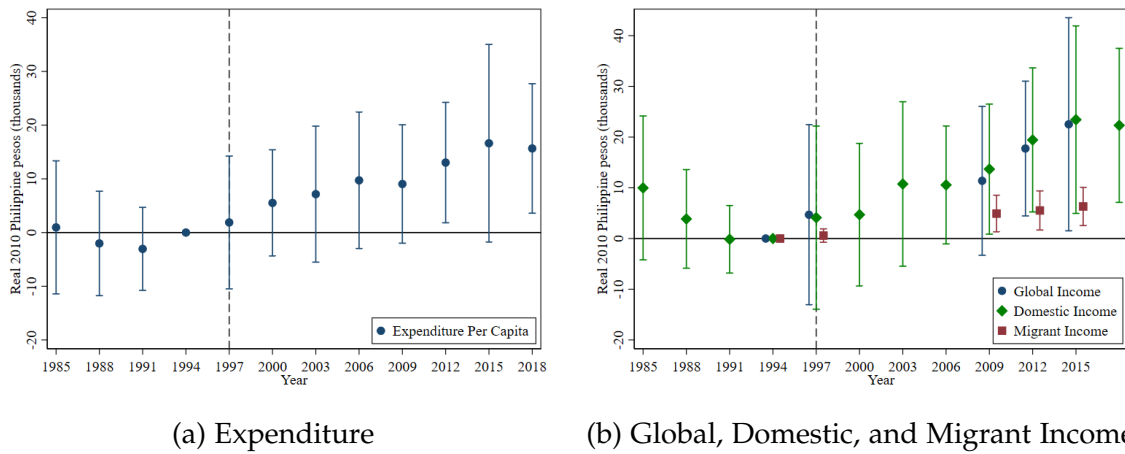
Results are in Table 3, columns 1-2. Each cell displays the coefficient β_1 on $Shiftshare_o \times Post_t$. We present estimates from regressions with different sets of pre-shock controls interacted with $Post_t$: destination controls only (Panel A), with additional province development status controls (Panel B), and with additional province industrial structure controls (Panel C). All regression results tables will have this structure.

The shock has positive and statistically significant effects on both domestic income and expenditure per capita. Coefficient estimates in the domestic income

regressions are stable across panels, and in Panel C the coefficient is statistically significantly different from zero at the 10% level. Coefficients in the expenditure regressions (column 2) are also stable across panels, and in Panel C the coefficient is statistically significantly different from zero at the 1% level.

The effects are large in magnitude. A one-standard-deviation shock (0.09) increases domestic income per capita by PhP1,348, and expenditure per capita by PhP1,224 (0.12 standard deviation in each case).

Figure 3: Event Studies for Expenditure and Income per Capita



Note: Regressions modify Equation (3) 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 3, Panel C (including province fixed effects, year fixed effects, and controls for differential trends with respect to pre-shock province and destination characteristics). 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 3, we now include partially-treated year 1997 in the sample. 95% confidence intervals shown. Standard errors are clustered at the province level.

We also present event study diagrams illustrating dynamics of impacts, and testing for pre-trends. We estimate a modified Equation (3) in which we include the partially-treated year 1997 in the sample, and interact $Shiftshare_o$ 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 3a for expenditure and Figure 3b 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 slight negative trend from 1985-1991

and no trend in 1991-1994. There is also no large or statistically significant effect in 1997 for either outcome. For both outcomes, coefficients are positive and become larger over time after 1997. This increase in the magnitude of coefficients in the post-shock period is consistent with increases in domestic income per capita resulting from gradual accumulation of human and physical capital over time.

We statistically confirm the absence of pre-trends with “placebo” regressions using the specification of equation (3), but for data in the pre-period (1985-1997 inclusive). We replace the indicator for the post-period, $Post_t$, with an indicator for a placebo post-period, 1994 and 1997. The years 1985, 1988, and 1991 are the placebo pre-period. Results are in the top panel of Appendix Table A3, columns 1 and 2. The coefficients on $Shiftshare_o \times Post_t$ are small in magnitude and none are statistically significantly different from zero. These regressions confirm that there are no differential pre-trends.

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.

Due to data constraints (see Section 3), we can only examine migrant and global income over five triennial periods: one pre-shock period (1994), one “partially-treated” period (1997), and three post-shock periods (2009, 2012, and 2015). In regression analyses we exclude 1997, but include it in event-study analyses.

Regression results for global, domestic, and migrant income per capita are in columns 3-5 of Table 3. Within each Panel, the coefficient in column 3 is mechanically 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, and C.

Impacts are large in magnitude. The coefficient estimate in column 3, Panel C indicates that each one-standard-deviation shock increases global income per capita by 2,275 pesos (24,463 pesos \times 0.093) in 2009-2015 (0.18 standard deviation). Corresponding effect sizes for domestic income and migrant income per capita

are 1,758 and 517 pesos, or 0.17 and 0.18 standard deviations respectively.

The coefficient estimate on migrant income (5.558) indicates that the initial shock to migrant income is substantially magnified over time: for each unit migrant income per capita shock (measured by our shift-share variable), migrant income per capita is over five times higher a decade later. We will turn shortly to the mechanisms behind this substantial 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 3b shows event study diagrams for migrant and global income per capita (along with domestic income results discussed above). There are no apparent pre-trends in the short 1994-1997 pre-shock period. The effects are positive in the 2009-2015 post-periods; point estimates are stable for migrant income, while global income point estimates are increasing. We also provide tests of the statistical significance of pre-trends in the bottom panel of Appendix Table A3, columns 1 and 2. Pre-trend coefficients are small in magnitude and are not statistically significantly different from zero, confirming the absence of pre-trends.

5.3 Ruling Out Exports and FDI as Mechanisms

An important interpretive question is whether the coefficient β_1 solely reflects changes in (current and potential) migrant income. Here we examine other potential mechanisms: exports and foreign direct investment (FDI). We test directly whether these other international flows are affected by the same shocks.

We first consider the value of manufactured exports per capita. We construct this outcome variable at the province-year level by aggregating firm survey microdata.²⁵ We estimate regression equation (3) where the dependent variable is in levels (PhP) and in inverse hyperbolic sine (IHS) transformation. We examine samples including all years (columns 1-2), as well as a restricted set of periods for “long run” results (1994-1996 vs. 2009-2015, columns 3-4). Results are in Ap-

²⁵These data are available in years 1994, 1996, 1998, 1999, 2006, 2009, 2010, 2012, 2013, 2014, and 2015. For further detail, see Appendix Section A.7.

pendix Table A5. In no regression is there a large or statistically significant impact on manufactured exports.

It is also of interest to examine agricultural exports, but no corresponding data exists for this outcome. We therefore examine agricultural income per capita, which should encompass any increase in agricultural exports. In Appendix Table A6 we present regression estimates of equation (3) where the dependent variables are agricultural income per capita at the province-year level, in total as well as split into wage and non-wage (own production) income. We also show the impact on non-agricultural domestic income per capita for comparison. These outcomes come directly from the FIES data. The first four columns show results for the full set of triennial periods from 1985-2018, and the last four the periods for “long-run” results (1994 vs. 2009, 2012, and 2015).

The results in columns 1-3 and 5-7 reveal that there is no large or statistically significant impact on agricultural income (total, wage, and non-wage).²⁶ The impact of the shift-share shock on domestic income per capita appears to be entirely driven by the impact on non-agricultural income (columns 4 and 8). These results indicate that increases in agricultural export income (a subset of agricultural income) are unlikely to be driving the effects on domestic income.

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 regressions analogous to Appendix Table A1 (the tests for relationships between pre-shock overseas-destination characteristics and the exchange rate shocks), but this time in a panel context where the outcome variable is annual FDI flows to the Philippines from a particular country in a given year.²⁷

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, columns 1-2), the “long run” (comparing 1996 with 2009-2015, columns 3-4), as well as robustness to controls for overseas country characteristics (the same included in Table 3) in Panels A and B. Observations are weighted by the destination’s aver-

²⁶The standard deviation of the shift-share variable is 0.093. The coefficients in both Appendix Tables A5 and A6 indicate that such a shock would have very small effects relative to the sample mean or standard deviation of either manufactured exports or agricultural income per capita.

²⁷These data are from the Philippine Statistics Authority. For further detail, see Appendix Section A.7.

age exposure weight ω_{do0} across provinces, following [Borusyak et al. \(2022\)](#). This analysis tests 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 very unlikely that FDI flows to specific provinces are related to the shift-share shock. Results in Appendix Table [A7](#) indeed show no large or statistically significant relationship between FDI flows and the exchange rate shocks.²⁸

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

5.4 Mechanisms

We now examine potential mechanisms through which these substantial increases in income take place. We examine educational investments, migrant skill levels and occupations, and domestic wage and entrepreneurial income.

