Wealth Heterogeneity and the Income Elasticity of Migration[†]

By Samuel Bazzi*

How do income shocks affect international migration flows from poor countries? Income growth not only increases the opportunity cost of migration but also eases liquidity constraints. I develop a method to separate these countervailing individual effects and identify the overall income elasticity of migration. Using new administrative and census data from Indonesia, I find that positive agricultural income shocks increase labor emigration flows, particularly in villages with relatively more small landholders. However, in the most developed rural areas, persistent income shocks reduce emigration. Overall, the findings highlight the important role of wealth heterogeneity in shaping migration flows as incomes rise. (JEL F22, J43, O13, O15, Q11, Q12, R23)

O ver 40 million individuals migrated internationally between 2005 and 2010 (Abel and Sander 2014). A recent Gallup poll (Esipova, Ray, and Pugliese 2011) suggests that more than one billion individuals in the global labor force, most from developing countries, aspire to migrate abroad for work. Migrants typically realize substantial income gains (McKenzie, Stillman, and Gibson 2010; Yang 2008a). Moreover, the potential global productivity gains from greater labor mobility are extremely large (Clemens 2011). Yet, policy debates on the future of migration are often mired in controversy.

One fundamental point of contention in rich countries is how easing immigration barriers will affect migration flows from poor countries. This debate arose in the context of European Union enlargement (Constant 2011), post-WWII immigration policy reform in the United States (Massey and Pren 2012), and current foreign policy efforts to manage migration from Africa and the Middle East to Europe (Crush 2015). Understanding how migration flows respond to short-run income shocks is

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an important input to this debate. In other words, holding policy fixed, what is the income elasticity of migration?

The key empirical challenge in answering this question is that income growth can have two countervailing effects. For some, it will increase the opportunity cost of migration and lead them to stay at home (see, e.g., Abramitzky, Boustan, and Eriksson 2013, on historical Norway). For others, it will ease liquidity constraints and make migration feasible (see, e.g., Angelucci 2015, on modern Mexico). This paper shows how to disentangle these heterogeneous individual responses and identify the overall income elasticity of migration.

I adapt a standard migration choice model to incorporate fixed costs, wealth heterogeneity, and transitory and persistent income shocks.[1] Most international migrants from developing countries hail from rural areas, and given the availability of uniquely rich data from rural Indonesia, I focus the model on agricultural villages. In this setting, land-poor households may be unable to afford to send migrants abroad, and the land-rich may lack the incentives to do so. However, if cash-in-advance (CIA) constraints bind, then positive productivity or revenue shocks may enable small landholders to finance previously unaffordable costs of migration. Meanwhile, relatively larger landholders who are not liquidity constrained may subsequently retain labor at home to take advantage of higher expected future returns to agriculture.

Using household survey data, I provide evidence consistent with these microfoundations of the model. First, I document a cross-sectional inverted U relationship between international migration and landholdings consistent with prior studies using other measures of wealth (Hatton and Williamson 1998, McKenzie and Rapoport 2007, and Orrenius and Zavodny 2005). Moreover, for households with small landholdings, both transitory rainfall and persistent rice price shocks increase the probability of sending a family member abroad. For larger landholders, transitory shocks have null effects, whereas persistent shocks have smaller and even negative effects on emigration.

Both shocks have large impacts on household income, and I focus on rice for two reasons. First, it is Indonesia's most important agricultural product. Second, in early 2004, the government banned rice imports with the goal of raising the returns to farming. Historically, such imports stabilized domestic prices. As a result of the ban, farmers operated in autarky for several years, and in late 2005 domestic prices began climbing and eventually surpassed historical peaks. I exploit the spatial variation in this persistent price shock due to predetermined import exposure, which is exogenous with respect to migration trends for reasons detailed in Section IV.

The heterogeneous household responses to rainfall and price shocks imply an ambiguous aggregate income elasticity of migration that I resolve by borrowing insights from heterogeneous firm trade theory (Melitz 2003) to derive a model of village-level migration flows. I first document that landholdings follow a Pareto distribution using microdata from a 2003 Agricultural Census of 40 million households. In the model, this power law distribution allows me to tractably aggregate

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[1] Throughout this paper, in referring to (agricultural) income, rainfall, or price shocks, I have in mind *positive shocks*.

individual migration choices with the sign and magnitude of the income elasticity governed by λ, the village-level dispersion parameter.[2]

I estimate these local income elasticities using comprehensive panel data on temporary international labor migration from nearly 52,000 villages. The results point on average to a positive elasticity due to the prevalence of liquidity constraints. Without such constraints, transitory rainfall shocks should not affect migration decisions whereas persistent price shocks should reduce migration flows. Instead, I find that both rainfall and rice price shocks lead to significant increases in the share of residents working abroad, and the elasticities are larger in villages with a greater mass of small landholders (high λ).

While liquidity constraints are the most important determinant of the income elasticity of migration for the average village, I find that opportunity costs are binding in certain regions. First, in villages with established recruitment agencies, the up-front costs are relatively low given the pervasiveness of debt contracts that reduce cash-in-advance constraints. In these villages, price shocks have a null effect on migration flows compared to the large positive effect in villages without established agencies. Rainfall shocks have positive effects in both types of villages, but the effects are significantly larger in villages without recruiters. These asymmetric effects of transitory and persistent income shocks are indicative of the opportunity cost mechanism. I provide further evidence of this mechanism in the most developed agricultural areas where opportunity costs may be particularly high due, for example, to dense markets for complementary inputs to expand production as rice prices rise. Villages in the top quartile of initial agricultural gross domestic product (GDP) experience a significant reduction (no change) in migration flows after rice price (rainfall) shocks, whereas those in the poorest quartile experience a significant increase after both shocks.

An important innovation of my framework is that it rationalizes zero migration, which is useful for several reasons. First, zeros are pervasive in migration datasets[3] but cannot be explained by workhorse random utility models (Grogger and Hanson 2011). Second, policy objectives often differ with respect to expanding emigration opportunities to new regions versus new (poor) emigrants in high emigration regions. However, existing econometric approaches conflate the extensive margin of having any emigrants and the intensive margin of migration flows, which can lead to biases and make it difficult to identify these policy-relevant differences. Using a two-step Heckman (1976) selection framework suggested by the model, I find that failure to account for the importance of liquidity constraints along the extensive margin leads to underestimates of the income elasticity of migration flows. These results should be viewed as a first step towards more rigorously dealing with zeros in the study of migration (akin to early efforts in trade, e.g., Helpman, Melitz, and Rubinstein 2008).

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[2] Using the Pareto, I can compare elasticities across villages at different levels of development where migrants may hail from different parts of the distribution. Allen (2014) also exploits this useful Pareto property to compare the price elasticity of rice trade flows across regions of the Philippines with different λ. With comprehensive landholdings data, I can estimate the λ coefficients in an initial step. Absent such rich data, simulation-based estimation would be feasible.

[3] In the widely used Global Migrant Origin Database, over 30 percent of 226×225 bilateral pairs of countries have zeros.

I use the two-step results to back out structural estimates of the fixed costs of temporary migration that range from 3–6 years of typical household savings across the country. These costs comprise both direct contract fees as well as search and psychological costs. A simple quantitative exercise reveals that a large fraction of households remain constrained even when up-front costs are as low as 20 percent of total costs, suggesting considerable scope for policy to alleviate liquidity constraints.

My key contribution is to resolve uncertainty about the relationship between income and emigration by reconciling micro and macro approaches. Clemens (2014) details contradictory results on the sign and magnitude of the income elasticity of migration. My survey-based estimates of elasticities that vary with landholdings are consistent with growing micro-level evidence exploring other types of wealth heterogeneity and income shocks.[4] Yet, we have lacked the tools for linking these heterogeneous choices to (sub)national emigration flows, which are often more readily observable than individual panel data on emigration (see, e.g., McKenzie, Theoharides, and Yang 2014; Shrestha 2016). As a result, standard gravity models of migration tend to find mixed results or a null coefficient on origin country income growth (e.g., Mayda 2010). My approach clarifies how the liquidity and opportunity cost effects of income growth at the micro level can offset each other in macro data. Hence, migration flows depend not only on cross-country income differences but also on the income distribution within origin countries.[5]

By incorporating opportunity costs, I find smaller income elasticities than prior studies in developing countries. For example, Angelucci (2015), and Bryan, Chowdhury, and Mobarak (2014) find a large increase in labor emigration among very poor, rural households in response to cash transfers. These experiments identify the nonlabor income elasticity of migration in the lower tail of the wealth distribution. By comparison, my estimates are based on the entire rural population and labor income, both of which provide greater scope for the offsetting effects of opportunity costs.

At the micro level, my approach to disentangling liquidity and opportunity cost effects of rising income generalizes a strategy developed in Abramitzky, Boustan, and Eriksson (2013). Using data from nineteenth century Norway and the United States, they exploit parental assets as a source of *inter*household variation in liquidity constraints for children who then face different opportunity costs based on *intra*-household variation in inheritance of those assets. In their setting, strong diaspora networks kept costs sufficiently low that opportunity costs dominated liquidity constraints. I offer a way to explore the relative importance of these two forces in modern developing countries where rainfall and commodity price shocks have large effects on income, and there remains considerable variation in migration costs and access to intermediaries, both of which are amenable to policy.

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[4]For example, rainfall shocks increase rural to urban migration in India but only among small landholders (Jayachandran 2006); earthquakes differentially affect Salvadoran households depending on landholdings (Halliday 2006) or credit access (Yang 2008b); and cash transfers have larger effects on poorer South African households (Ardington, Case, and Hosegood 2009).

[5]This new framework has parallels to literature on the aggregate consumption or labor supply response to income shocks in the presence of individual heterogeneity (e.g., Attanasio et al. 2015, Jappelli and Pistaferri 2014).

The remainder of the paper is structured as follows. Section I develops the model. Section II provides background on migration, agriculture, and data sources. Section III presents reduced-form evidence on the income elasticity. Section IV proposes a two-step estimation procedure consistent with the model. Section V presents the main empirical results. Section VI provides estimates of migration costs and quantifies the prevalence of liquidity constraints. Section VII concludes.

I. A Model of Income Heterogeneity and Migration Flows

This section develops a model of temporary international migration flows from rural villages. I add wealth heterogeneity as well as transitory and persistent income shocks to an otherwise standard migration choice problem in which individuals cannot borrow against future earnings. Agricultural landholdings are the main source of wealth and income heterogeneity, alleviating financial constraints to migration but also incentivizing further allocation of household labor to domestic production after exogenous productivity or revenue shocks. Beyond these key ingredients, I keep the model as simple as possible to enable a tractable mapping from data on individual heterogeneity to aggregate migration flows. I discuss robustness after presenting the baseline predictions.

A. *Environment*

Each village $v = 1, \ldots, V$ is home to N_v households indexed by i. Utility at time t is $\Pi_{ivt} = p_{vt} Y_{ivt}$ at home, where p_{vt} is the exogenously given farmgate price for one unit of commodity $\mathcal{Y}$ (e.g., rice). Output is produced according to a constant returns to scale technology, $Y_{ivt} = \sigma_{vt} K_v^\theta R_{iv}^\beta$,[6] where σ_{vt} is the level of rainfall; K_v is publicly available capital; and R_{iv} is i's landholdings or area planted in hectares (ha). Each household has $\mathcal{L}$ units of labor to allocate to work at home and abroad.

After earning agricultural income at the end of period t, household i allocates earnings between financing migration abroad for one period and consumption (i.e., everything else). International migrants from village v working in destination j in period t can earn gross wages W_{vjt} net of costs C_{vjt}. At the time of decision making, individuals face uncertainty about future income at home while learning net wages abroad in $t + 1$ as stipulated in contracts offered by local intermediaries. In an unconstrained setting, the household sends one member abroad next period if her net returns to migration exceed the foregone expected income at home:

$$(1) \qquad W_{vj,t+1} - C_{vj,t+1} \geq E_t[MRPL_{iv,t+1}],$$

where $MRPL$ is the marginal revenue product of labor, and $E[MRPL_{iv,t+1}] \propto E[\Pi_{iv,t+1}]$. At the end of $t + 1$, the migrant returns home, and the household repeats the decision process.

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[6] There is strong evidence of constant returns to scale on Indonesian rice farms (Benjamin 1995; Mundlak, Larson, and Butzer 2004).