5.4.1 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 population at large.²⁹

In Table [4](#) we present results from estimating regression equation [\(3\)](#) 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 0.67 percentage points higher secondary comple-

²⁸The standard deviation of the exchange rate shock, $\bar{\Delta}R_d$, is 0.040. Appendix Table [A7](#)'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.

²⁹Positive 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, 2019](#); [Khanna and Morales, 2019](#); [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](#)).

Table 4: Effects of Migrant Income Shock on Education

	Share Completed:		
	(1)	(2)	(3)
	Primary School	Secondary School	College
<i>Panel A. Destination controls only</i>			
$Shiftshare_o \times Post$	-0.002 (0.046)	0.092 (0.039)**	0.027 (0.030)
<i>Panel B. Additional province development status controls</i>			
$Shiftshare_o \times Post$	0.013 (0.036)	0.077 (0.042)*	0.059 (0.028)**
<i>Panel C. Additional province industrial structure controls</i>			
$Shiftshare_o \times Post$	0.015 (0.032)	0.073 (0.031)**	0.054 (0.019)***
Obs.	444	444	444
Dep. Var. Mean	0.789	0.486	0.133
Dep. Var. St. Dev.	0.114	0.146	0.046

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 3. All regressions include province and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions (Borusyak et al., 2022). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

tion, and 0.50 percentage points higher college completion. Point estimates in those regressions are relatively stable across sets of controls and statistically significantly different from zero at the 5% and 1% levels, respectively, in Panel C.³⁰

These educational responses to the shock are plausible in magnitude. We gauge magnitude plausibility by examining the extent to which the increases in education we document are associated with increases in household income, since loosened financing constraints are likely a key reason behind the increase in education. Our regression results, comparing Panel C of Table 3 (col 3) with Table 4 (column 3) indicate that about 4,530 pesos higher global income is associated with 0.01 higher college completion.³¹

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

³⁰Falsification tests in Appendix Table A3 (middle panel, columns 1-3) and event-study graphs of lead and lag coefficients of $Shiftshare_o$ in Appendix Figure A8, subfigure (b), confirm the absence of pre-trends for these education outcomes.

³¹Note 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.

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 slightly smaller: 4,530 PhP is “needed” to generate the same increase in college completion.

5.4.2 Migrant Skills and Occupations

The increase in education in the population may also raise migrant workers’ skill levels. We first examine whether the shocks to migrant income have a causal impact on the share of migrants who are skilled, defined as having at least college (14 years) education. This outcome is available for international migrants in the Philippine Census. Periods included in the regression are the Census years 1990, 1995, 2000, 2007, 2010, and 2015.

In column 1 of Table 5, we report results from estimating equation (3) where the dependent variable is the share of international migrants who are skilled. There is a substantial positive effect that is stable across panels with different sets of controls. The coefficient in Panel C is statistically significantly different from zero at the 1% level. A one-standard-deviation higher shock leads to 1.8 percentage points higher share of migrants who are skilled (0.13 standard deviations).³²

Is this increase in migrant educational levels associated with working in higher-skilled jobs? We examine impacts on the propensity to enter skilled international migrant work. These analyses require the migrant contract data, so the periods included in the regression are 1994, 2009, 2012, and 2015 (as in Table 3, columns 3-6). The dependent variable is migrant contracts per 10,000 working age (age 20-64) population.

We estimate equation (3) for migrant contracts in four quartiles of occupations, ordered from lowest (1st quartile) to highest (4th quartile) education levels.³³ Results are in columns 2-5 of Table 5. There are positive effects on new international

³²For this outcome, there is no evidence of pre-trends in Appendix Table A3 (middle panel, column 4) or in Appendix Figure A8, subfigure (c).

³³The 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. Years of education data refer to 1992-1996 (pre-shock) contracts. The contract data do not include migrant worker education, so 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. Quartiles are somewhat uneven in size due to lumpiness in the distribution of contracts across occupations.

Table 5: Effects of Migrant Income Shock on Contract Types and Migrant Skill

	Census	Contracts per 10,000 Working Age People			
	(1)	(2)	(3)	(4)	(5)
	Share Skilled Migrants	1st Quartile Education	2nd Quartile Education	3rd Quartile Education	4th Quartile Education
<i>Panel A. Destination controls only</i>					
$Shiftshare_o \times Post$	0.165 (0.052)***	16.546 (65.065)	3.249 (7.237)	64.683 (26.474)**	57.422 (15.382)***
<i>Panel B. Additional province development status controls</i>					
$Shiftshare_o \times Post$	0.210 (0.061)***	5.968 (72.066)	-0.509 (8.414)	55.807 (26.280)**	28.393 (17.146)*
<i>Panel C. Additional province industrial structure controls</i>					
$Shiftshare_o \times Post$	0.196 (0.059)***	1.044 (73.254)	-1.567 (8.873)	46.026 (21.630)**	19.841 (18.730)
Obs.	444	296	296	296	296
Dep. Var. Mean	0.338	94.191	8.694	24.690	43.096
Dep. Var. St. Dev.	0.135	71.725	6.616	19.297	32.762

Note: Unit of observation is the province-year. 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 variables in columns 2-5 are migrant contracts (per 10,000 working age population) in occupations in the 1st (lowest) through 4th (highest) quartiles of migrant years of education. For list of destination and provincial controls, see Table 3. All regressions include province and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions (Borusyak et al., 2022). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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 C for the 3rd (second to highest) quartile, while that on the 4th (top) quartile is also positive but not significantly different from zero.³⁴

In sum, migrant income shocks increase the share of migrant workers who are skilled (have college or more education), as well as migrant flows in higher-education occupations. These effects are likely to be mechanisms leading to the substantial gains in income over the long run.

³⁴For these outcomes, we examine pre-trends in Appendix Table A3 (bottom panel, columns 3-6) and in Appendix Figure A8, subfigure (d). None of the coefficients in the pre-trend regressions are statistically significantly different from zero. The coefficient for the 1st (lowest-education) quartile is large in magnitude, suggestive of a differential positive pre-trend for that outcome (but note we report no effect on that outcome in Table 5). For the more-skilled (3rd and 4th) quartiles, the coefficients in the pre-trend tests are not negligible, amounting to about two-thirds the magnitude of the corresponding coefficients in Table 5. Overall, we view these tests as providing modest (but not overwhelming) support for the absence of pre-trends for these outcomes representing migration in high-skilled occupations.

5.4.3 Entrepreneurial, Wage, and Other Domestic Income Sources

We now examine impacts on sub-types of domestic income. Table 6 presents regression results from estimating Equation (3) 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, wholesale/retail, transportation services, and rental of land/property). Other income includes pensions, interest, dividends, and other sources.

Table 6: Effects of Migrant Income Shock on Components of Domestic Income

	Domestic Income Components:		
	(1)	(2)	(3)
	Wage Income	Entrepreneurial and Rental Income	Other Income
<i>Panel A. Destination controls only</i>			
$Shiftshare_o \times Post$	10.022 (3.081)***	9.741 (1.295)***	4.054 (2.122)*
<i>Panel B. Additional province development status controls</i>			
$Shiftshare_o \times Post$	9.853 (4.507)**	8.289 (1.991)***	0.940 (1.954)
<i>Panel C. Additional province industrial structure controls</i>			
$Shiftshare_o \times Post$	9.733 (3.690)***	7.881 (1.487)***	1.291 (2.160)
Obs.	296	296	296
Dep. Var. Mean	15.110	10.155	5.434
Dep. Var. St. Dev.	7.779	3.311	2.414

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 3. All regressions include province and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions (Borusyak et al., 2022). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

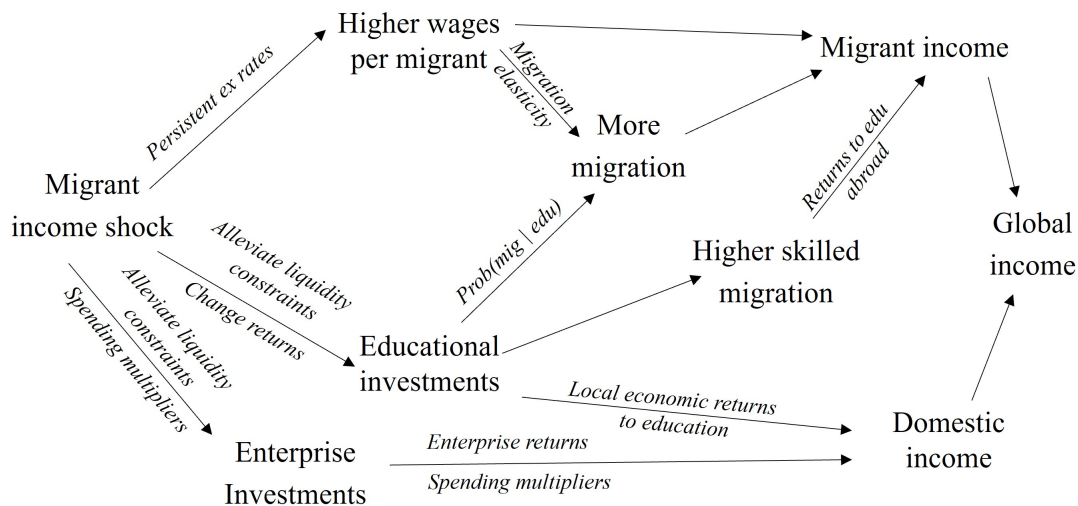
The shock led to increases in both wage income as well as entrepreneurial and rental income. Coefficient estimates for both these outcomes are robust to the set of controls. They are statistically significantly different from zero at conventional levels in Panel C, and similar to one another in magnitude. 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 are likely to reflect higher levels of education in the population, as well as increased capital investment in enterprises (both within and outside the

household). We explore this further in Section 6 below.

6 Model-Based Quantification and Discussion of Magnitudes

We now provide further insight into mechanisms and magnitudes of the results thus far. First, we outline a theoretical framework to shed additional light on the long-run effects on global income and its components, migrant and domestic income. We take a simple model-based approach to quantifying the contribution of educational investments to the long-run 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. In addition, the model allows us to shed light on 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 B contains the full details, derivations and calculations underlying the model. It also presents validation tests that show our simple and tractable framework does a good job of predicting changes in migration rates and various sources of income.

Figure 4: Stylized Overview of Possible Channels



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

In Figure 4 we present a stylized diagram to describe the various channels in the model through which the migrant income shock may affect global income.

The persistent migrant income shock drives higher wages per migrant; which in turn may lead to more migration and migrant income. The initial shock may also be invested in education, which may lead 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 drive increases in domestic earnings back home. If this overall high persistent migrant income is invested in domestic enterprises or drives local consumption spending demand, it may also raise domestic earnings. We provide full details of the model in Appendix Section B.

6.1 Contribution of the Education Channel

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

The college completion regression in Table 4 provides the estimate of the educational investment response to the shock. To estimate 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 (0.054) in Panel C, column 3 of Table 4 to estimate the change in the province's population share skilled. Then we estimate how migration (to different destinations, as well as remaining at origin) would change in response to the change in the population skill composition, presuming the same dyadic migration probabilities by skill (the probability someone with skill s migrates from origin o to destination d) from the pre-shock period (1995). That is, to estimate the changes in migration flows to the various destinations, we first take the difference between skill groups in the baseline proclivity to migrate to various destinations, and multiply this difference by the change in the share skilled.

Then, we calculate how both migrant and domestic income would change in response to such migration changes, presuming 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 us with estimates of the change in migrant and domestic income per capita due to the education channel. We estimate that the education channel explains 24.4% of the increase in migrant income, and 22.8% of the increase in domestic income. Global income is the sum of migrant and domestic income; the implied share of global income explained by increased education is 23.2%. In sum, the increases in education induced by the exogenous increase in migrant income account for roughly one-fourth of long-run income gains.

6.2 Explaining Impact on Migrant Income

We also use the model to explain the large increase in migrant income, relative to the initial migrant income shock measured by the shift-share variable (the coefficient estimate of 5.558 in Table 3's migrant income regression). As discussed above, 24.4% of the increase in migrant income is explained by increased educational attainment. We seek to explain the remaining three-fourths of the migrant income increase. Additional mechanisms leading to further migrant income gains 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 could change migration decisions, contributing to the eventual changes in long-run migrant income. In our gravity equation, the Fréchet parameter θ 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 B.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.³⁵

We then calculate the change in total migrant income resulting from all dyadic (origin-destination) changes in migration flows, by skill, along with changes in destination exchange rates. We presume that skill-specific migrant wages (in des-

³⁵We account for "indirect resorting": potential migrants simultaneously consider the full set of exchange rate changes in migration decisions, rather than simply choosing between migrating to specific destination- d or remaining at origin. For example, if Japan's exchange rate appreciates, while Malaysia's depreciates, migration to Malaysia will fall, but some individuals deterred from Malaysian migration will migrate to Japan instead of not migrating.

tinuation currency) in each destination are fixed at pre-shock levels, so that changes in migrant income are driven only by exchange rate shocks and changes in migration flows. We estimate that these factors explain an additional 75.5% of the change in migrant income. This is on top of the 24.4% of the increase in migrant income attributed to education investments. The modeled components therefore explain essentially all (99.9%) of the increase in migrant income.

In sum, the model accounts for the entire magnitude of the effect on migrant income. The five-fold magnification of the initial migrant income shock is fully 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 assumptions needed to explain the magnitude of the impact on domestic income per capita. The coefficient on the shift-share variable in the domestic income per capita regression of Table 3, Panel C, column 4 indicates that a PhP 1 migrant income shock leads to a PhP 18.91 increase in long-run domestic income. 22.8% of this increase is attributable to the increases in education investments (see Subsection 6.1). This leaves PhP 14.6 to be explained. We consider two mechanisms that could explain this remainder: 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). 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 3, Panel C indicates that the multiplier would operate on the portion of the 5.558 increase in migrant income per capita that is sent back to origin provinces. Assuming 70% 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 11.28 PhP ($5.558 \times 0.7 \times 2.9$). A simple demand multiplier thus explains 77.2% of the remaining 14.6 PhP.

We now consider an additional contributor to the increase in domestic income: migrant income could alleviate constraints on capital investments. The migrant

income shock was not a one-time windfall, but was sustained and grew over time, and so likely led to a sustained increase in capital accumulation. It is widely recognized that household enterprises and firms face binding constraints on capital investment (Karlan and Morduch, 2010), and that when such constraints are loosened, firms have high rates of return on investment. For example, 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).³⁶ Such returns likely explain part of the increases in wage and entrepreneurial incomes we document in Table 6.

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 in productive enterprises, and in which a demand multiplier also operates. We summarize the framework here; details are in Appendix Section B.7.1.

We trace the dynamics of domestic income per capita following the initial 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 3. 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.³⁷ 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 A7a, 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 $\alpha=0.7$, a PhP 1 initial migrant income shock becomes PhP 16.7 of domestic income by the year 2015. In Appendix Figure A7b, we set $\alpha=0.7$, and vary the initial rate of return on investment and trace the shock-induced domestic income in 2015. Our estimates range from 13.4 for a rate of return of

³⁶Similarly 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).

³⁷We 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)).

0.05, to 20.5 when the rate of return starts at 0.8 (the estimate of [de Mel et al. \(2008\)](#)).

We view this calculation primarily as a sanity check, demonstrating that a set of reasonable assumptions can generate the observed long-run impact on domestic income per capita. The framework does not incorporate all possible channels through which the effect on domestic income may arise. Importantly, we do not model potential escapes from poverty traps, such as those due to investment indivisibilities ([Ghatak, 2015](#); [Balboni et al., 2021](#); [Kaboski et al., 2022](#)). Considering escapes from poverty traps would make it even easier to explain the magnitude of the long-run effect on domestic income.

7 Conclusion

We study the long-run consequences of persistent increases in international migrant income for migrant-origin regions. We find that the vast majority of income gains are from *domestic* (origin-area) sources; gains in international migrant income, while also substantial, account for only a minority of gains. In addition, model-based estimates suggest that about one-fourth 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, as well as regulation to reduce market power of international labor market intermediaries (ensuring migrants retain more of their income gains). They might also include origin-country educational policies that raise population skill levels and make citizens more competitive for international jobs. Destination country policies include increases in legal immigration opportunities, enforcement against undocumented immigrants, and labor market policies that affect immigrants' ability to work legally. Our findings also have relevance for exchange rate policy in developing countries, highlighting that migrant-origin-currency devaluations can have positive long-run effects by raising current migrant income and returns to migration in migrant-sending areas.

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 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, 2018a; Nunn, 2019).

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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' name, date of birth, sex, destination country, date deployed, and home address in the Philippines.

To create a dataset that includes migrant wages, destination, and province of origin, we combine the datasets from POEA and OWWA using fuzzy matching techniques for the years 1992-1997 and 2007-2009. We match the POEA and OWWA data using first name, middle name, last name, date of birth, destination country, sex, and year of departure. We achieve a match rate of 95%. 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.³⁸ All wages are expressed in thousands of real 2010 Philippine pesos. We winsorize the wages at 99% within each destination-occupation category cell.³⁹

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.⁴⁰ We then multiply by the total

³⁸In 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.