However, cash-in-advance constraints may prevent some households from making an optimal migration choice based on equation (1). Only those with enough earnings from the prior period can afford the fraction $\tau_{vj} \in [0, 1]$ of total costs that must be paid prior to earning the first month's wage abroad. If $\tau_{vj} = 0$, then equation (1) fully describes migration choice as in standard models (e.g., Borjas 1987). If $\tau_{vj} > 0$, the financing available to individuals in village v will not cover all predeparture migration costs, including foregone time without wages. In this case, the fixed cost imposes a minimum wealth requirement, R_L, to migrate next period. Combining both conditions, households with the following landholdings will have a member working abroad in $t + 1$:

$$(2) \qquad \underbrace{\left(\frac{\tau_{vj} C_{vj,t+1}}{p_{vt} \sigma_{vt} K_v^\theta} \right)^{\frac{1}{\beta}}}_{R_{Lt}} \leq R_{iv} \leq \underbrace{\left(\frac{W_{vj,t+1} - C_{vj,t+1}}{E_t[p_{v,t+1} \sigma_{v,t+1}] \chi K_v^\theta} \right)^{\frac{1}{\beta}}}_{R_{Ut}},$$

where $\chi \in (0, 1)$ is the constant of proportionality, $MRPL = \chi \Pi$, common across households.

To summarize, realized per period utility when sending a member abroad in $t + 1$ is given by

$$u_{ivt}^* = \Pi_{ivt} - \tau_{vt} C_{vj,t+1},$$

$$u_{iv,t+1}^* = (\Pi_{iv,t+1} - MRPL_{iv,t+1}) + W_{vj,t+1} - (1 - \tau_{vj}) C_{vj,t+1},$$

which is only feasible when $\Pi_{ivt} \geq \tau_{vj} C_{vj,t+1}$. Meanwhile, utility from retaining the household member at home is simply $u_{ivt} = \Pi_{ivt}$ and $u_{iv,t+1} = \Pi_{iv,t+1}$. Inequality (2) contains the main cross-sectional relationship between individual income and migration choice. Further assumptions are required to identify the income elasticity of migration.

Landholdings (R_{iv}).—As documented in online Appendix D, the empirical distribution of landholdings is well represented by a Pareto distribution. Formally, within each village v, there is a continuum of households i with landholdings R_{iv} drawn from the density $\lambda_v \underline{R}^{\lambda_v} R_{iv}^{-\lambda_v - 1}$ with village-specific dispersion $\lambda_v > 0$ above some minimum threshold $\underline{R}$. The mean and variance of landholdings are decreasing in λ_v. A key feature of the Pareto distribution is that its shape is preserved over all truncated segments of the distribution above $\underline{R}$. This makes it possible to compare—without sacrificing tractability—migration rates across villages (and time) where migrants come from different parts of the landholdings distribution (due to different R_L and R_U).

Producer Prices (p_{vt}) *and Rainfall* (σ_{vt}).—Producer prices follow an $ARMA(1, q)$ process with heterogeneous AR parameters, $p_{vt} = \alpha_v p_{v,t-1} + \sum_{s=0}^{q} \upsilon_s e_{v,t-s}$, where $\theta_0 = 1$ and e_{vt} is a mean-zero shock. This specification encompasses unit root processes and permanent shocks. Meanwhile, I take a standard approach in the literature

(see Rosenzweig and Wolpin 2000) and assume that rainfall follows an i.i.d. process such that $\sigma_{vt} = \overline{\sigma}_v + a_{vt}$, where $\overline{\sigma}_v$ is the long-run average level of rainfall in village v, and a_{vt} is a mean-zero shock t.[7]

B. *Characterizing the Income Elasticity of Migration*

I characterize the income elasticity of migration using the following equations derived in online Appendix A and referred to as the *intensive margin*. Suppose first that CIA constraints are binding for some households so that $\tau_{vj} > 0$ and $R_L \geq \underline{R}$. In this case, the change in the log migration rate is

$$(3) \qquad \Delta \ln\left(\frac{M_{v,t+1}}{N_{v,t+1}}\right)$$

$$= \frac{\lambda_v}{\beta} \, \Delta \ln p_{vt} + \Delta \ln \left[\left(\frac{\overline{\sigma}_v + a_{vt}}{\tau_{vj} C_{vj,t+1}}\right)^{\frac{\lambda_v}{\beta}} - \left(\frac{\overline{\sigma}_v \alpha_v \chi}{W_{vj,t+1} - C_{vj,t+1}}\right)^{\frac{\lambda_v}{\beta}} \right],$$

where M_{vs} is the number of village v residents working abroad in period s; and N_{vs} is village population including migrants. If, on the other hand, CIA constraints are not binding among potential migrants (i.e., $R_L < \underline{R}$ or $\tau_{vj} = 0$), then

$$(4) \qquad \Delta \ln\left(\frac{M_{v,t+1}}{N_{v,t+1}}\right)$$

$$= \ln \left[1 - \left(\frac{\alpha_v p_{vt} \overline{\sigma}_v \chi K_v^\theta}{W_{vj,t+1} - C_{vj,t+1}}\right)^{\frac{\lambda_v}{\beta}} \right] - \ln \left[1 - \left(\frac{\alpha_v p_{v,t-1} \overline{\sigma}_v \chi K_v^\theta}{W_{vjt} - C_{vjt}}\right)^{\frac{\lambda_v}{\beta}} \right].$$

These expressions imply the following propositions with proofs in online Appendix A.

PROPOSITION 1: *If cash-in-advance constraints are not binding for any households in village v, then the change in the migration rate between t and $t+1$ is uncorrelated with rainfall shocks a_{vt} and $a_{v,t-1}$, and decreasing (increasing) in recent (past) prices $p_{vt}(p_{v,t-1})$. Conversely, if cash-in-advance constraints are binding for some households, then the change in the migration rate is increasing in recent (past) rainfall shocks a_{vt} ($a_{v,t-1}$), and increasing in price shocks $\Delta \ln p_{vt}$.*

This proposition delivers a straightforward test for interpreting the sign of the income elasticity of migration. Transitory shocks only affect migration flows if liquidity constraints are binding. The more persistent price shocks should affect migration choices in either case. However, the elasticity of migration flows with

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[7] In online Appendix E.5, I show that these formulations are supported by the data. Note that $a_{v,t-k}$ for $k > 0$ are elements of the error term $\sum_{s=0}^{q} \upsilon_s e_{v,t-s}$, and hence past productivity shocks have a direct effect on current prices. However, contemporaneous rainfall and prices are uncorrelated, and $\text{cov}_t(p_{v,t+1}, \sigma_{v,t+1}) = 0$.

respect to price shocks is always increasing in the presence of liquidity constraints.[8] Recalling equation (2), the mass of households induced into migration by a drop in R_{Lt} is always greater than the mass of households induced out of migration by a drop in R_{Ut}. The magnitude of this response then depends on the shape of the landholdings distribution.

PROPOSITION 2: *If cash-in-advance constraints are binding, the increase in migration rates after positive price shocks $\Delta \ln p_{vt}$ and recent rainfall shocks a_{vt} is larger in villages with a greater mass of small landholders (high λ_v). In the absence of cash-in-advance constraints, the decrease in migration rates after an increase in prices p_{vt} is larger in villages with a greater mass of large landholders (low λ_v).*

If CIA constraints are binding, then income shocks should have the strongest effects on migration choice among the poor. Thus, all else equal, positive rainfall and price shocks should induce greater migration flows from villages with a relatively higher share of small landholders. Deaton (1991) shows that serial correlation in incomes (here, the *ARMA* prices) reduces the scope for income smoothing among liquidity-constrained households. A large positive income shock relaxing some of those constraints might then make it possible for poor households to undertake international migration as a means of ex ante risk diversification (as in Stark and Levhari 1982, Rosenzweig and Stark 1989). Moreover, to the extent that positive covariate income shocks loosen informal credit markets, we should expect a larger migration response in villages with less ex ante inequality where the scope for inter-household borrowing is more limited (see Genicot 2006). The dispersion parameter λ_v captures in a reduced-form way the potential thickness of these informal credit markets. Applying a structural interpretation, the cross-partial effect of price shocks and λ_v on migration flows is exactly $1/\beta$, the inverse of the share of land in the production function.

On the other hand, if CIA constraints are not binding, then increases in output prices lead to a reduction in migration flows with a steeper decline in villages with a greater mass of large landholders. This differential reduction occurs because price increases provide a stronger disincentive to migrate among households with more land and hence a higher *MRPL*.

In summary, based on a simple two-regime setup with and without cash-in-advance constraints, Propositions 1 and 2 provide a convenient mapping from changes in individual income to aggregate emigration flows. Before turning to empirics, I discuss model robustness.

C. *Discussion: Robustness*

I address the plausibility of three sets of assumptions underlying the model with reference to the empirical setting detailed further in the following section. First, the implicit homogeneity of costs and preferences within villages keeps things tractable

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[8] This result hinges on the monotonicity of the landholdings distribution and the absence of increasing returns to scale.

but is not essential. Moreover, the assumption of ex ante certainty over wages abroad is in keeping with the dominant mode of low-skill labor migration from Asia (McKenzie, Theoharides, and Yang 2014) and can be relaxed. If uncertainty was negatively correlated with wealth, for example, this would amplify the mechanisms above.

Second, the assumptions about cash-on-hand are consistent with the limited land markets and low savings rates in rural areas. In theory, households could sell land to finance migration costs, but like other developing countries, land markets are very thin and poorly functioning across Indonesia (see World Bank 2008). Additionally, the key predictions are isomorphic to a model in which households with landholdings above some threshold may obtain a loan to finance up-front costs. In practice, though, the lack of land titles largely preclude collateralized lending in rural areas (Dower and Potamites 2014). Furthermore, according to the *Indonesia Family Life Survey* from 2007, less than one-fourth of rural households have sufficient savings to cover the lower bound up-front costs (US$350) discussed in Section IIC. These percentages are even lower for the land-poor (e.g., those with less than 0.5 ha).

Third, the assumptions about the value of household labor can be relaxed.[9] The key concern is that households need not sacrifice productivity at home when a member emigrates, and households with large landholdings need not have higher opportunity costs of migration. Two factors support my formulation of opportunity costs in inequality (1). First, Squires and Tabor (1994) show for Indonesia that land and labor are *q* complements, which implies that an increase in land raises the marginal product of labor. They also show that hired and family labor are imperfect substitutes (due, e.g., to monitoring frictions, Bharadwaj 2015), which suggests that some but perhaps not all of the lost productivity can be replaced by hiring outside workers (e.g., using remittances from the migrant). Ultimately, though, given there is not surplus labor, the *MRPL* in (1) remains strictly positive and implies some trade-off between retaining labor at home versus abroad.

II. Emigration and Agriculture in Indonesia[10]

Approximately 700,000 labor migrants leave Indonesia annually. Most depart through formal recruitment agencies, stay abroad for 2–3 years in countries across (South)East Asia and the Middle East, and tend to work in construction, agriculture, and household services. Recently, women have comprised a growing share of total legal migrant outflows, accounting for 50–80 percent annually. I provide here additional details on why Indonesia is a useful setting for identifying the relationship between income and migration flows through the lens of the model developed above.

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[9]The assumptions about the collective household and homogeneity of labor are made for tractability but do not affect the qualitative predictions. Ignoring intra-household bargaining is conservative in terms of characterizing liquidity constraints. In a micro model with similar primitive conditions, Delpierre (2012) shows that introducing intra-household bargaining—in particular, allowing for imperfect commitment (to remit) between the migrant and remaining members—tends to exacerbate the financial barriers to investment in profitable migration opportunities. Moreover, incorporating skill heterogeneity that is uncorrelated with landholdings (as in Munshi 2003) has no effect on the model predictions. If R_{iv} is drawn jointly and positively correlated with S_{iv}, the main qualitative predictions remain unchanged.