³⁹When destination-occupation cells have fewer than 100 observations, we aggregate these cells and winsorize at the occupation level.

⁴⁰For 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 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 regression specification is the same as in Appendix Table [A1](#). 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 3](#)), 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,

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.

etc. from abroad; and dividends from investments abroad. Migrant remittances 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

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.

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 B). 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 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.6 Regression Controls

A.6.1 Destination-Level Controls

Destination-level controls are 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.⁴¹ The baseline destination contract variables are the following four variables from the 1995 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.6.2 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 Exports and Foreign Direct Investment

In Section 5.3, 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

⁴¹For 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 1995). We used the following estimate: $gdppc_{1995}^{currentUS\$} = gdppc_{1995}^{2010US\$} \times \frac{gdppc_{1999}^{currentUS\$}}{gdppc_{1999}^{2010US\$}}$

manufacturing establishments in the sample.⁴² 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.⁴³

B 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.

B.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)

⁴²Data are not released for province-year cells with fewer than three firms, for confidentiality reasons. We impute zeros for these province-year observations.

⁴³The average share of yearly FDI not broken down by country is 6.9%.

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:

$$V_{idost} = w_{dst}\epsilon_{dot}R_{dt}(1 - \tau_{dot})q_{id} \equiv w_{dost}R_{dt}(1 - \tau_{dot})q_{id} \quad A4$$

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 \(2019\)](#).⁴⁴ 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:⁴⁵

$$\pi_{dost} = \frac{(w_{dst}R_{dt}(1 - \tau_{dot})\epsilon_{dot})^\theta}{\sum_k (w_{kst}R_{kt}(1 - \tau_{kot})\epsilon_{kot})^\theta} \quad A5$$

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

B.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 ($s = \{h, u\}$).⁴⁶ 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 locations and skill levels:

$$Y_{ot} = \sum_{s=h,u} \left[\ell_{ost} \sum_d (\pi_{dost} w_{dost} R_{dt}) \right] \quad A6$$

Our shift-share variable isolates exogenous variation in only the migrant income portion of Y_{ot} , due to the 1997 exchange rate shocks. Let $\tilde{\Delta}$ refer to a short-run change. $\tilde{\Delta}R_d$ is the short-run change in destination d exchange rate.⁴⁷

⁴⁴Here, θ is the elasticity of migration with respect to the destination wage. In the standard formulation: $F(q_1, \dots, q_D) = \exp\left\{-\left[\sum_{d=1}^D q_d^{-\theta}\right]\right\}$. 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.

⁴⁵Full derivations are in the Supplementary Appendix of our NBER Working Paper, [Khanna et al. \(2022\)](#).

⁴⁶We micro-found the education decisions in Supplementary Appendix S2 of [Khanna et al. \(2022\)](#).

⁴⁷In practice, we use the short-run 1997-1998 change following the July 1997 crisis to construct the shift-share variable.

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.⁴⁸

$$\tilde{\Delta}Y_o = \sum_{s=h,u} \left[\ell_{os0} \sum_d (\pi_{dos0} w_{dos0} \tilde{\Delta}R_d) \right] \equiv Shiftshare_o \quad A7$$

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 A7:

$$Shiftshare_o = \sum_{s=h,u} \sum_d \frac{L_{os0}}{Pop_{o0}} \frac{L_{dos0}}{L_{os0}} w_{dos0} \tilde{\Delta}R_d = \sum_d (\omega_{do0} \tilde{\Delta}R_d) \quad A8$$

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

B.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 workers h in origin o is:

$$\Delta \ell_{oht} = \frac{1}{\Psi} \Delta Y_o = \frac{1}{\Psi} \sum_{s=h,u} \left[\ell_{os0} \sum_d (\pi_{dos0} w_{dos0} \tilde{\Delta}R_d) \right] = \frac{1}{\Psi} \underbrace{\sum_d \omega_{do0}}_{MigInc_{o0}} \times \underbrace{\frac{\sum_d \omega_{do0} \tilde{\Delta}R_d}{\sum_d \omega_{do0}}}_{Rshock_o}, \quad A9$$

where $\frac{1}{\Psi}$ captures the effect of the migrant income shock on skill share.⁴⁹ The regression result in column 3 of Table 4 is our quantitative estimate of this skill

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. We discuss this further in Subsection 4.2.1.

⁴⁸The origin as a destination drops out as there are no exchange rate changes for the origin.

⁴⁹In 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 for our quantification.

response. Below, we unpack the implications of these changing skill shares.

B.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 Frchet 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 A5 yields the estimating equation:

$$\log \pi_{dost} = \theta \log w_{dst} + \theta \log R_{dt} + \theta \log (1 - \tau_{dot}) - \log \left[\sum_k (w_{kst} R_{kt} (1 - \tau_{kot}) \epsilon_{kot})^\theta \right] + \theta \epsilon_{dot} \quad \text{A10}$$

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.⁵⁰

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

Here, the Δ s 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 A8. We estimate $\theta = 3.42$.

B.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: $\pi_{doht} \ell_{oht} + \pi_{dout} \ell_{out}$. 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:⁵¹

⁵⁰As 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.

⁵¹The 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 A39 shows a version with these indirect effects.

$$\begin{aligned}
\Delta Flows_{ot} = & \underbrace{\Delta \ell_{oht} \sum_{d \neq o} (\pi_{doh0} - \pi_{dou0})}_{\text{Education channel in outflows}} + \underbrace{\theta \sum_{d \neq o} (\ell_{oh0} \pi_{doh0} + \ell_{ou0} \pi_{dou0}) \frac{\Delta R_{dt}}{R_{d0}}}_{\text{Exchange rate channel in outflows}} \quad \text{A11} \\
& - \underbrace{\theta \left(\ell_{oh0} \pi_{ooh0} \frac{\Delta w_{oht}}{w_{oh0}} + \ell_{ou0} \pi_{oou0} \frac{\Delta w_{out}}{w_{ou0}} \right)}_{\text{Domestic income stemming outflows}} - \underbrace{\chi_o}_{\text{Indirect re-sorting}}
\end{aligned}$$

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 $\pi_{doh0} - \pi_{dou0}$. 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 $\ell_{oh0} \pi_{doh0} + \ell_{ou0} \pi_{dou0}$. 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 Equations A9 and A11 to be:

$$\Delta \ell_{oht} \sum_{d \neq o} (\pi_{doh0} - \pi_{dou0}) = \frac{1}{\Psi} \underbrace{\sum_{d \neq o} (\pi_{doh0} - \pi_{dou0})}_{\text{Skill bias in outmigration}} \left(\underbrace{\sum_d \omega_{do0}}_{\text{MigInc}_o} \times \underbrace{\frac{\sum_d \omega_{do0} \tilde{\Delta} R_d}{\sum_d \omega_{do0}}}_{\text{Rshock}_o} \right) \quad \text{A12}$$

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 4, and obtain (b) the skill-differential in migration probabilities $\pi_{doh0} - \pi_{dou0}$ from the raw data. Figure A2a 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 A9. Migration responses to these, in turn, depend on the Frchet parameter θ , estimated in section B.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 A11.

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 A9 in Appendix Figure A3a. 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: $\frac{\Delta \ell_{oht} \sum_d (\pi_{doh0} - \pi_{dou0})}{Flows_{ot}^{OLS}}$. Appendix Figure A3b 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 A10).⁵² 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 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.

B.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.

$$\underbrace{\Delta \ell_{oht} \left(\sum_{d \neq o} w_{doh0} \pi_{doh0} R_{d0} - \sum_{d \neq o} w_{dou0} \pi_{dou0} R_{d0} \right)}_{\text{Education channel in migrant income}} + \underbrace{\theta \left(\sum_{s=h,u} \left[\ell_{os0} \sum_d (\pi_{dos0} w_{dos0} \Delta R_{dt}) \right] \right)}_{\text{Exchange rate channel in migrant income}} - \tilde{\chi}_{o2} \quad \text{A13}$$

Here, we know $\Delta \ell_{ost}$ is a function of the migrant income shock from Equation A9. We define $\beta^{mig} = (\sum_{d \neq o} w_{doh0} \pi_{doh0} R_{d0} - \sum_{d \neq o} w_{dou0} \pi_{dou0} R_{d0})$ as the migrant skill premium. The education channel contribution to the change in income is simply

⁵²Theoretically, the education channel contribution can be negative if the low-skilled have a higher migration probability.

$\frac{\beta^{mig}}{\psi} \tilde{\Delta}Y_o$. Similarly, the exchange rate channel is simply $\theta \tilde{\Delta}Y_o - \tilde{\chi}_{o2}$, 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.⁵³ 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 3 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 4. The second component is the probability-weighted skill-premium abroad β^{mig} . We plot the skill premium $(w_{doh0} - w_{dow0})$ at the origin-destination pair in Figure A2b.⁵⁴

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 A13.

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 3. We plot the relationship between these predicted flows in Figure A4a. As before, we see a strong upward sloping relationship in Figure A4a 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 A4b). We do a similar exercise for the exchange rate channel in migrant income. On average, the education channel explains 24.4% of the increase in migrant income, and the exchange rate channel explains 75.5% (Table A10).⁵⁵

B.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

⁵³As before, the second-order indirect effects of changes in location choice are captured by $\tilde{\chi}_{o2} \equiv \theta \sum_{s=h,u} \sum_d \left[\ell_{ost} w_{dst} \pi_{dost} \left(\sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}} \right) + \pi_{oost} \frac{\Delta w_{ost}}{w_{ost}} \right) \right]$.

⁵⁴Returns 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.

⁵⁵It is not unreasonable for our model to explain a little more than the entirety of the changes, as we use baseline earnings in various destinations that may change for reasons unrelated to the shocks.

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 simple and tractable. While the underlying mechanisms are not modeled, our framework captures the ultimate affect 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:

$$\Delta W_{ot} = \underbrace{\Delta \ell_{oht} \left(\underbrace{w_{oh0}\pi_{ooh0}}_{\text{skilled wage at home}} - \underbrace{w_{ou0}\pi_{oou0}}_{\text{unskilled wage at home}} \right)}_{\text{Education channel in domestic income}} + \underbrace{\sum_{s=h,u} \ell_{os0}\pi_{oos0} (\Delta w_{ost}) - \tilde{\chi}_{o1}}_{\text{Direct wage (and resorting) channel}} \quad \text{A14}$$

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).⁵⁶ 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 B.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, $\Delta w_{ost} \equiv \zeta \left(\frac{\beta^{mig}}{\Psi} + \theta\right) \tilde{\Delta}Y_o$. We empirically estimate the associated regression:

$$\begin{aligned} \Delta W_{ot} &= \underbrace{\sum_{s=h,u} \ell_{os0}\pi_{oos0} \left(\zeta \left(\frac{\beta^{mig}}{\Psi} + \theta \right) \tilde{\Delta}Y_o \right)}_{\text{Direct wage channel}} + \underbrace{\frac{1}{\Psi} \tilde{\Delta}Y_o (w_{oh0}\pi_{ooh0} - w_{ou0}\pi_{oou0})}_{\text{Education channel in domestic income}} \\ &= \left(\zeta \left(\frac{\beta^{mig}}{\Psi} + \theta \right) + \frac{\beta^{dom}}{\Psi} \right) \underbrace{\sum_d \omega_{do0}}_{\text{MigInc}_{o0}} \times \underbrace{\frac{\sum_d \omega_{do0} \tilde{\Delta}R_d}{\sum_d \omega_{do0}}}_{\text{Rshock}_o}, \quad \text{A15} \end{aligned}$$

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 3 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 ed-

⁵⁶The indirect resorting is $\tilde{\chi}_{o1} \equiv \sum_{s=h,u} \ell_{ost}\pi_{oost}w_{ost} \left(\sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}} \right) + \pi_{oost} \frac{\Delta w_{ost}}{w_{ost}} \right) - \sum_{s=h,u} \ell_{ost}\pi_{oost}\theta \Delta w_{ost}$

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 3. We plot the relationship between these predicted flows in Appendix Figure A5a. 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 A9. 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 A14.

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 A5b. We do a similar exercise for the direct wage channel. On average, the education channel explains 22.8% of the increase in domestic income, whereas the direct wage channel explains 60.8% (Table A10). The remaining component is likely driven by other aggregate changes to the income distribution.

B.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 18.95 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 3, Panel C col 4. 22.8% 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 14.6 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 14.6 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 ($m_\infty = 6.3$), and passes through our migrant income coefficient for 2009 ($m_{12} = 4.9$) from the event study ([Figure 3](#)).

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.⁵⁷

Appendix [Figures A7a](#) and [A7b](#) trace out the shock-induced domestic income generated under these assumptions. The remaining 14.6 PhP increase in migrant income per capita is fully explainable, and is well within plausible assumptions. See the main text for discussion.

B.8 Change in Global Income: Predictions and Decomposition

Together, the longer-term change in the global income of individuals is:⁵⁸

$$\left(\frac{\beta^{mig} + \beta^{dom}}{\Psi} + \theta + \zeta \left(\frac{\beta^{mig}}{\Psi} + \theta \right) \right) \Delta Y_o - \tilde{\chi}_o \quad A16$$

There is intuition behind this relationship.⁵⁹ First, higher skill-premia (the β terms) imply that as individuals acquire schooling, incomes (both domestic and 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 3](#). Overall changes in expenditure (column 4 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

⁵⁷The functional forms for the path of migrant income and rate of returns on savings are as follows: $m_t = \frac{6.32t^2 - 1.95t - 0.37}{t^2 + 3t}$ 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.

⁵⁸The derivation for global income is in Supplementary Appendix [S5](#) of our NBER Working Paper, [Khanna et al. \(2022\)](#).

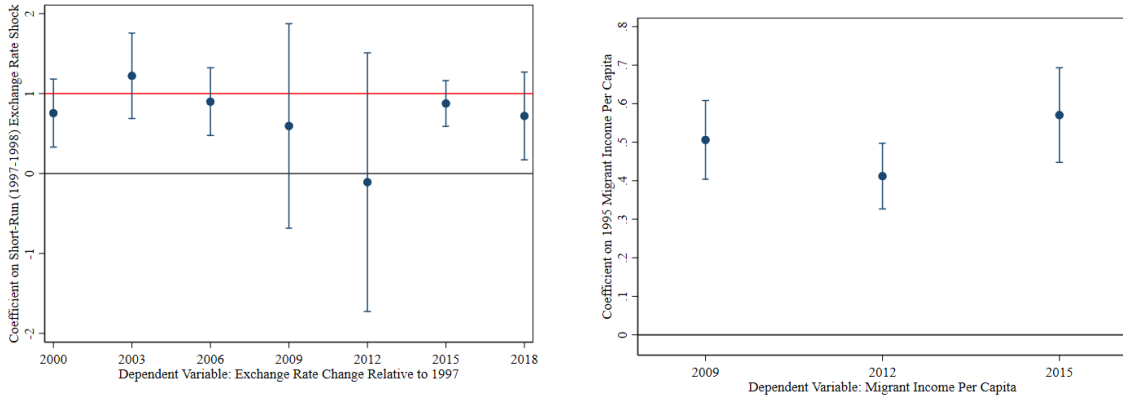
⁵⁹The total indirect effect on global income due to location resorting is $\tilde{\chi}_o \equiv \theta \sum_{s=h,u} \sum_d \left[\ell_{ost} w_{dst} \pi_{dost} \left(\sum_{d \neq o} \left(\pi_{dost} \frac{\Delta R_{dt}}{R_{dt}} \right) + \pi_{oost} \frac{\Delta w_{ost}}{w_{ost}} \right) \right] - \theta \sum_{s=h,u} [\ell_{ost} \pi_{oost} \Delta w_{ost}]$

our reduced form estimates, rationalize the magnitudes, and quantify the contribution of each channel discussed.⁶⁰

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 3 for global income. Appendix Figure A6a 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 A6b plots the distribution of this contribution across provinces. Table A10 shows that the education channel explains 23.2% of the overall increase in global income, while the changes in earnings potential (both at home and abroad) explain 64.2% of the overall increase in global income. Overall, the model explains 87.3% of the increase in global income.

C Additional Tables and Figures

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



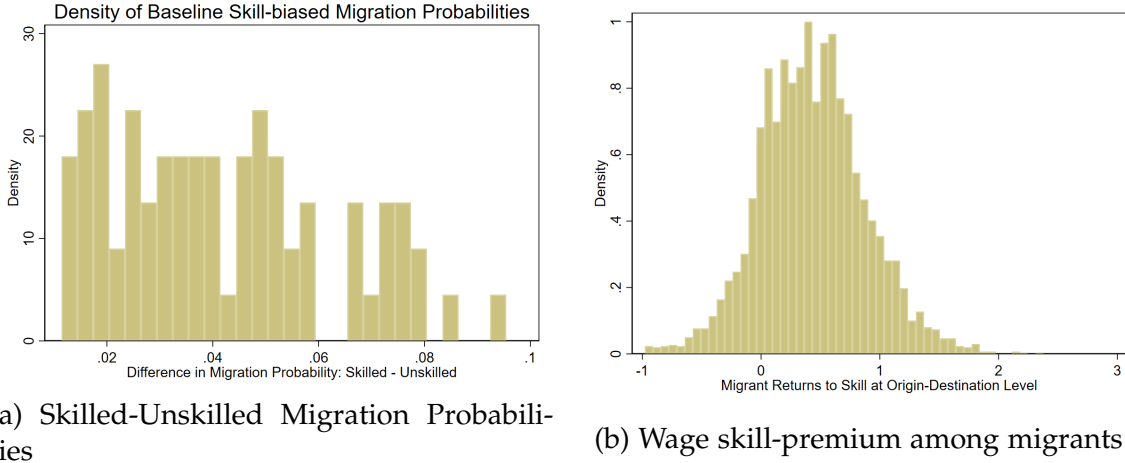
(a) $\hat{\Delta}R_d$ and Future Exchange Rate Changes

(b) Province-Destination Migrant Income

Notes: (a) Coefficient estimates from regressing destination exchange rate changes relative to 1997 for 2000-2018 triennially on $\hat{\Delta}R_d$, 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_{d00} (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.