[10]See online Appendix C for details on all variables used in this paper. All substantive, unreferenced empirical claims on migration in this section are supported by evidence in a supplementary note (Bazzi 2012).
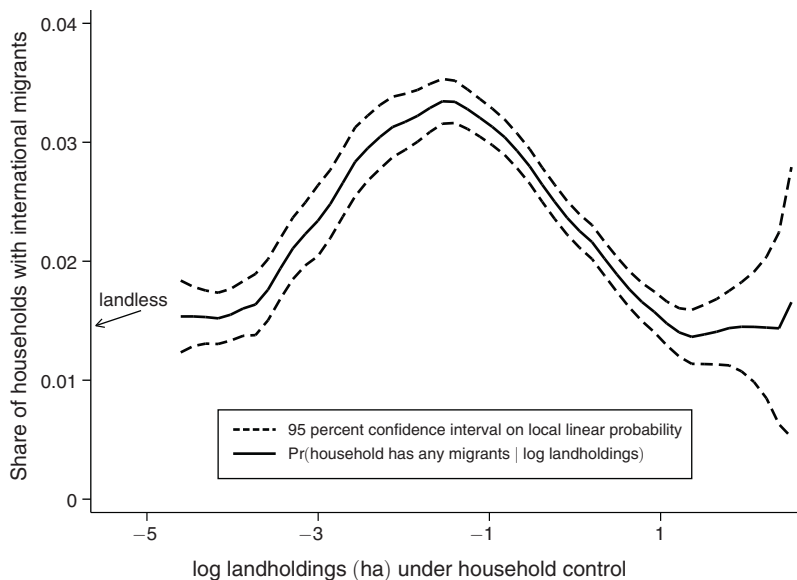
FIGURE 1. MIGRANTS DRAWN FROM THE MIDDLE OF THE LANDHOLDINGS DISTRIBUTION

Notes: Calculations based on nationally representative household survey (*Susenas*) data collected in July 2005. The nonparametric regression curve and analytic confidence band is based on a local linear probability regression of an indicator for whether a household member worked abroad from 2002–2005 on log landholdings under household control. The estimates employ a bandwidth of 0.4 and an Epanechnikov kernel. There are a total of 257,906 households in the data and 124,472 report controlling any landholdings at the time of enumeration. Both the mean estimate for migration probabilities in landless households and the nonparametric regression employ sampling weights. The top percentile of landholdings are trimmed from the figure for presentational purposes.

A. *An* Inverted U *in Migration Choice and Landholdings*

I begin by establishing an important cross-sectional implication of the model. Based on nationally representative household survey data from 2005, Figure 1 reveals that households with members working abroad as labor migrants tend to come from the middle of the landholdings distribution. This relationship is consistent with inequality (2), which suggests that the land-poor cannot afford to migrate while the land-rich lack the incentives to do so. This points to a mix of liquidity constrained and unconstrained households. For some, rising income may then lead to greater emigration, and for others it may lead to less, giving rise to the ambiguous income elasticity of migration flows.

B. *Measuring Migration Flows at the Village Level*

The main data on temporary international labor migration come from a triennal administrative census of villages known as Village Potential or *Podes*.[11] These

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[11] The village is a relevant unit of analysis for several reasons: the strength of migration networks typically varies across villages; policy barriers to migration do not vary across villages within the same region; and all villages are small enough as to be price-takers in regional and certainly national agricultural product markets.

TABLE 1—SUMMARY STATISTICS: INTERNATIONAL LABOR MIGRATION FROM INDONESIAN
VILLAGES

	Stocks, 2005			
	Mean	Median	SD	Max
Village population	3,216	2,095	4,123	78,986
Number of emigrants	17	1	61	1,996
Emigrants/population	0.006	0.0005	0.019	0.832
1(any emigrants abroad)	0.54	—	—	—
Number of emigrants | emigrants > 0	31	8	80	1,996
Emigrants/population | emigrants > 0	0.010	0.003	0.025	0.832

	Stocks, 2008			
	Mean	Median	SD	Max
Village population	3,377	2,187	4,330	82,215
Number of emigrants	20	2	64	998
Emigrants/population	0.007	0.001	0.020	0.759
1(any emigrants abroad)	0.59	—	—	—
Number of emigrants | emigrants > 0	35	9	81	998
Emigrants/population | emigrants > 0	0.012	0.004	0.026	0.759

	Changes (Δ), 2005–2008			
	Mean	Median	SD	Max
Δ number of emigrants	4	0	52.3	998
Δ emigrants/population	0.110	0	1.92	59.2
Δ number of emigrants | emigrants > 0	6	1	73	995
Δ emigrants/population | emigrants > 0	0.14	0.016	2.55	59.2
Δ log emigrants/population	0.106	0.062	1.01	5.67

	2005	2008
Share of Indonesian population from rural areas	0.59	0.59
Share of Indonesian emigrants from rural areas	0.82	0.83
Total emigrants, all villages	1,113,244	1,349,540

Notes: The statistics are calculated for all 65,966 villages matched in *Podes* 2005 and 2008. The qualitative patterns remain unchanged when restricting to villages with agricultural activities and assets recorded in the Agricultural Census of 2003. However, the mean and median stock migration rate figures are quantitatively larger when restricting to these non-urban villages. See online Appendix C for a description of the determinants of a rural area.

data span the universe of Indonesian villages in 2005 and 2008 and record the total number of village residents working abroad for a "fixed wage and time period."[12] Comparisons with other, more aggregate sources suggest that *Podes* captures the vast majority of labor emigration during this period.

Table 1 reveals several facts about international migration from Indonesian villages. First, similar to other large developing countries, the number of emigrants is small relative to population size. However, emigration rates vary significantly across villages. Second, international labor migration is relatively more common from rural areas. Whereas 60 percent of the population resides in rural areas, nearly 85 percent of migrants hail from these areas. Third, migration rates increase on

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[12] The data are obtained primarily from key informants in the village government with additional input and corroboration from officials in the subdistrict and district government. Village officials have historically been the first line of bureaucracy from which potential migrants must obtain legal permission to work abroad (Spaan 1994). Today, these officials authorize the national ID cards required to work outside the country (Bank Indonesia 2009).

average by approximately 11 percent between 2005 and 2008. Lastly, the extensive margin cannot be ignored: 45 percent of villages did not have any residents working abroad in 2005, but 40 percent of the national increase in migrant outflows through 2008 originated in these villages.

C. *Migration Costs and the Predeparture Financial Context*

The financial costs of migration tend to be large relative to household income. Around 2005, official placement and recruitment fees ranged from $800 to $1,200 US dollars (Bank Indonesia 2009) relative to GDP per capita of US$1,300. Survey data suggest out-of-pocket costs paid prior to departure range from $350 to $900 US dollars, and around 85 percent of households with migrants were unable to finance these costs purely out of their own savings (World Bank 2009). However, less than 5 percent of migrants borrow from formal financial institutions, which view migrants as high risk given the difficulty of tendering repayments and the lack of creditworthiness of potential family cosigners. An estimated 80 percent of up-front costs are financed through informal borrowing from family, friends, and recruitment agencies (World Bank 2010).

Some recruiters offer interlinked contracts that allow borrowing against future earnings. However, even those contracts requiring little cash-in-advance have potentially large implicit costs. Such debt contracts typically withhold earnings for several months after beginning employment abroad and impart effective annual interest rates over 60 percent. Given 1–3 months of predeparture training without pay, these contracts may constrain migration choices in households unable to cope with an extended period of lost income by a productive member. Hence, financial constraints could prove binding even when interlinkage requires no predeparture financing by the migrant.

Measuring Migration Costs.—Empirically, I use several proxies for migration costs: (i) distance to the nearest city from which labor migrants depart Indonesia (there are 19 embarkation points); (ii) distance to the (sub)district capital; (iii) the shares of ethnic Chinese, Arabs, and Muslims in the village as of 2000; and (iv) the plurality destination of migrants in 2005. Measures (i) and (ii) capture the most relevant distance-based variation in access to foreign labor markets, while (iii) accounts for information and search costs as well as potential discriminatory policy barriers. Beyond the Arab/Muslim connection to the Middle East, ethnic Chinese have connections with employment agencies in major Asian destinations. Measure (iv) accounts for migration costs and demand shocks common across villages that historically sent migrants to a given destination.

D. *Landholdings: Data and Distribution*

The Pareto dispersion parameter, λ_v, is meant to capture the distribution of within-village income gains as a result of rainfall and price shocks. I estimate these λ_v for every village using newly prepared data from the 2003 Agricultural Census, which contains universal micro records on the landholdings of 40 million

households. Around 22.3 million households own or rent some agricultural land with 58 percent growing rice in the 2002–2003 growing season. Around 70–75 percent of rice growing households are net producers (McCulloch 2008).

I follow Gabaix and Ibragimov (2011) to recover λ_v for each village via an OLS regression of the log rank$(-1/2)$ on the log landholding size (above $\underline{R} = 0.1$ ha) using three available measures of land: total agricultural landholdings, wetland holdings, and total rice paddy area planted in 2002–2003.[13] The estimated λ_v based on total landholdings are smoothly distributed with a mean of around 1.55, range from 0.16 to 28.4, and have a moderate right skew towards villages with a greater mass of small landholders (see online Appendix D).

The constant minimum bound assumption ($\underline{R}_v \equiv \underline{R} \; \forall v$) serves an important role along the extensive margin (see Section IVA) but also poses a practical difficulty because the share of households above $\underline{R} = 0.1$ ha varies across villages. This is a common problem in the empirical literature comparing size distributions across administrative entities (e.g., Soo 2005). I pursue a reduced-form solution that controls for the share of households above $\underline{R} = 0.1$ ha.

There are several reasons to view landholdings as an exogenous source of wealth and productivity over the medium-run horizon in this study. Land is primarily transferred through inheritance, and substantial market imperfections imply limited short-run turnover. Moreover, the local distribution of landholdings is extremely persistent. Regressing district-level $\hat{\lambda}$ from 2003 on $\hat{\lambda}$ from 1963, I cannot reject that the autoregressive coefficient equals one (see online Appendices C and D).

E. *Rainfall, Rice Prices, and Income*

There are several reasons why rainfall and rice price shocks capture income changes relevant to international migration from Indonesia.[14] I describe these shocks and income responses here.

Rainfall Shocks.—I map monthly rainfall data at the district level from the National Oceanic and Atmospheric Administration Global Precipitation Climatology Project (NOAA–GPCP) into province-specific rice growing seasons following Maccini and Yang (2009). The rainfall level in year t corresponds to total rainfall (in centimeters) during the season beginning in late $t-1$ and ending in mid-t. Consistent with the rainfall–yield relationship in Indonesia (see Levine and Yang 2014), I specify the rainfall shock in t as the log deviation of the current level from the long-run district-level mean $(1953–2008)$ excluding t. To the extent that rainfall is measured

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[13] There is no consensus on the most appropriate method for selecting $\underline{R}$. Clauset, Shalizi, and Newman (2009) propose a promising approach that appears too computationally demanding in the present context. Gabaix (2009) argues that visual inspection should suffice in most cases. I impose $\underline{R} = 0.1$ ha as the baseline and consider alternatives in robustness checks.

[14] Rice is the most important agricultural product in Indonesia, and rainfall and labor are strongly complementary in production. Also, women, who comprise a large share of labor migrants, account for 40–45 percent of total labor employed in rice cultivation. Finally, international migration tends to be countercyclical with respect to the rice planting season as seen in auxiliary administrative data for later years.
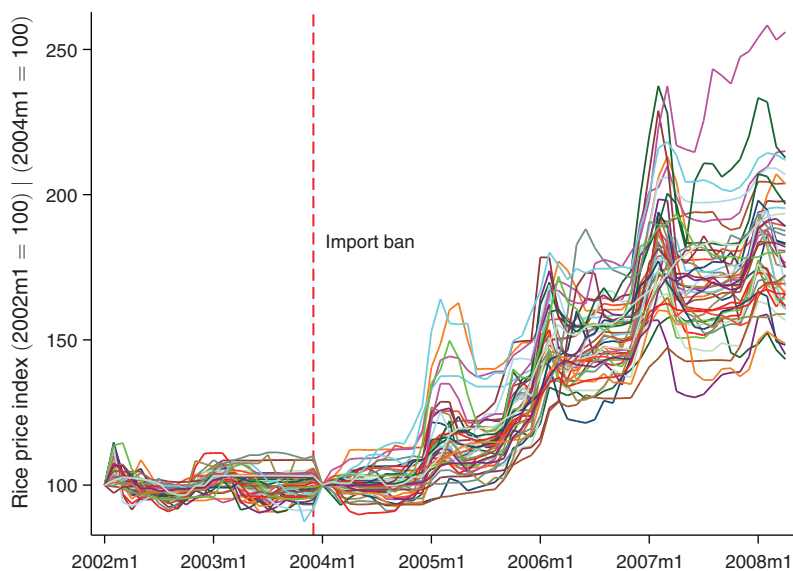
FIGURE 2. THE EVOLUTION OF RICE PRICES IN INDONESIAN CITIES, 2002–2008

Notes: The index is initially normalized to equal 100 in January 2002. For the purposes of comparing before and after the ban, the bottom half of the graph re-initializes and re-normal-izes the index to equal 100 at the time of the import ban in January 2004. The rice price index is produced by the Central Bureau of Statistics for cities across the Indonesian archipelago based on prices collected in major markets within those cities. Though these estimates are based on consumer retail prices, I discuss evidence in online Appendix E suggesting that retail, farmgate, and wholesale prices move in lockstep from 2000–2008. The data were obtained from Wimanda (2009).

with error, the results are lower bounds for the true effects of these transitory shocks.[15]

Rice Price Shock.—I exploit substantial spatial and time series variation in the domestic rice price caused by a ban on rice imports beginning in 2004. While rarely exceeding 5 percent of national rice consumption, imports historically stabilized domestic prices (Dawe 2008). Prior to 2004, a 20 percent ad valorem tariff had been the primary measure of protection. The ban effectively raised the tariff to over 150 percent, thereby shutting down private sector imports.

Although the import ban applied universally, the size of the subsequent price shock varied considerably across regions. Figure 2 demonstrates this by comparing a rice price index across cities from January 2002 to March 2008.[16] In online Appendix E.1, I provide empirical evidence consistent with a trade model that predicts larger price

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[15] Maccini and Yang (2009) propose dealing with this measurement error by using rainfall in neighboring loca-tions as an instrument for rainfall in own location. While the exclusion restriction is plausible in their setting, it is less credible in this context where economic conditions in nearby areas may have direct effects on labor allocation decisions at home.

[16] This urban consumer-based index provides the most reliable measure of regional rice prices over this time period. Relative to unobservable producer prices in local rural markets, the index should be more likely to capture regional general equilibrium effects of the import ban.

increases in villages where domestic producers faced greater pre-ban import competition, which is increasing in proximity to domestic ports and major wholesale markets, and the overseas markets from which Indonesia's imports originate.[17]

There are two main explanations for the obvious lack of arbitrage by domestic traders. First, in the wake of decentralization in post-Suharto Indonesia, the state logistics agency (*Bulog*) played a much more limited role in procuring, moving, and equilibrating rice supplies across the archipelago. Second, during the liberal import regime from 1999–2003, private traders developed strong ties with foreign suppliers. The decline of *Bulog* and the path dependence of these private international buyer-seller networks slowed the process of adjustment to the lack of imported rice.

What is crucial for identification is that these spatial price shocks are uncorrelated with preexisting emigration trends. In all specifications, I allow for the distance to emigration points (and all cost proxies noted in Section IIC) to have differential effects over time. This ensures that any observed relationship between rice price shocks and migration is not driven by the correlation between (preexisting trends in) openness to trade and openness to migration. This is important given that many port cities are also emigration hubs. Crucially, the elasticity of price shocks with respect to port/shipping distance remains large even after conditioning on distance to the nearest emigration hub, the elasticity on which is small and insignificant (see online Appendix Table E.1).

Finally, as shown in online Appendix Table E.2, $\hat{\lambda}_v$ is uncorrelated with the rice price shock as well as trends in the pre-ban period. This helps rule out the concern that villages with low $\hat{\lambda}_v$, which tend to generate more total output and hence import less, experience smaller price shocks.

Income Shocks.—Online Appendix Table E.3 shows that rainfall and rice price shocks increase household expenditures per capita—as a proxy for poorly measured income—in rural areas. Households respond to rainfall shocks as though they are relatively transitory with an elasticity around 0.25. However, agricultural households respond to the policy component of the rice price shock as though it was more persistent if not permanent; the elasticity is statistically indistinguishable from unity when the price shock is instrumented with the port/shipping distance. Meanwhile, online Appendix Table E.4 shows that agricultural wages rise after rainfall shocks and are more responsive (positively) to annual price changes after the import ban. Overall, these results confirm a general increase in the returns to agricultural labor and land after productivity and revenue shocks.

One appealing aspect of examining rainfall shocks and a (policy-induced) price shock together is that a positive rainfall shock increases income today (in the short run), whereas the price shock is decreasing in the rainfall shock, and thus the residual persistence in the price shock is associated with higher (expected) future income. This asymmetry will prove useful in disentangling the opportunity cost mechanism in Section VB.

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[17] After the import ban, prices grew faster in regions more closely connected to ports and the main rice trade routes from Thailand and Vietnam. I corroborate these results using data from the Central Bureau of Statistics on port-level imports. Areas with high initial imports experienced faster price growth after the ban.

TABLE 2—AGRICULTURAL INCOME SHOCKS AND MIGRATION CHOICE IN MICRO DATA

	(1)	(2)	(3)	(4)
rainfall shock, t	0.200	0.212	1.109	1.712
	(0.115)	(0.112)	(0.578)	(0.606)
rainfall shock, $t \times$ landholdings (ha)			−0.267	−3.844
			(0.580)	(1.416)
rainfall shock, $t \times$ landholdings (ha) squared				1.583
				(0.647)
price shock, t		0.762	3.752	3.892
		(0.340)	(1.687)	(1.729)
price shock, $t \times$ landholdings (ha)			−0.581	−3.128
			(1.176)	(1.875)
price shock, $t \times$ landholdings (ha) squared				0.802
				(0.513)
Observations	1,902	1,380	1,380	1,380

Notes: The table reports conditional fixed effects logit of equation (5) for whether a household has any migrants departing in year $t + 1$. Columns 1–2 (3–4) report average marginal effects (point estimates). The sample comprises a balanced panel of households with any migrants over the period 2000–2006 as recorded in the nationally representative *Susenas* household survey conducted in mid-2006. The *rainfall shock* in period t is defined as the log deviation of the current season's rainfall from the long-run local mean. The price shock in period t is defined as the log difference in the local rice price at the end of period t and $t − 1$. All columns include year fixed effects. See online Appendix F.9 for additional details on the specification and *Susenas* data. Standard errors are clustered at the district level.

III. The Income Elasticity of Migration: Reduced-Form Evidence

This section presents reduced-form evidence on how wealth heterogeneity and income shocks affect international migration at both the individual-level and village-level. The results help motivate a new, theoretically consistent approach to identifying the income elasticity of migration using data on (sub)national migration flows.

A. *Individual-Level Micro Elasticities*

First, I provide evidence of heterogeneous income elasticities using nationally representative household survey data (*Susenas*) collected in mid-2006 from nearly 10,000 households in 670 villages. Table 2 reports average marginal effects (AMEs) of income shocks on migration choice (recorded retrospectively) from 2000 to 2006 based on variants of the following specification:

$$(5) \qquad \Pr(migrate_{iv,t+1} = 1) = \mathbf{shock}'_{vt}\boldsymbol{\alpha} + (\mathbf{shock}_{vt} \times f(land_i))'\boldsymbol{\beta}$$

$$+ \psi_i + \psi_t + e_{iv,t+1}$$

using a conditional fixed effects logit where $migrate_{iv,t+1} = 1$ if household i in village v had any migrants depart in year $t + 1$; **shock** comprises the rainfall shock as defined above and Δ log price index; $f(land_i)$ is a linear or quadratic function of household landholding size; $\psi_i (\psi_t)$ are household (year) fixed effects; and $e_{iv,t+1}$ is an idiosyncratic error term. The positive and precisely estimated AMEs in

columns 1–2 show that both shocks increase the probability that households send a member to work abroad. In columns 3–4 in Table 2, the income elasticities are larger among small landholders. In the quadratic specification in column 4 in Table 2, the implied AMEs are positive and significant for households with roughly less than 0.6 ha but negative and/or insignificant for larger landholders.

Although the patterns in Table 2 are suggestive of both the liquidity and opportunity cost mechanisms underlying the model, data constraints make it difficult to precisely isolate the latter mechanism. Figure 3 reports estimated AMEs based on a more flexible function of $f(land_i)$. The patterns are consistent with the heterogeneous elasticities in columns 3–4 in Table 2, but the negative price elasticity for large landholders is not statistically significant. This is due in part to the small sample size (only 276 households with any migrants since 2000), and the panel ending in mid-2006, which leaves little time for the price shocks seen in Figure 2 to pass through to household incomes and change expectations. Together, these imply a lack of power to flexibly identify heterogeneous effects across the landholdings distribution and especially the potential disincentive effects of rising prices for large landholders. These sort of data constraints are common in the study of international migration given the paucity of reliable survey data spanning many years and origins. Nevertheless, the model developed in Section I provides a convenient way to incorporate underlying heterogeneity into the estimation of income elasticities based on the more comprehensive village-level panel data.

B. *Village-Level Macro Elasticities*

A reduced-form interpretation of Propositions 1 and 2 suggests the following estimating equation:

$$(6) \quad \frac{M_{v,t+1}}{N_{v,t+1}} = \theta_p \, price \, shock_{vt} + \theta_{p\lambda} \left(price \, shock_{vt} \times \hat{\lambda}_v \right)$$

$$+ \theta_a \, rainfall \, shock_{vt} + \theta_{a\lambda} \left(rainfall \, shock_{vt} \times \hat{\lambda}_v \right)$$

$$+ \xi_t + \xi_v + \varepsilon_{v,t+1},$$

which effectively aggregates individual migration choices to the village level and allows the overall elasticity to vary with local heterogeneity in paddy landholdings, $\hat{\lambda}_v$.[18] The ξ_v (ξ_t) are village (period) fixed effects, and the sample includes all villages including those with no migrants. For village v in period $t = 2005$ $(t + 1 = 2008)$, the price shock is the annualized growth in the log price index from 2005m4–2008m3 (2002m1–2005m3), and the transitory rainfall shock is the sum of annual log deviations from long-run (1953–2008) averages in 2003–2005 (2006–2008).

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[18] See online Appendix H for details on the balanced panel construction.

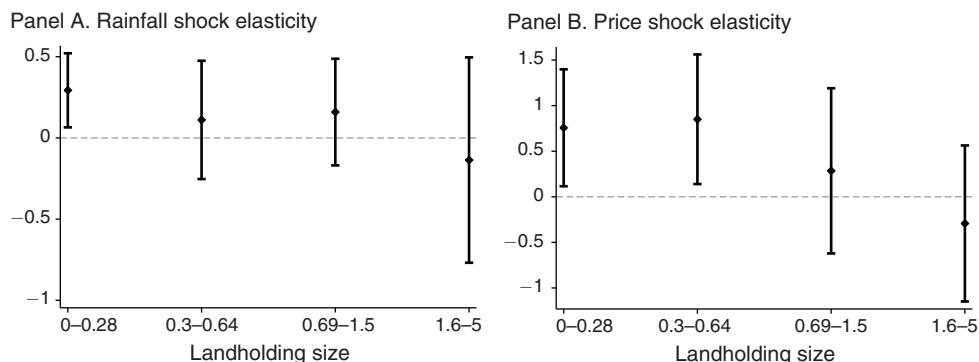Panel A. Rainfall shock elasticity　　　　　　Panel B. Price shock elasticity

FIGURE 3. INCOME SHOCKS AND HETEROGENEOUS MIGRATION CHOICES

Notes: These figures report 90 percent confidence intervals on the average marginal effects of the income shocks for each landholding size bin based on equation (5). See the notes to Table 2 for details on the specification.

TABLE 3—REDUCED-FORM ESTIMATES OF THE INCOME ELASTICITY OF MIGRATION

	Fixed effects OLS		Semiparametric Tobit	
	(1)	(2)	(3)	(4)
rainfall shock	0.0011	0.0004	0.0056	−0.0029
	(0.0003)	(0.0008)	(0.0009)	(0.0043)
	[0.0011]	[0.0012]	[0.0031]	[0.0059]
rice price shock	0.0085	0.0081	0.0189	−0.0025
	(0.0016)	(0.0026)	(0.0040)	(0.0113)
	[0.0064]	[0.0072]	[0.0141]	[0.0198]
rainfall shock $\times \hat{\lambda}$		0.0004		0.0051
		(0.0005)		(0.0029)
		[0.0010]		[0.0048]
price shock $\times \hat{\lambda}$		0.0002		0.0138
		(0.0013)		(0.0074)
		[0.0027]		[0.0134]
Observations	89,312	89,312	89,312	89,312

Notes: This table reports estimates of θ parameters in equation (6). The dependent variable in all specifications is the stock migration rate in village v in period t (emigrants/population or M_{vt}/N_{vt}), the mean of which is 0.006. Here, *rainfall shock* is the cumulative log deviation from long-run mean rainfall in the growing seasons ending in 2006–2008 for t and 2002–2005 for $t - 1$; *rice price shock* is the respective annualized log growth rate between 2005m4–2008m3 and 2002m1–2005m3. The estimated Pareto exponent $\hat{\lambda}$ is obtained for paddy area planted in 2002; higher values indicate less dispersion in landholding sizes. The regressions also include an indicator for period 2 (not reported). In the two-period panel with fixed effects, the OLS specification is equivalent to first-differences. To interpret the coefficients in columns 3–4 as marginal effects, simply multiply the value for a given variable by the share of the sample with nonzero migration rates, 0.609. See Honoré (2008) for details. Standard errors in parentheses $(\cdot)$ are clustered at the village level and in brackets $[\cdot]$ are additionally robust to clustering within districts. A cluster/block bootstrap with 1,000 replications is used to obtain the latter for the semiparametric estimator.