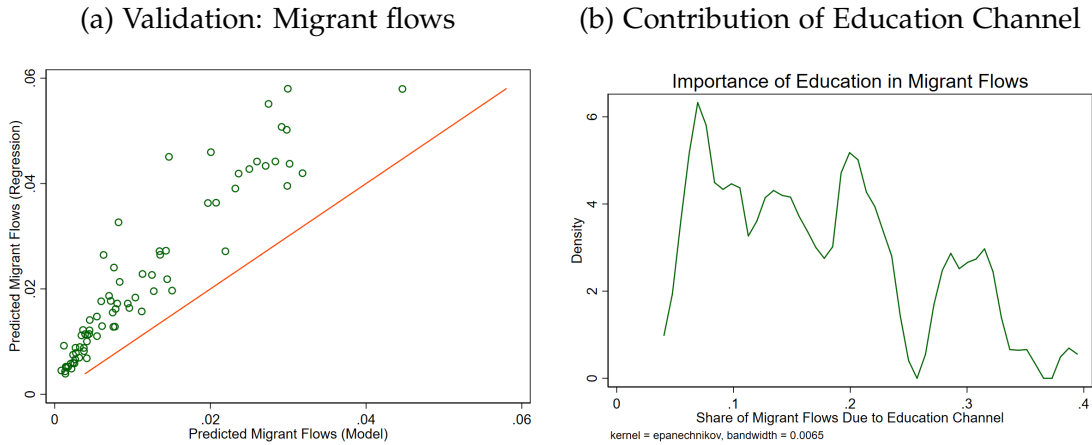
⁶⁰A short note on the model equilibrium. While simple to introduce, we do not explicitly model production to keep the analysis tractable and self-contained. Changes in production, whether at large firms or household enterprises, will affect domestic wages, changes to which are captured in our framework. 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 A2: Skill Level, Migration Probabilities, and Migrant Wages



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 A3: Model Validation & Contribution of Education Channel in Migrant Flows

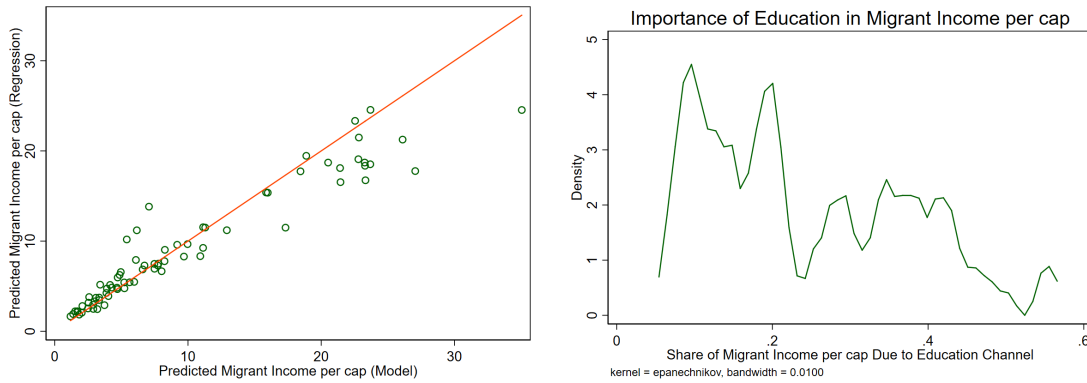


Notes: Figure A3a plots the predicted flows of migrants vs the predicted flows as determined by the components of Equation A11. The red line has an angle of 45 degrees. Each point represents a province. Figure A3b plots the province-level distribution of the contribution of the education channel in predicting migrant flows:

$$\frac{\Delta l_{ost} \sum_k (\pi_{kos0} - \pi_{kou0})}{Flows_{ot}^{OLS}}$$

Figure A4: Model Validation & Contribution of Education in Migrant Income

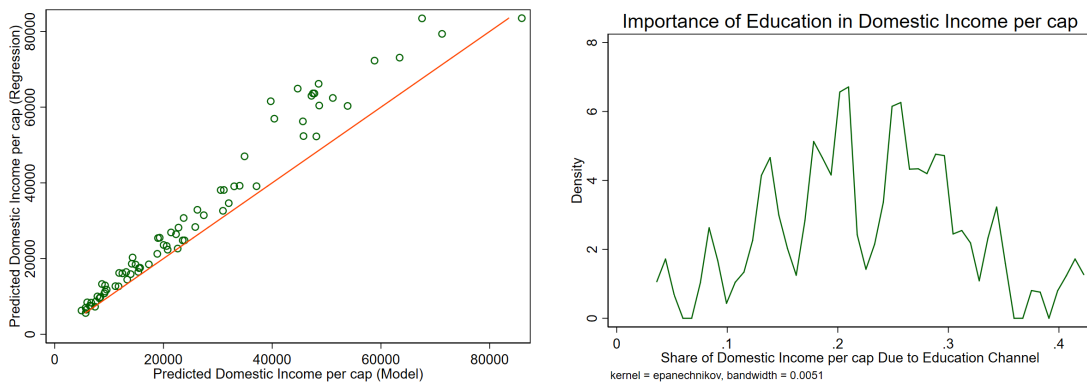
(a) Validation: Migrant Income per capita (b) Contribution of Education Channel



Notes: Figure A4a 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 A4b plots the province-level distribution of the contribution of the education channel in predicting migrant income per capita.

Figure A5: Model Validation & Contribution of Education in Domestic Income

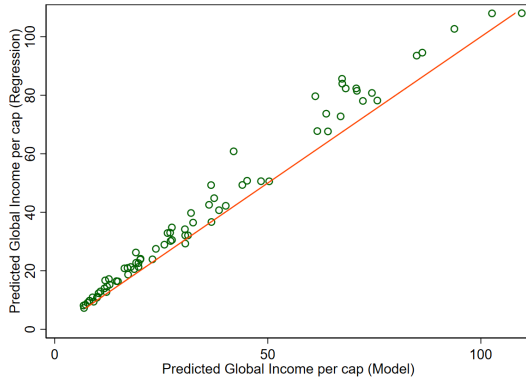
(a) Validation: Domestic Income per capita (b) Contribution of Education Channel



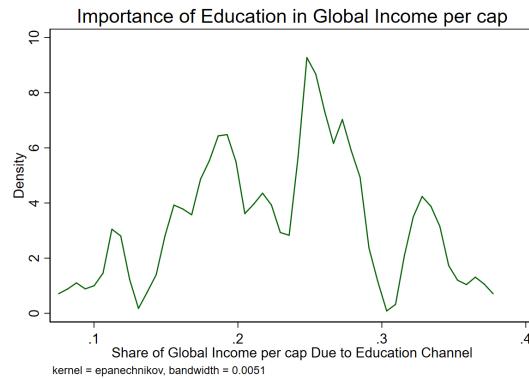
Notes: Figure A5a plots the predicted domestic income per capita from the regressions vs the predicted domestic income per capita as determined by the education and exchange rate components. The red line has an angle of 45 degrees. Each point represents a province. Figure A5b plots the province-level distribution of the contribution of the education channel in predicting domestic income per capita.

Figure A6: Model Validation & Contribution of Education to Global Income

(a) Validation: Global Income per capita

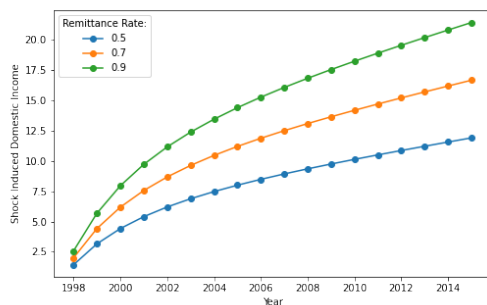


(b) Contribution of Education Channel

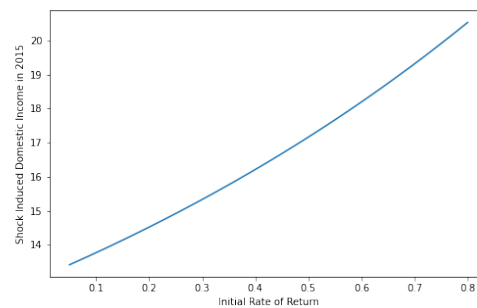


Notes: Figure A6a plots the predicted global income per capita (domestic plus migrant income) from the regressions vs the predicted global income per capita as determined by the education and exchange rate components. The red line has an angle of 45 degrees. Each point represents a province. Figure A6b plots the province-level distribution of the contribution of the education channel in predicting global income per capita.

Figure A7: Explaining Effect on Domestic Income: Sensitivity to Key Assumptions

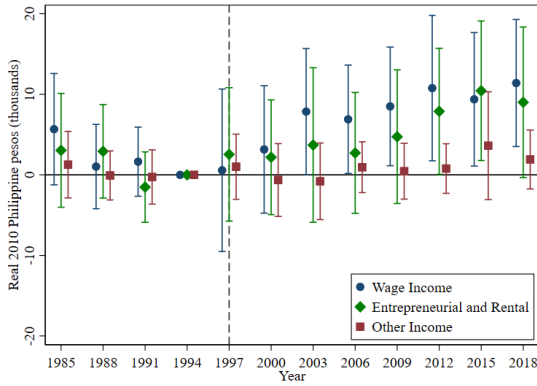


(a) Domestic Income Effects by Share of Migrant Income Spent at Origin (α)

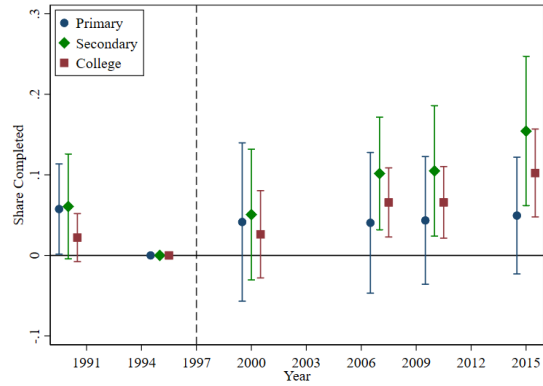


(b) Impact on Domestic Income by 2015, by Initial Rate of Return to Capital

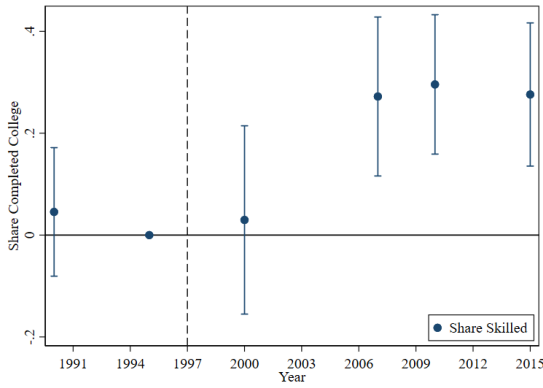
Figure A8: Event Studies for Other Outcomes



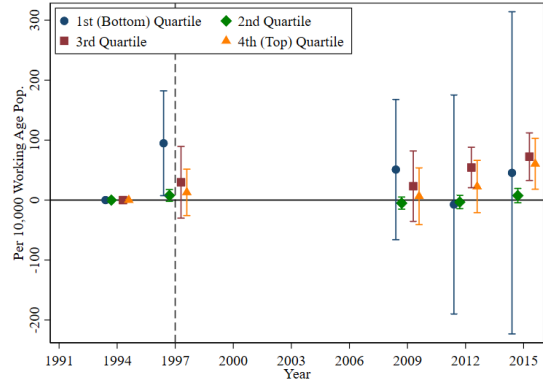
(a) Domestic Income Subcomponents



(b) Educational Attainment



(c) Share of OFWs Skilled



(d) OFW Occupations by Education Quartile

Note: Regressions modify Equation (3) to include interactions between $Shiftshare_o$ and indicator variables for each pre- and post-shock year. Panel (a) corresponds to outcomes in Table 6, panel (b) corresponds to outcomes in Table 4, and panels (c) and (d) 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 (PhP_{17.8}/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: Exchange Rate Shocks and Baseline Destination Characteristics

	Dependent Variable: Exchange Rate Change (ΔR_{it})						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1995 GDP Per Capita	-0.001 (0.007)						-0.004 (0.011)
Average Contract Salary		-0.009 (0.248)					0.144 (0.347)
Share of Contracts Professional			-0.005 (0.188)				-0.099 (0.339)
Share of Contracts Manufacturing				-0.137 (0.213)			-0.317 (0.253)
Share of all 1995 Contracts					0.073 (1.011)		0.374 (1.152)
1994-1996 Exchange Rate Change						0.434 (0.435)	0.085 (0.670)
Observations	104	104	104	104	104	104	104
Dep. Var. Mean	0.406	0.406	0.406	0.406	0.406	0.406	0.406
Dep. Var. St. Dev.	0.138	0.138	0.138	0.138	0.138	0.138	0.138
Joint F-Test P-value							0.833

Note: The table reports coefficients from regressions of the exchange rate shock on baseline destination characteristics, weighting by baseline migrant income in each destination (following [Borusyak et al. \(2022\)](#)). GDP per capita is in thousands 1995 USD. Average contract salary is in millions 2010 PHPs (17.8 PhP per PPP US\$ in 2010). Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A2: Baseline Province Characteristics and Shock Components

	Share Rural	Asset Index	Baseline Domestic Income Per Capita	Baseline Expenditure Per Capita	Baseline Primary Sector Share	Baseline Industrial Sector Share	Baseline Service Sector Share	Baseline Financial Sector Share
Panel A. MigInc₀₀ only								
<i>MigInc₀</i>	-0.029 (0.010)***	0.277 (0.037)***	1.608 (0.484)***	1.867 (0.374)***	-0.037 (0.007)***	0.015 (0.003)***	0.020 (0.004)***	0.003 (0.001)***
Panel B. Rshock₀ only								
<i>Rshock₀</i>	1.696 (0.568)***	-10.631 (3.330)***	-56.358 (29.634)*	-62.457 (27.546)**	1.294 (0.499)**	-0.602 (0.242)**	-0.599 (0.261)**	-0.093 (0.041)**
Panel C. Shiftshare₀								
<i>Shiftshare₀</i>	0.241 (0.351)	-1.754 (1.524)	-26.605 (17.422)	-15.362 (13.596)	0.153 (0.265)	-0.088 (0.116)	-0.032 (0.136)	-0.033 (0.026)
<i>MigInc₀₀</i>	-0.121 (0.147)	0.960 (0.635)	12.170 (7.370)	7.928 (5.732)	-0.097 (0.110)	0.049 (0.048)	0.032 (0.056)	0.016 (0.011)
<i>Rshock₀</i>	0.430 (0.907)	0.415 (3.844)	56.500 (45.967)	23.324 (35.618)	0.035 (0.693)	-0.025 (0.298)	-0.073 (0.407)	0.063 (0.069)
<i>N</i>	74	74	74	74	74	74	74	74
Dep. Var. Mean	0.643	-0.636	26.173	24.368	0.567	0.121	0.299	0.013
Dep. Var. SD	0.193	1.023	8.677	7.891	0.175	0.082	0.095	0.013

Note: Table reports coefficients from three regressions for each baseline province characteristic: regressing (a) only on baseline migrant income per capita *MigInc₀₀*, (b) only on income weighted exchange rate shock *Rshock₀*, and (c) their interaction, $Shiftshare_{0} = MigInc_{00} \times Rshock_{0}$, with controls for the main effects of *MigInc₀₀* and *Rshock₀*. Income and expenditure are in thousand 2010 PhP (17.8 PhP per PPP US\$ in 2010). Service sector excludes financial services, which is examined in as separate outcome. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A3: Placebo Regressions

Variables Constructed from FIES Data						
Pre Period: 1985, 1988, 1991; Post Period: 1994, 1997						
	(1)	(2)	Domestic Income Subcomponents			
			(3)	(4)	(5)	
	Domestic Income Per Capita	Expenditure Per Capita	Wage Income	Entrepreneurial and Rental Income	Other Income	
$Shiftshare_o \times Post$	-2.527 (15.331)	2.248 (13.258)	-2.510 (9.122)	-0.205 (4.831)	1.530 (4.608)	
Obs.	369	369	369	369	369	
Dep. Var. Mean	26.962	25.372	11.585	10.843	6.313	
Dep. Var. St. Dev.	10.150	8.951	6.879	3.620	2.740	