Table 3 presents estimates of the income elasticities in equation (6). Columns 1–2 employ an OLS fixed effects estimator. Columns 3–4 use a more flexible semiparametric Tobit or trimmed least absolute deviations (LAD) (Honoré 1992), which accounts for the nonlinear dependent variable. The positive estimates of θ_a and

θ_p in columns 1 and 3 are consistent with liquidity constraints having important aggregate implications. At the mean in column 1, migration rates increase by 0.18 (1.4) percent for every 1 percent increase in rainfall (price) shocks. In columns 2 and 4, the shocks have larger positive effects in villages with a greater mass of small landholders ($\hat{\theta}_{p\lambda} > 0$ and $\hat{\theta}_{a\lambda} > 0$). However, several estimates are imprecise with inference sensitive to the level of clustering.

Overall, the coefficients in Table 3 are consistent with a positive income elasticity of migration that is larger in villages with relatively more poor households. However, neither the OLS nor the LAD approach can be used to distinguish between binding liquidity constraints on the extensive or intensive margin of international migration flows. As I argue next, it is necessary to disentangle these two margins in order to understand how the aggregate income elasticity of migration depends on both liquidity constraints and opportunity costs.

IV. A Two-Step Estimating Framework

This section proposes a two-step estimating framework motivated by the prevalence of zeros in typical migration data. The setup offers practical advantages over existing approaches in the literature.

A. *A Theoretical Characterization of the Extensive Margin*

There are several reasons why financial and other barriers to migration may differ between villages with and without past migration. The model in Section I makes it possible to characterize these differences, and I do so for two reasons. First, testing Propositions 1 and 2 requires specifying the villages to which equations (3) and (4) apply as each implicitly assumes nonzero migrant stocks in both periods (regardless of log-linearization). Second, identifying *potential* migration flows from villages with no migrants requires a novel strategy.

To observe any migrants from village v in period t, at least one individual must be able to afford to migrate and deem migration profitable. Formally, if the CIA constraint $\tau_{vj} > 0$ (and $R_L \geq \underline{R}$), the migration rate (M_{vt}/N_{vt}) equals zero whenever the maximum village v landholding $\max_k R_{kv} \equiv \tilde{R}_v < R_L$ or the minimum landholding $\min_\ell R_{\ell v} \equiv \underline{R}_v > R_U$. If $\tau_{vj} = 0$, $M_{vt}/N_{vt} = 0$ whenever $\underline{R}_v > R_U$. The properties of extreme order statistics then imply that heavily populated villages are more likely to have any international migrants—a relationship with both purely statistical and substantive economic content as discussed below.[19]

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[19] Focusing on the case where $\tau_{vj} > 0$ and $R_L \geq \underline{R}$,

$$\Pr\left(\underline{R}_v \leq R_U, \tilde{R}_v \geq R_L\right) = 1 - R_{\overline{U}}^{-\lambda_v N_v} - \left(1 - R_L^{-\lambda_v}\right)^{N_v}.$$

This finite sample formulation can be rationalized by appealing to the truncation in equation (2) and the practical limits of village size. Here, $\tilde{R}_v$ follows a Stoppa distribution (Kleiber and Kotz 2003), and $\underline{R}_v$ follows a Pareto distribution with dispersion $\lambda_v N_v$. Eaton, Kortum, and Sotelo (2012) apply a similar rationale in a gravity model with a finite number of heterogeneous firms. Taking a population approach, however, implies

$$\Pr\left(\underline{R}_v \leq R_U, \tilde{R}_v \geq R_L\right) = \left(1 - e^{-R_U^{\lambda_v}}\right)\left(1 - e^{-R_L^{-\lambda_v}}\right).$$

The model implies an ambiguous relationship between the landholdings distribution, income shocks, and the extensive margin. The probability that any villagers find migration profitable (can afford to migrate) is increasing (decreasing) in λ_v. Thus, we have two cases: (i) no household can afford to send migrants despite available income gains; or (ii) all households can afford to send migrants but the income gains are insufficient. If (i) holds, then income growth increases the extensive margin probability, and vice versa for (ii). However, if CIA constraints do not bind (and $R_L < \underline{R}$), then income shocks decrease the extensive margin probability.

If the location of $\left(R_L, R_U, \underline{R}_v, \tilde{R}_v \right)$ is known for each village, then we can derive first the probability of having any migrants and then the scale of migration flows. In practice, income shocks can have different effects along each margin with important implications for estimation.

B. *Beyond Zero: A Latent Variable Formulation*

I propose a two-period Heckman (1976) selection approach as an alternative to existing methods for handling zeros in the migration literature.[20] To begin, note that the model implies the following expected migration rate in period *s*:

$$(7) \qquad E\left(\frac{M_{vs}}{N_{vs}}\right) = \underbrace{E\left(\mathbf{1}\{R_{Ls} \leq R_{iv} \leq R_{Us}\}|\tilde{R}_v \geq R_{Ls}, \underline{R}_v \leq R_{Us}\right)}_{\text{intensive margin}}$$

$$\times \underbrace{\Pr\left(\tilde{R}_v \geq R_{Ls}, \underline{R}_v \leq R_{Us}\right)}_{\text{extensive margin}},$$

where $M_{vs}/N_{vs} \in [0, 1)$. This expression clarifies that the reduced-form estimates in Table 3 reflect a mixture of the extensive and intensive margin elasticities.

However, separating these two margins matters for policy. Intuitively, the determinants of outflows from villages with a long history of emigration plausibly differ from those in villages with no recent connection to international labor markets. For example, in villages with no migrants, informational constraints may be relatively more binding than financial constraints in preventing emigration among the poor, whereas the opposite may be true in villages with a long migration history. I provide a first step towards accounting for these types of differences.

In justifying the econometric framework, it is important to establish first that zero migration is not a statistical artifact. Adapting the model in Armenter and Koren (2014) developed for trade data, I compare the empirical incidence of zeros

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Zero migration can still arise in this case but does so irrespective of the number of potential migrants. Formally, $N_v \to \infty \Rightarrow \tilde{R}_v \sim \text{Fréchet}(\lambda_v)$ and $R_v \sim \text{Weibull}(1, \lambda_v)$ in the limit (Gumbel 1958), and $\tilde{R}_v \perp \underline{R}_v$ asymptotically. This approach is analogous to that in the Helpman, Melitz, and Rubinstein (2008) gravity model with a continuum of heterogeneous firms. When $R_L < \underline{R}$, the equations above simplify, respectively, to $1 - R_U^{-\lambda_v N_v}$ and $1 - e^{-R_U^{\lambda_v}}$.

[20]These include OLS on the migration rate (Mayda 2010) or the log migration rate +1 (Ortega and Peri 2013), Tobit (Mayda 2010), restricting to nonzero observations (Grogger and Hanson 2011), and Poisson quasi-maximum likelihood estimation (QMLE) (Beine, Docquier, and Özden 2011).

with that arising from a model in which migrants (balls) are drawn randomly from villages (bins) with probability proportional to village population. By this metric, only 5.5 percent of the 27,297 zero migration villages in 2005 can be deemed an atheoretical regularity in sparse data (see online Appendix G.1 for details on this generalizable method).

Formally, I estimate the change in migration rates between 2005 (t) and 2008 ($t + 1$) using a two-step approach that accounts for the 20 percent of villages that enter ($M_{vt} = 0, M_{v,t+1} > 0$) and exit ($M_{vt} > 0, M_{v,t+1} = 0$) and allows the extensive margin thresholds to be correlated across periods:

$$m_{vt}^* = \mathbf{Z}_{v,t-1}' \phi_t + u_{vt};$$

$$m_{v,t+1}^* = \mathbf{Z}_{vt} + u_{v,t+1}' \phi_{t+1},$$

$$\Delta \ln\left(\frac{M_{v,t+1}}{N_{v,t+1}}\right) = \Delta \mathbf{X}_{vt}' \Theta + \Delta \varepsilon_{v,t+1} \quad \text{if and only if}$$

(8) $$m_{vt}^*, m_{v,t+1}^* > 0,$$

where m_{vs}^* is a continuous latent variable, and $\mathbf{Z}_{vs}$ and $\mathbf{X}_{vs}$ comprise, respectively, the determinants of the extensive and intensive margin. This setup could be construed as a panel sample selection problem (Rochina-Barrachina 1999). I account for selection into the intensive margin using parametric (Poirier 1980) and semiparametric (Das, Newey, and Vella 2003) procedures that include functions of the predicted extensive margin probabilities in the second-step regression (see online Appendix B).[21]

Exclusion Restrictions.—Credible identification of the second-step parameters Θ requires that a subset of variables in $\mathbf{Z}$ shift the extensive but not the intensive margin. I propose here several candidate instruments based on the model and empirical context.

First, I consider maximum and minimum landholdings within the village. The range of landholding sizes is informative about the range of wealth among potential migrants. Whether the wealthiest finds migration affordable and the poorest finds migration profitable are sufficient to identify nonzero migration. However, neither are informative about the *share* of the population that finds migration profitable and affordable. Hence, both are theoretically excludable.

The landholdings extrema give rise to another exclusion restriction: population size. The expected maximum (minimum) landholdings is increasing (decreasing) in village population. In this respect, population size bounds potential wealth. It also purges the (minimal) purely statistical variation in zeros uncovered in the

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[21] The key assumption of the two-step estimating framework is that the error in the intensive margin equation is a multiple of the errors in the extensive margin, plus some noise independent of the extensive margin. This latent variable setup has parallels in estimating the labor supply elasticity in the presence of nonparticipation (Blundell, Bozio, and Laroque 2011), and demand system parameters in the presence of zero consumption (Yen 2005).

balls-and-bins test. Finally, population size affects the extensive margin through potential migrant market size as perceived by recruiters based in cities.

A simple framework detailed in online Appendix G.2 relates recruiter activity to predetermined factors external to the village. First, the probability of recruiter visits is increasing in district population and decreasing in travel distances between villages within the district. Second, all else equal, recruiters are more likely to visit districts with fewer villages. Possible instruments therefore include the leave-v-out district population, number of villages, and area (as a proxy for inter-village distance). Online Appendix Table G.1 provides evidence supporting these predictions, and I address concerns about instrument validity in Section VC but turn now to the main results.

V. The Income Elasticity of Migration: Evidence from a Two-Step Model

This section presents the main empirical results accounting for the extensive and intensive margins of international migration flows. First, I report baseline estimates of the two-step model. Second, I provide additional evidence on the two mechanisms underlying the estimated income elasticity of migration and reconcile the results with prior studies. Finally, I discuss robustness.

A. *Landholdings Heterogeneity, Income Shocks, and Migration*

In all specifications of the two-step model in (8), I cluster standard errors at the district level, and reported second-step significance levels are based on a bootstrap-t procedure (see online Appendix B).

Extensive Margin: First-Stage.—Table 4 shows key results for the extensive margin equations:

$$\Pr(M_{vs} > 0) = \mathbf{shock}'_{vs}\boldsymbol{\eta}_s + f(\tilde{R}_v, \underline{R}_v)'\boldsymbol{\rho}_s + \mathcal{Z}'_{vs}\boldsymbol{\gamma}_s + u_{vs},$$

where $\text{corr}(u_{v,2008}, u_{v,2005}) \neq 0$, $\mathbf{shock}$ comprises rainfall and price shocks, $\mathcal{Z}$ is the vector of second-stage controls (see below) and excluded instruments, and $f(\cdot)$ is some function of the extreme order statistics of the landholdings distribution. I report estimates based on a seemingly unrelated linear probability model (SU-LPM) (Zellner and Lee 1965), which is used in the semiparametric correction procedure (Das, Newey, and Vella 2003—henceforth, DNV). The parametric Poirier (1980) approach based on a bivariate probit delivers very similar but more precisely estimated results.