Variables Constructed from Census Data				
Pre Period: 1990; Post Period: 1995				
	Share Aged 20-64 Completed:			
	(1)	(2)	(3)	(4)
	Primary School	Secondary School	College	Share Skilled Migrants
$Shiftshare_o \times Post$	-0.058 (0.076)	-0.061 (0.062)	-0.022 (0.027)	-0.045 (0.104)
Obs.	148	148	148	148
Dep. Var. Mean	0.734	0.383	0.112	0.301
Dep. Var. St. Dev.	0.114	0.117	0.038	0.095

Variables Constructed from Contract Data						
Pre Period: 1994; Post Period: 1997						
	Contracts per 10,000 Working Age People					
	(1)	(2)	(3)	(4)	(5)	(6)
	Global Income Per Capita	Migrant Income Per Capita	1st Quartile Education	2nd Quartile Education	3rd Quartile Education	4th Quartile Education
$Shiftshare_o \times Post$	4.693 (20.147)	0.579 (4.369)	94.758 (125.611)	7.695 (20.999)	29.691 (175.461)	12.897 (103.683)
Obs.	148	148	148	148	148	148
Dep. Var. Mean	33.485	3.893	45.449	6.000	18.254	19.579
Dep. Var. St. Dev.	13.519	2.874	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 3 (global, domestic, and income; and domestic income subcomponents), Table 4 (education outcomes), and Table 5 (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 and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions (Borusyak et al., 2022). *** p<0.01, ** p<0.05, * p<0.10.

Table A4: 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
<i>Panel A. Destination controls only</i>						
$Shiftshare_o \times Post$	-0.002 (0.023)	-0.016 (0.012)	-0.013 (0.033)	-0.007 (0.028)	-0.047 (0.021)**	-0.040 (0.046)
<i>Panel B. Additional province development status controls</i>						
$Shiftshare_o \times Post$	-0.008 (0.018)	-0.018 (0.014)	-0.010 (0.028)	-0.011 (0.023)	-0.046 (0.019)**	-0.036 (0.038)
<i>Panel C. Additional province industrial structure controls</i>						
$Shiftshare_o \times Post$	-0.020 (0.019)	-0.019 (0.011)*	0.001 (0.028)	-0.027 (0.022)	-0.045 (0.020)**	-0.019 (0.037)
Obs.	207	207	207	207	207	207
Dep. Var. Mean	0.027	0.026	-0.001	0.032	0.043	0.012
Dep. Var. St. Dev.	0.020	0.013	0.017	0.024	0.021	0.029

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 3. All regressions include province and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions (Borusyak et al., 2022). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A5: Effects of Migrant Income Shock on Manufactured Exports

	Manufactured Exports per Capita			
	Full Period		Long Run	
	(1) Levels	(2) IHS	(3) Levels	(4) IHS
<i>Panel A. Destination controls only</i>				
$Shiftshare_o \times Post$	3.486 (10.234)	0.589 (1.096)	8.318 (15.466)	1.359 (1.697)
<i>Panel B. Additional province development status controls</i>				
$Shiftshare_o \times Post$	2.870 (12.143)	0.275 (1.279)	2.492 (18.519)	0.831 (1.920)
<i>Panel C. Additional province industrial structure controls</i>				
$Shiftshare_o \times Post$	1.823 (12.259)	0.078 (1.306)	-0.569 (18.268)	0.475 (1.920)
Obs.	888	888	370	370
Dep. Var. Mean	2.667	0.609	2.669	0.596
Dep. St. Dev.	8.640	1.155	8.745	1.153

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%. "IHS" is inverse hyperbolic sine transformation. 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 3. All regressions include province and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions (Borusyak et al., 2022). *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Effects of Migrant Income Shock on Agricultural Income

	Full Period: Triennial 1985-2018				Long Run: 1994, 2009, 2012, and 2015			
	(1) Agricultural Income	(2) Agricultural Wage Income	(3) Agricultural Non-Wage Income	(4) Non Agricultural Income	(5) Agricultural Income	(6) Agricultural Wage Income	(7) Agricultural Non-Wage Income	(8) Non Agricultural Income
<i>Panel A. Destination controls only</i>								
$Shiftshare_o \times Post$	-2.721 (3.414)	-2.209 (1.083)**	-0.512 (2.653)	15.692 (6.512)**	-2.469 (3.823)	-0.972 (1.006)	-1.498 (3.172)	26.287 (3.859)***
<i>Panel B. Additional province development status controls</i>								
$Shiftshare_o \times Post$	0.718 (2.610)	-1.193 (1.120)	1.911 (1.753)	12.209 (9.190)	2.321 (3.043)	0.391 (1.047)	1.929 (2.339)	16.761 (5.106)***
<i>Panel C. Additional province industrial structure controls</i>								
$Shiftshare_o \times Post$	1.326 (2.869)	-1.256 (0.962)	2.582 (2.027)	13.163 (8.891)	2.815 (3.279)	0.512 (0.937)	2.303 (2.570)	16.090 (5.514)***
Obs.	813	813	813	813	296	296	296	296
Dep. Var. Mean	5.024	1.583	3.442	24.861	6.410	1.621	4.789	24.289
Dep. Var. St. Dev.	3.518	1.174	3.271	11.206	3.649	1.156	3.228	11.595

Note: Unit of observation is the province-year. Data from the Family Income and Expenditure Survey (FIES). For list of destination and provincial controls, see Table 3. All regressions include province and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions (Borusyak et al., 2022). *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Exchange Rates and Foreign Direct Investment to Philippines

	FDI			
	Full Period		Long Run	
	(1) Levels	(2) IHS	(3) Levels	(4) IHS
<i>Panel A. No Controls</i>				
$\bar{\Delta R}_d \times \text{Post}$	-55.635 (52.915)	-1.327 (3.043)	-68.153 (56.414)	-1.482 (2.864)
<i>Panel B. Destination Controls</i>				
$\bar{\Delta R}_d \times \text{Post}$	-17.003 (17.100)	0.917 (1.065)	-30.807 (20.109)	0.363 (1.088)
Obs.	2,288	2,288	520	520
Dep. Var. Mean	12.145	1.788	14.221	1.941
Dep. Std. Dev.	19.237	1.782	22.425	1.806

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 3. 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 A8: Estimating θ using Poisson Pseudo-maximum Likelihood

	OLS	PPML	PPML
	Change in Migrants		
$\text{Log}(\Delta R_d)$	9.374* (5.146)	3.471** (1.720)	3.417** (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 A9: Impacts on Domestic Income by Skill, Migrant Income, and Migrant Shares

	1994, 2009, 2012, and 2015			Census
	(1) Domestic Income Per Capita Skilled	(2) Domestic Income Per Capita Unskilled	(3) Migrant Income Per Migrant	(4) Migrant Share Age 20 - 64
<i>Panel A. Destination controls only</i>				
<i>Shiftshare_o × Post</i>	56.942 (20.917)***	13.162 (5.346)**	98.761 (118.020)	0.007 (0.012)
<i>Panel B. Additional province development status controls</i>				
<i>Shiftshare_o × Post</i>	21.287 (14.781)	11.266 (5.826)*	199.601 (154.790)	0.013 (0.014)
<i>Panel C. Additional province industrial structure controls</i>				
<i>Shiftshare_o × Post</i>	18.488 (17.094)	10.729 (5.635)*	203.489 (157.317)	0.013 (0.014)
Obs.	296	296	296	444
Dep. Var. Mean	65.934	22.362	319.519	0.018
Dep. Var. St. Dev.	18.778	7.120	104.876	0.016

Note: Unit of observation is the province-year. Overseas worker rate values are from the Census and covers 1990, 1995, 2000, 2007, 2010, and 2015. Migrant income per migrant is calculated from POEA/OWWA data. 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 3. All regressions include province and year fixed effects. Standard errors are exposure-robust, accounting for correlation of shocks across provinces, based on estimation of shock-level regressions (Borusyak et al., 2022). *** p<0.01, ** p<0.05, * p<0.10.

Table A10: Overall Changes and Model-based Decomposition of Flows and Income

	Migrant Flows	Domestic Income	Migrant Income	Global Income
Mean	0.011	26.101	4.087	30.189
Std. Dev.	(0.008)	(9.405)	(2.993)	(11.340)
Impact of 1-std.-dev. shock	0.001	1.758	0.517	2.275
Increase as % of mean	11%	6.7%	12.6%	7.5%
Share of global income increase	—	77.3%	22.7%	100.0%
Model-based decomposition:				
Education channel	17.2%	22.8%	24.4%	23.2%
Exchange rate channel	29.7%	—	75.5%	17.2%
Direct wage channel	—	60.8%	—	47.0%
Explained by model	46.9%	83.6%	99.9%	87.3%

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.