In column 1 of Table 4, the positive estimate on log maximum landholdings ($\tilde{R}_v$) and negative estimate on log minimum landholdings ($\underline{R}_v$) support the threshold formulation. Villages with higher maximum landholdings and lower minimum landholdings (above 0.1 ha) are more likely, respectively, to have any individuals able to finance migration costs and with positive expected income gains from migration. The alternative formulation of $f(\cdot)$ in column 2 of Table 4 suggests that the extensive margin probability is higher in villages with larger populations and a greater

TABLE 4—EXTENSIVE MARGIN FIRST-STAGE ESTIMATES

	SU-LPM estimator				Bivariate probit estimator			
	2008	2005	2008	2005	2008	2005	2008	2005
	(1)		(2)		(3)		(4)	
log maximum landholdings	0.032 (0.005)	0.036 (0.006)			0.123 (0.018)	0.126 (0.019)		
log minimum landholdings	−0.045 (0.011)	−0.035 (0.011)			−0.180 (0.039)	−0.140 (0.039)		
Pareto exponent $\hat{\lambda}$			−0.006 (0.005)	−0.010 (0.005)			−0.037 (0.020)	−0.054 (0.021)
log village population			0.076 (0.007)	0.071 (0.007)			0.279 (0.020)	0.253 (0.022)
log district population less v	0.154 (0.036)	0.142 (0.033)	0.109 (0.035)	0.101 (0.034)	0.541 (0.113)	0.496 (0.108)	0.373 (0.114)	0.344 (0.108)
log district area less v	−0.059 (0.019)	−0.063 (0.019)	−0.058 (0.019)	−0.061 (0.019)	−0.182 (0.058)	−0.193 (0.055)	−0.185 (0.059)	−0.195 (0.055)
log distance to subdistrict capital	−0.021 (0.005)	−0.022 (0.005)	−0.019 (0.005)	−0.020 (0.005)	−0.083 (0.018)	−0.084 (0.017)	−0.076 (0.018)	−0.076 (0.017)
log distance to nearest emigration center	−0.019 (0.030)	−0.013 (0.029)	−0.019 (0.030)	−0.012 (0.029)	0.003 (0.097)	0.009 (0.090)	0.003 (0.099)	0.011 (0.092)
rice price shock	0.091 (0.390)	0.238 (0.391)	0.083 (0.387)	0.217 (0.416)	0.145 (1.279)	0.953 (1.247)	0.151 (1.306)	0.875 (1.282)
rainfall shock	0.035 (0.028)	0.034 (0.027)	0.035 (0.028)	0.034 (0.027)	0.094 (0.097)	0.093 (0.086)	0.101 (0.099)	0.100 (0.088)
Number of villages	44,665		44,665		44,665		44,665	

Notes: The table reports estimates of the extensive margin in equation (8). The dependent variable equals one if the village reports any residents working abroad at time s. The estimated Pareto exponent $\hat{\lambda}$ is for paddy area planted in 2002; higher values indicate less dispersion in landholding sizes. Results are similar for other landholdings measures. Additional covariates included in all specifications but not reported here include: log distance to the subdistrict capital and nearest emigration center, the share of households with landholdings above 0.1 hectares, the share of wetland in total agricultural land in the village, an indicator for whether the government classifies the village as urban, Muslim population share, ethnic Chinese population share, ethnic Arab population share, and an indicator for whether the village is accessible by motorized land transport. SU-LPM connotes seemingly unrelated linear probability models and estimates the LPM models for 2005 and 2008 jointly through a feasible generalized least squares procedure. Standard errors are clustered at the district level (using a block bootstrap procedure with 1,000 replications for the SU-LPM estimates) for all specifications.

mass of large landholders (low $\hat{\lambda}_v$).[22] Taking the model seriously, these results suggest that liquidity constraints matter more than incentive constraints on the extensive margin. In the typical village with no migrants, all households fall below the minimum wealth requirement $\tilde{R}_v$. Given the central role of λ_v in the second stage, I retain the specification in column 2 of Table 4 moving forward.

Rainfall and rice price shocks have positive, albeit statistically insignificant, effects on the extensive margin. This explains some of the muted reduced-form results in Table 3. These income shocks are large but do not have enough of an impact on first movers to lead to any average effect on the extensive margin. Finally, the point estimates for log village v population and log district population and area support the recruiter location choice framework discussed in Section IVB.

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[22] Recall that λ_v and population N_v fully determine the expected locations of $\tilde{R}_v$ and $\underline{R}_v$ (see footnote 19).

Intensive Margin: Second-Stage.—In Table 5, I estimate variants of the following second-step equation for migration flows:

$$(9) \quad \Delta \ln\left(\frac{M_{v,t+1}}{N_{v,t+1}}\right) = \theta_a \Delta \, rainfall \, shock_{vt} + \theta_{a\lambda}\left(\Delta \, rainfall \, shock_{vt} \times \hat{\lambda}_v\right)$$

$$+ \theta_p \Delta \, price \, shock_{vt} + \theta_{p\lambda}\left(\Delta \, price \, shock_{vt} \times \hat{\lambda}_v\right)$$

$$+ \mathbf{X}_v' \boldsymbol{\theta} + \mathcal{D}_{j(v)} + f\left(\hat{P}_{v,t+1}, \hat{P}_{vt}\right) + \Delta \varepsilon_{v,t+1},$$

which is consistent with the comparative statics in Section IB *and* the selection framework in Section IVB. Here, $\Delta \ln\left(\frac{M_{v,t+1}}{N_{v,t+1}}\right)$ is the change in the log migration rate between 2005 and 2008; $\mathbf{X}_v$ is a vector of time-invariant controls including, among others, $\hat{\lambda}_v$ and the proxies for migration costs noted in Section IIC; and $\mathcal{D}_{j(v)}$ are 11 fixed effects for the plurality destination of migrants from v in 2005.[23] The selection terms, $\hat{P}_{v,t+1}$ and $\hat{P}_{vt}$, are based on the specification in column 2 of Table 4 and equal the sum of two (bivariate) Mills ratios in the parametric Poirier procedure or a third-order polynomial in the propensity scores in the Das, Newey, and Vella procedure, but results are robust to other functional forms. These terms are jointly significant at the 1 percent level in all specifications.

The first key result in column 2 of Table 5 shows that agricultural income shocks increase migration rates after adjusting for selection. Proposition 1 suggests that the elasticity is positive because liquidity constraints are binding for enough households in the average village, thereby preventing the uptake of profitable migration opportunities. However, the smaller and imprecise selection-unadjusted OLS estimates of θ_p and θ_a in column 1 suggest that ignoring the extensive margin understates the importance of these financial constraints. Table 4 showed, using landholdings distribution statistics, that financial constraints are more binding than incentive constraints along the extensive margin. Thus, the correction terms account for the fact that villages in Table 5 have relatively fewer liquidity-constrained households than zero migration villages not in this table.

Both rainfall and rice price shocks have economically significant effects in column 2 of Table 5. A 10 percent increase in cumulative rainfall shocks between periods implies roughly a 4 percent increase in migration rates. At the mean, a one standard deviation increase in rainfall shocks leads to nearly a doubling of migration rates, or around 5 additional migrants per village relative to a base of 17 in 2005. Although somewhat imprecise, the estimate of θ_p implies that a 10 percent increase in the annualized price shock between periods is associated with roughly a 9 percent increase in the migration rate. The key elasticities are similar in panel B of Table 5 using the Poirier correction procedure.

The remaining columns of Table 5 show how the landholdings distribution shapes the income elasticity of migration. Column 3 shows that rainfall shocks have larger

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[23] The time-invariant covariates (listed in the notes to Tables 4 and 5) are not necessary in the second stage but are included to be consistent with the model. The estimates for these variables have been suppressed from the tables but are available upon request. All results are robust to dropping time-invariant controls altogether.

TABLE 5—TWO-STEP ESTIMATES OF THE INCOME ELASTICITY OF MIGRATION

Panel A. Semiparametric correction procedure	OLS (1)	(2)	(3)	(4)	(5)
Δ rainfall shock	0.086 (0.133)	0.390 (0.139)	0.113 (0.171)	0.167 (0.176)	−0.013 (0.183)
Δ price shock	−0.134 (0.433)	0.919 (0.487)	0.910 (0.484)	−1.031 (0.822)	−2.420 (0.824)
Δ rainfall shock $\times \hat{\lambda}$			0.165 (0.059)	0.140 (0.065)	0.086 (0.057)
Δ price shock $\times \hat{\lambda}$				1.116 (0.423)	0.858 (0.387)
Δ rainfall shock $\times$ share households > 0.1 ha					0.599 (0.148)
Δ price shock $\times$ share households > 0.1 ha					4.275 (0.898)
Joint significance of selection correction terms	—	[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]
Panel B. Parametric correction procedure		(6)	(7)	(8)	(9)
Δ rainfall shock		0.253 (0.136)	0.045 (0.170)	0.110 (0.174)	0.045 (0.186)
Δ price shock		0.457 (0.447)	0.465 (0.447)	−1.750 (0.776)	−2.077 (0.831)
Δ rainfall shock $\times \hat{\lambda}$			0.126 (0.057)	0.087 (0.061)	0.037 (0.061)
Δ price shock $\times \hat{\lambda}$				1.314 (0.400)	0.954 (0.376)
Δ rainfall shock $\times$ share households > 0.1 ha					0.377 (0.142)
Δ price shock $\times$ share households > 0.1 ha					2.218 (0.785)
Joint significance of selection correction terms		[< 0.001]	[< 0.001]	[< 0.001]	[< 0.001]
Number of villages	24,855	24,855	24,855	24,855	24,855

Notes: The table reports estimates of equation (9) in the text. The dependent variable in all specifications is Δ log (emigrants/total population) between 2005 and 2008 and has mean 0.11. The sample size in the bottom row corresponds to the columns in both panels; Δ *rainfall shock* is the difference in cumulative log deviations from long-run mean rainfall between the growing seasons ending in 2006–2008 and 2002–2005; Δ *rice price shock* is the difference in annualized log growth rates between 2005m4–2008m3 and 2002m1–2005m3. The estimate of λ_v is based on paddy area planted; higher values indicate less dispersion in landholding sizes. Columns 2–5 are based on the Das, Newey, and Vella (2003) procedure and include a third-degree polynomial in the propensity scores for the extensive margin in 2005 and 2008 based on column 2 of Table 4. Columns 6–9 are based on the Poirier (1980) procedure and include the bivariate Mills ratios given in online Appendix B based on column 4 of Table 4. The excluded instruments in this table and all subsequent tables are as reported in Table 4. Additional covariates in all specifications but not reported here include all those variables reported in the notes below Table 4. These predetermined or time-invariant covariates are included so as to allow for their effects to vary over time. Standard errors are clustered at the district level, and the significance levels are based on the block bootstrap-*t* procedure with 1,000 replications described in online Appendix B.

positive effects in villages with a greater mass of small landholders. The estimate of $\theta_{a\lambda} = 0.165$ implies that villages with $\hat{\lambda}_v$ at the seventy-fifth percentile (with landholdings $mean_v = 0.23$ ha, $Gini_v = 1/(2\lambda_v − 1) = 0.39$) have elasticities around 0.8, whereas villages at the twenty-fifth percentile ($mean_v = 0.42$ ha, $Gini_v = 0.62$) have elasticities around 0.4. This differential survives in column 4

alongside the interaction with price shocks, which also have larger effects on migration in villages with a greater mass of small landholders. The estimate $\hat{\theta}_{p\lambda} = 1.116$ implies that villages with $\hat{\lambda}_v$ at the seventy-fifth percentile exhibit an elasticity around 0.9 whereas villages with $\hat{\lambda}_v$ at the twenty-fifth percentile have an elasticity around 0.3. Overall, despite the increase in expected future income, the boost in current incomes is leading to an increase in migration flows, especially from villages with relatively more small landholders for whom the wage gains from migration are highest. Moreover, in column 5, these heterogeneous income elasticities remain economically and statistically significant when allowing for interactions with the share of households with landholdings above 0.1 ha.

Two additional results point to landholdings as the central source of household heterogeneity shaping the income elasticity of migration. First, in online Appendix Table F.1, I allow the elasticities to vary with a measure of wealth heterogeneity that is not based on landholdings. The Elbers, Lanjouw, and Lanjouw (2003) Poverty Mapping exercise for Indonesian villages in 2000 (Suryahadi et al. 2005) provides a Gini coefficient for predicted household expenditures per capita that I use to construct an implied Pareto dispersion parameter, $\lambda(expenditure)$, capturing variation in education, demographics, and (non-land) assets.[24] Adopting the specification in column 4 of Table 5 (re-estimated in column 1), I find positive, albeit insignificant, coefficients on the interactions of $\lambda(expenditure)$ and agricultural income shocks. Column 3 in Appendix Table F.1 combines these interactions with the original measure of $\lambda(land)$ and shows that landholdings dispersion retains its significant role in mediating the effect of income shocks even after accounting for residual wealth heterogeneity from other sources.

Second, in online Appendix F.1, I show that key elasticities vary in intuitive ways depending on the sensitivity of the type of landholdings (underlying λ) to rainfall and rice price variability. For example, the heterogeneous effect of rainfall shocks in column 4 of Table 5 is muted when focusing on λ for wetland that is less reliant on rainfall. Meanwhile, the heterogeneous effect of price shocks is muted for λ based on total agricultural land, some of which is used for growing crops besides rice. I use the estimates in this table to validate the model by applying equation (3) to recover a Cobb Douglas coefficient on land $\left(\hat{\beta} = 1/\hat{\theta}_{p\lambda}\right)$ consistent with results in the agricultural literature.

On balance, the main results in Table 5 highlight the importance of liquidity constraints in determining the aggregate income elasticity of migration from rural Indonesia. However, as argued below, these elasticities mask the role of opportunity costs in shaping migration flows.

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[24] Although myriad household characteristics were used in these proxy means, nearly 80 percent of the variation in predicted expenditures across villages is explained by education. The correlation of $\lambda(expenditure)$ with the preferred λ for land is around 0.22, suggesting that the two are capturing different aspects of within-village income inequality.

B. *Interpreting the Income Elasticity*

Given the expenditure response to income shocks noted in Section IIE, the baseline estimates of the rice price and rainfall elasticity (column 2, panel A, Table 5) imply an *average* income elasticity of migration around 1 for persistent shocks and around 0.1 for transitory shocks, respectively.[25] These elasticities are plausible given the associated income gains. For example, the increase in rice prices between early 2005 and 2008 raised (consumption-adjusted) profits per harvest on average by US$35 for a household with 0.25 ha of paddy landholdings and US$165 for a household with 0.75 ha of landholdings (see online Appendix E.5). These are sizable gains given that many households bring in 2–3 harvests per year, and less than 30 percent of households with less than 1 ha of land have cash savings greater than US$350, the minimum placement cost (see Sections IC and IIC). It is less straightforward to benchmark the rainfall effects, but the rainfall elasticity of rice output estimated in Levine and Yang (2014) suggests similarly meaningful income gains on the margin.

Overall, the income elasticities that I estimate are smaller than other recent estimates for rural, developing country populations. Angelucci (2015) finds an income elasticity of migration from rural Mexico to the United States of around 2.3, and Bryan, Chowdhury, and Mobarak (2014) find an elasticity of rural to urban migration within Bangladesh of around 1.1. The former may be larger because fixed costs are higher for international than for internal moves and/or the *Oportunidades* cash transfers were part of a more permanent welfare program than the one off transfers in the Bangladesh experiment.

One potentially important distinction is that my estimates are based on village-level regressions, whereas these studies are based on household-level regressions. Nevertheless, the implied income elasticities from the household-level regression in column 2 of Table 2 are only slightly smaller than the village-level elasticities. In Section VD, I reconcile these micro and macro elasticities.

Perhaps most importantly, though, the larger effects in both studies are plausibly due to their focus on nonlabor income transfers to the very poorest rural households. By comparison, the elasticities that I estimate are based on the entire rural population and on labor income, both of which imply greater scope for offsetting effects of opportunity costs. I now provide evidence that these opportunity costs bind for some part of the rural Indonesian population.

On the Opportunity Cost Mechanism.—While liquidity constraints are the most important determinant of the income elasticity of migration for the average village, there are settings in which opportunity costs may be binding. For example, in villages with deep presence of recruitment agencies, cash-in-advance constraints may be limited given the pervasiveness of interlinked contracts as detailed in Section IIC. Also, in the most vibrant agricultural economies, the opportunity cost of migration

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[25] This calculation presumes that savings rates are zero (i.e., expenditures equal income). In practice, these income elasticity estimates should be scaled down by $(1 - s)$ where s is the average savings rate. This would further reduce the size of these elasticities relative to the other recent estimates in the literature discussed below.

TABLE 6—EVIDENCE ON THE OPPORTUNITY COST MECHANISM

	(1)	(2)
Δ *rainfall shock* $\times$ recruiter presence	0.262 (0.154)	
Δ *rainfall shock* $\times$ no recruiter presence	0.450 (0.136)	
Δ *price shock* $\times$ recruiter presence	0.054 (0.627)	
Δ *price shock* $\times$ no recruiter presence	1.746 (0.467)	
Δ *rainfall shock* $\times$ agricultural GDP, quartile $= 1$		0.597 (0.305)
Δ *rainfall shock* $\times$ agricultural GDP, quartile $= 2$		0.184 (0.200)
Δ *rainfall shock* $\times$ agricultural GDP, quartile $= 3$		0.205 (0.188)
Δ *rainfall shock* $\times$ agricultural GDP, quartile $= 4$		-0.055 (0.161)
Δ *price shock* $\times$ agricultural GDP, quartile $= 1$		3.468 (1.067)
Δ *price shock* $\times$ agricultural GDP, quartile $= 2$		0.612 (0.541)
Δ *price shock* $\times$ agricultural GDP, quartile $= 3$		-1.168 (0.766)
Δ *price shock* $\times$ agricultural GDP, quartile $= 4$		-2.055 (0.677)
Number of villages	24,855	24,493

Notes: This table allows the main effects estimate from column 2 in Table 5 to vary in column 1 with an indicator for whether there are recruitment agencies based in the village as reported in *Podes*, and in column 2 with quartiles of the district-level agricultural GDP in 2002 (higher quartiles are richer). The sample is slightly reduced in column 2 due to missing GDP for some districts. See the notes to Table 5 for additional details on the specification. Standard errors are clustered at the district level, and the significance levels are based on the block bootstrap-t procedure with 1,000 replications described in online Appendix B.

may be particularly high as rice prices rise given the thick markets for complementary inputs to expand production. Table 6 provides evidence in line with these hypotheses.

First, column 1 of Table 6 shows that price shocks have a large positive effect ($\theta_p = 1.75$) in villages with no recruitment agencies and a null effect ($\theta_p = 0.05$) in villages with such agencies. I identify this statistically significant difference by augmenting the baseline specification (column 2, panel A of Table 5) with a measure from *Podes* capturing the presence of recruitment agents.[26] Meanwhile, transitory rainfall shocks have significant positive effects in both types of villages, but the

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[26] The question asks about agencies targeting female migrants. However, many agencies offer contracts to men as well, which can be seen from confidential administrative data on migrant placements by agencies since 2014, as reported by the Indonesian government and made available to me for an ongoing experiment involving these agencies. Note that the specification also includes the agency dummy on its own. Although agency presence is not strictly exogenous, this measure identifies those villages where agencies have had a longstanding presence known to the village head.

elasticity is statistically significantly larger in villages without such agents. Taken together, these results show not only that cash-in-advance constraints are more binding in villages without recruitment agents but also that opportunity costs matter in villages with deep recruiter presence. If opportunity costs did not matter, then we should find a large price shock elasticity in these villages just as we see for the rainfall elasticity. This asymmetry in the response to transitory and persistent shocks offers direct evidence of the two offsetting effects of rising income obscured in the baseline average elasticities.

Column 2 in Table 6 provides additional evidence of these asymmetries by showing negative price shock elasticities in the most advanced agricultural areas. In particular, I allow the elasticities to vary with the quartile of agricultural GDP measured at the district level in 2002. For villages in the bottom quartile, both rainfall and price shocks have large and statistically significant effects on migration flows with elasticities of 0.6 and 3.5, respectively. This points to the liquidity constraints mechanism, which remains important in the second quartile as well. However, in the top quartile, rainfall shocks have null effects, whereas price shocks have a large *negative* effect of -2.05 significant at the 5 percent level. This suggests that opportunity costs dominate liquidity constraints in the most advanced agricultural areas of the country, which is consistent with increasing returns to farm labor.

C. *Robustness*

The previous sections highlighted several findings that clarify how to interpret a positive income elasticity of international migration flows. In this section, I rule out concerns about confounding changes in agricultural wages, the endogeneity of price shocks, the role of internal migration, and violations of the exclusion restrictions in the two-step model. Online Appendix F further shows robustness to: alternative specifications for and measurement of the rainfall and price shocks; alternative choices of $\underline{R}$ in the estimation of λ_v; controlling for demographic structure in the village; and accounting for outliers (in M_{vt} and $\hat{\lambda}_v$), illegal migration, and the quality of population registers.

Accounting for Agricultural Wages.—Although I do not incorporate general equilibrium wage effects in the model, temporary emigration flows are likely too small to cause changes in local agricultural wages (see Table 1). However, some of the effects of rainfall and rice price shocks on migration flows may operate through wages. If so, then adding wage shocks to equation (9) should dampen the elasticities on the other shocks and enter with a similar sign. Online Appendix F.2 shows that this is the case. Agricultural wage shocks (at the district level) have a positive, albeit insignificant, elasticity, and the elasticities on rainfall and rice price shocks fall by around one-fourth.

Instrumenting for the Price Shock.—In online Appendix Table F.4, I show that the qualitative baseline results are unchanged when using predetermined import exposure measures as instrumental variables (IV) for realized price changes. That is, I instrument for the price shock with distance to the nearest port and shipping

distance to Bangkok and Ho Chi Minh City. The identifying assumption is that conditional on the distance to the nearest emigration center across Indonesia, distance to rice trade routes only affects international migration through the rice price shock. While acknowledging potential concerns about validity and strength, these IV results increase confidence that the spatial variation in the price shock is uncorrelated with pre-trends in migration flows.

Internal Migration.—Insomuch as internal migrants, which cannot be separately identified, affect population records (N_{vs}), differences in the dependent variable, $\Delta \ln(M_{v,t+1}/N_{v,t+1})$, could be driven by internal rather than international migration flows. However, two factors suggest that the direction of bias goes against my findings. First, positive rainfall shocks at home reduce internal out-migration according to district-level and household-level regressions (see online Appendix F.8 and Kleemans and Magruder 2012, respectively). Second, rural areas of Indonesia experience positive net immigration during periods of high commodity prices (Hugo 2000). Both mechanisms imply that income shocks increase population size and hence attenuate key elasticities in Table 5.

Validity of Exclusion Restrictions.—Online Appendix F.3 shows that key two-step results do not hinge on the associated excludability assumptions. In varying the exclusion restrictions used to estimate second-step parameters, I find no systematic or significant departures from the baseline results.[27]

D. *Reconciling Micro and Macro Elasticities: A Validation Exercise*

The main household-level and village-level regressions point to heterogeneity in the income elasticity of migration. While the two approaches deliver similar qualitative insights on this heterogeneity, this brief subsection evaluates the quantitative mapping from heterogeneous individual choices in Table 2 to heterogeneous macro elasticities in Table 5.

In particular, I combine the landholding size-specific elasticities from columns 3–4 of Table 2 and village-specific dispersion parameters $\hat{\lambda}$ to construct implied village-level income elasticities of migration. For each village v, I first assign the elasticities to the share of households at the given landholding size range implied by $\hat{\lambda}$. I then sum those weighted AMEs across the village population to recover a village-level *implied income elasticity* that can be compared to the *actual elasticity* obtained from the Θ parameters in column 4 of Table 5 (see online Appendix F.9 for further background).

Table 7 shows that the implied elasticities are not only highly correlated with but also have similar central tendencies to the actual elasticities. These stark similarities are not purely mechanical. Rather, they corroborate the aggregation of

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[27] Of course, this only provides a partial test of validity. One concern is that the instruments for the extensive margin are merely picking up unobservable village-level migration networks with direct effects on the intensive margin. However, this would imply downward biased income elasticities because for villages induced into the second stage, the costs of migration are relatively lower and hence wealth should be less of a binding constraint on emigration in the lower tail of the landholdings distribution.

TABLE 7—COMPARING ELASTICITIES BASED ON MICRO AND MACRO DATA

Elasticity summary statistic:	mpctileean	SD	25th pctile	Median	75th pctile	Correlation w/village-level reg.
Δ price shock						
Aggregating micro data AMEs (linear R_{iv})	0.776	0.011	0.771	0.778	0.783	0.836
Aggregating micro data AMEs (quadratic R_{iv})	0.698	0.030	0.683	0.702	0.718	0.898
Village-level regression	0.747	0.473	0.440	0.680	0.974	—
Δ rainfall shock						
Aggregating micro data AMEs (linear R_{iv})	0.224	0.005	0.222	0.225	0.227	0.836
Aggregating micro data AMEs (quadratic R_{iv})	0.226	0.018	0.214	0.226	0.238	0.977
Village-level regression	0.389	0.059	0.351	0.381	0.417	—

Notes: This table reports elasticities of flow migration rates with respect to rainfall and rice price shocks based on two approaches. *Aggregating Micro Data AMEs* elasticities are computed based on columns 3–4 in Table 2 as the sum of nationally representative average marginal effects (AMEs) of shocks at landholding sizes $\in \{0.1, 0.2, \ldots, 2.5\}$ weighted by the share of households in the village falling within each of the given size ranges as implied by the estimated Pareto dispersion parameter $\hat{\lambda}$. *Village-Level Regression* elasticities are based on the estimates of θ parameters using village-level data in column 4 of Table 5 computed at each percentile of $\hat{\lambda}$. The elasticities are restricted to villages in the second-step sample (i.e., those with any migrants in 2005 and 2008) in keeping with the inclusion only of households with any migrants from 2000–2006 in the fixed effects migration choice regressions.

heterogeneous household choices proposed in the model and operationalized empirically in Section VA. As I document next, the scale and timing of migration costs play an important role in shaping these elasticities.

VI. Migration Costs, Liquidity Constraints, and Policy

In this final section, I recover structural estimates of migration costs in order to quantify the prevalence of financial constraints and present potential policy implications.

A. *Migration Costs: A Simple Calibration*

I begin by using the two-step regression framework and a simple calibration procedure to estimate fixed migration costs for all villages, including those with no migrants. I use equation (3) to recover village-specific costs associated with prevailing two-year contracts overseas.

The analysis proceeds in five steps, detailed further in online Appendix F.10. First, using baseline estimates from Table 5, I predict the change in migration rates, $\Delta \ln(M_{v, t+1}/N_{v, t+1})$, for all villages. Second, I recover the Cobb Douglas coefficient on landholdings. Third, I estimate village-specific autoregressive parameters, α_v, for rice prices at a biannual frequency. Fourth, I plug in the appropriate empirical analogues for rice price shocks, $\Delta \ln p_{vt}$, and rainfall, $\overline{\sigma}_v + a_{vt} = \sigma_{vt}$. Fifth, I use the official, destination-specific monthly gross wages reported by Bank Indonesia (2009) to calculate wage offers, W_{vjt}. I then set $\tau_{vj} = 1$ and solve analytically for migration costs, C_{vjt}.

Table 8 reports estimated costs of US$2,356 for the average village with a range from $115 to $8,692. These average costs are around twice as large as the typical placement costs (see Section IIC) and hence must be capturing psychological and

TABLE 8—SUMMARY STATISTICS ON ESTIMATED VILLAGE-SPECIFIC MIGRATION COSTS
(*in US dollars*)

	Mean	SD	Min	Median	Max
Estimated village-specific cost	2,356	690	115	2,185	8,692
… As share of district average annual HH expenditures	2.02	0.68	0.14	1.91	8.75

Notes: The village-specific costs (in 2006 US dollars, roughly) are recovered from the structural equation in column 4 of Table 5. Household expenditure estimates are based on survey data from 2006 representative at the district level.

other costs (e.g., search) beyond those paid as part of the fixed fee charged by recruiters. The map in Figure 4, panel A, demonstrates some of the geographic variations in costs, which appear to be relatively lower in areas of Java and South Sulawesi that are better connected to international air transport hubs, and the eastern coast of Sumatra and western coast of Kalimantan, which are a short distance to Malaysia and Singapore.

B. *Characterizing the Prevalence of Liquidity Constraints*

Using the above results, I show here how the timing of migration costs determines the prevalence of liquidity constraints. Table 8 reveals that estimated costs are around two years of *total* expenditures for a household in the typical village (according to *Susenas* data for 2006–2007). In some poor and/or remote regions, costs exceed 4–5 years of total expenditures (see Figure 4, panel B). Given the low savings rates and limited cash-on-hand for most rural households, these estimates imply that migration is only feasible for a large part of the population when some fraction $(1 - \tau)$ of those costs can be deferred until after earning some income abroad (or financed through conventional borrowing). As noted above, the most common arrangement involves recruiters paying some or all of the up-front costs and then garnishing migrants' wages. Taking the model seriously and applying the estimated costs, I recover for each village the fraction of households that are liquidity constrained for a given up-front cost burden, $\tau \in (0, 1)$, based on empirical analogues of $R_L^{-\lambda_v}$ in equation (2).

Figure 5 then answers the following policy-relevant question: If individuals must pay 100τ percent of migration costs before earning the first month's wage abroad, then what fraction of the population will be unable to migrate despite expected income gains from doing so? The curves represent the average prevalence of liquidity constraints across all villages in 2005 and 2008, respectively. The results suggest that nearly half of all households in the average village are unable to allocate labor abroad when migrants have to pay as little as 20 percent of the fixed costs up-front. Moreover, when $\tau > 0.6$, nearly all households are unable to send members abroad. These stylized findings may seem stark, but they are consistent with available survey evidence cited in Section IIC suggesting that no migrants pay the full costs out of pocket. Moreover, nearly half of all rural villages do not have any international migrants, which can be explained by binding liquidity constraints according to the

Panel A. Average costs for two-year contracts (US dollars)
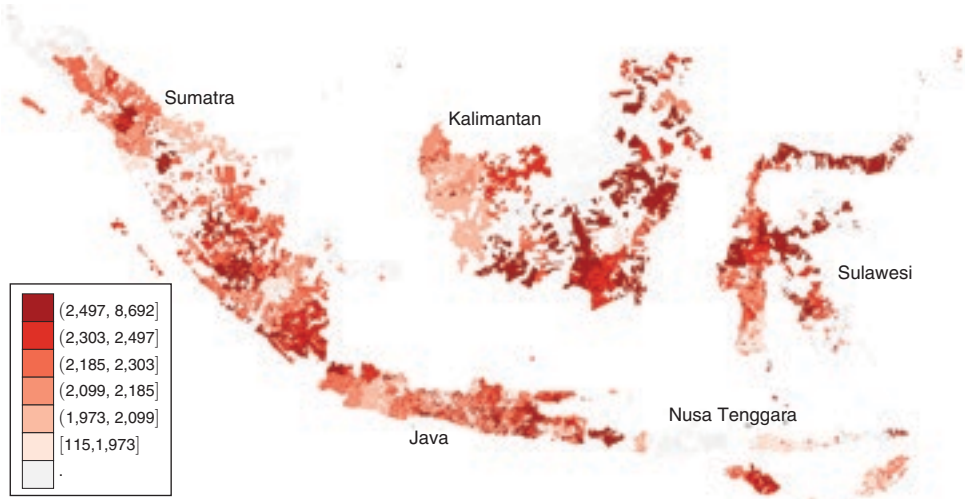
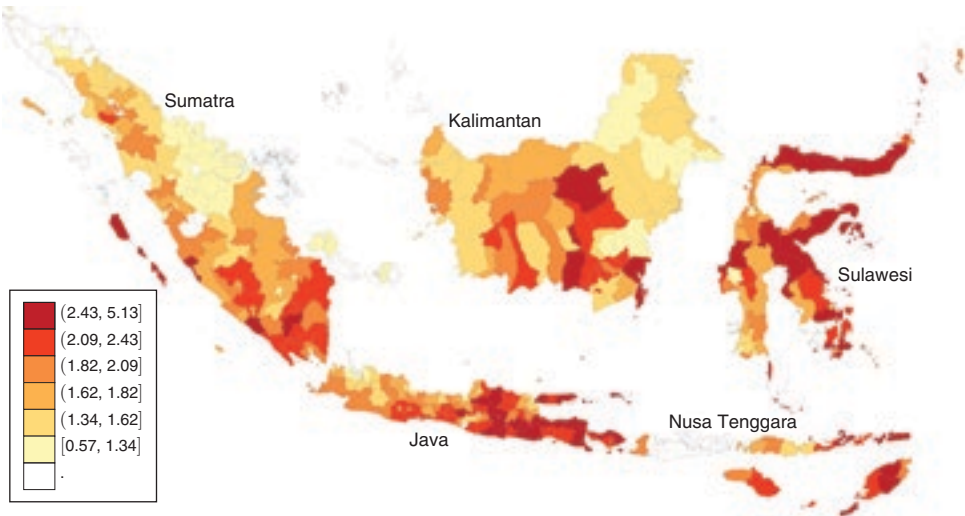Panel B. Average costs/annual household expenditure

FIGURE 4. ESTIMATED VILLAGE-SPECIFIC MIGRATION COSTS, BY DISTRICT

Notes: The shading corresponds to sextiles. The village-specific costs (in 2006 US dollars) are recovered from the structural model for all villages in the baseline regression from column 4 of Table 5. To obtain the district averages in panel B, I first weight each village's costs by its population in 2005 and then divide by the appropriately weighted estimate of average household expenditures per capita in *Susenas*. Estimates are missing for certain districts on account of villages in those districts being excluded from the two-step model as a result of missing data from one of the main datasets or no households with landholdings in the village.

extensive margin regressions in Table 4. In online Appendix F.11, I provide empirical evidence on how formal and informal intermediaries reduce the cost burden.

VII. Conclusion

This paper proposed a novel framework for identifying the income elasticity of migration. Drawing upon a rich empirical context in Indonesia, I uncovered new
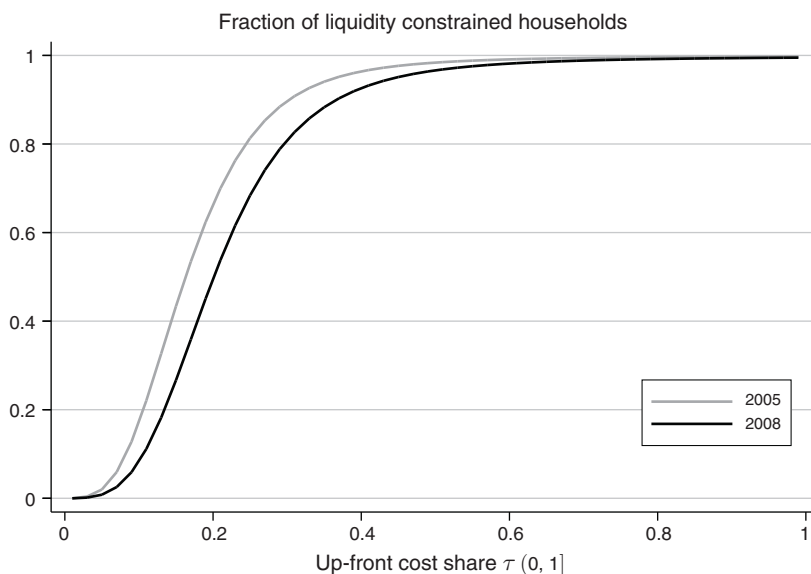
FIGURE 5. UP-FRONT COST SHARING AND THE PREVALENCE OF LIQUIDITY CONSTRAINTS

Notes: The village-specific costs (in 2006 US dollars, roughly) are recovered from the two-step model estimates using the procedure described in the text. Estimates of fraction liquidity constrained based on the structural model.

evidence on the extent to which financial constraints and opportunity costs shape international migration flows from low income settings. Positive rainfall and rice price shocks were associated with greater international migration, particularly in villages with a greater mass of small landholders. However, price shocks reduced migration flows from the most agriculturally developed rural areas where the opportunity costs were plausibly highest. Auxiliary household survey data supported the heterogeneous choices underlying these macro elasticities.

Extending the insights in this paper to a generalized gravity framework for explaining migration flows is an important task for future research. Whether the empirical results extend to other migration channels and developing countries is a question to which the model can be readily adapted. These extensions include a longer time horizon, other dimensions of income heterogeneity outside the agricultural context, and multiple destinations.

Overall, though, this paper offers a new set of tools for engaging with the ongoing debate as to how global migration patterns will evolve as incomes continue to grow across the developing world. These findings are important for broader debates on spatial labor misallocation and productivity (Lagakos and Waugh 2013, Young 2013). If positive income shocks enable liquidity-constrained households to send migrants *and* incentivize unconstrained households to retain (former) migrants, then the overall welfare gains may be quite large. These welfare implications should be quantified in future work.

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