Selection and Heterogeneity in the Returns to Migration*

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Abstract

There is considerable debate on the returns to rural-urban migration in developing countries, and magnitudes differ depending on the empirical methods used. We aim to reconcile these divergent estimates by explicitly accounting for the role of heterogeneity in the returns to migration. We develop a correlated random coefficient model that allows for location-specific skills and heterogeneous returns that we estimate using rich longitudinal data from Indonesia, China, and Tanzania. This model lets us extrapolate the returns identified from switcher sub-populations to non-switchers—a group of particular interest to policymakers deciding whether to encourage migration as a development strategy. Our results reveal considerable heterogeneity in the returns to migration and show a clear pattern in the relationship between absolute and comparative advantage across countries: those with the lowest consumption in rural areas stand the most to gain from migrating. This suggests that migration is a pro-poor strategy but that barriers to migration may prevent workers from realizing their potential. As such, individuals appear to be inefficiently sorted across space; therefore, encouraging migration could lead to large returns in aggregate output.

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1 Introduction

As economies develop, labor typically migrates out of rural areas into higher-productivity sectors in cities. Yet, a puzzling phenomenon persists across the developing world: striking consumption gaps between rural and urban areas persist, even after decades of rapid urbanization. Urban residents consistently consume two to three times more than their rural counterparts, a gap that remains even after accounting for cost-of-living differences, educational attainment, and other observable characteristics (Young, 2013; Gollin, Lagakos and Waugh, 2014; Herrendorf and Schoellman, 2018).

With countries undergoing structural transformation and rapid urbanization, why do we still observe such striking disparities? This puzzle lies at the heart of debates on labor allocation, productivity, and welfare in developing economies. One view suggests that labor is misallocated across space due to frictions or policies, implying that reducing these barriers could increase productivity and welfare. Another perspective posits that workers efficiently sort themselves based on unobserved characteristics, such as location-specific skills, which would make these wage gaps less amenable to policy intervention. A key input into this debate—and essential for informed policy decisions—is reliable estimates of the returns to migration. In other words, good policy decisions require robust estimates of the causal effect of migration on individual consumption and earnings.

In this paper, we estimate the consumption returns to rural-urban migration for both migrant and non-migrant populations. Different empirical methods rely on distinct subpopulations for identification, which can lead to divergent results in the presence of heterogeneous returns. By explicitly accounting for the heterogeneity in returns across different subpopulations, we provide a framework that helps reconcile the wide range of estimates of rural-urban migration returns found in the literature. Our results also contribute estimates of the returns to migration for non-migrants, a large and important sub-population whose returns are unidentified in standard models.

To study the returns to migration, we leverage rich longitudinal data from Indonesia, China, and Tanzania, totaling over 75 thousand individuals across the three countries, for whom we observe location choices and labor market outcomes for three to five periods spanning several years. We use these rich data to estimate the observational returns to rural-urban migration, meaning the returns for those observed to migrate in the data. We then turn to non-parametric approaches to examine the extent to which migration returns vary across migration histories, which sheds light on the plausibility of the assumptions that underlie standard panel data estimators. Further, we develop a

model that acknowledges that workers have location-specific skills, which are rewarded differently in rural and urban labor markets. Building on the Roy (1951) model and its extensions, our model accounts for unobserved heterogeneity and comparative advantage in the returns to migration.

Our methodological innovation is to cast this model as a group random coefficient model that imposes a specific restriction on the form of the heterogeneous returns, inspired by Suri (2011) and Tjernström, Ghanem, Michuda, Barriga-Cabanillas, Lybbert and Michler (2026). By restricting the returns to urban migration to be linear in comparative advantage, we are able to extrapolate returns to non-migrants—an important sub-population whose returns are typically unidentified in standard models.

Our analysis yields four main results. First, pooled OLS regressions reveal large average rural-urban consumption gaps, ranging from 40 log points in Indonesia to 74 log points in Tanzania, consistent with previous findings in the literature. Second, these gaps decrease to 21-57 log points when we include controls and further narrow to 7-15 log points with the addition of individual fixed effects. While individual fixed effects controls for time-invariant individual characteristics, this approach also effectively restricts identification to individuals who migrate between urban and rural areas. For comparison, we therefore re-estimate our OLS results using a sample of only switchers and obtain estimates similar to those from the fixed-effects models (3-12 log points with controls). These patterns suggest that selection into migration may play a larger role than time-invariant characteristics in explaining the estimated consumption gaps. The importance of selection motivates us to further investigate the returns to migration across different switcher sub-populations, based on migration histories.

Third, we examine the observational returns to urban location across different migration histories and document striking heterogeneity. This suggests that standard panel data estimators, like fixed-effects models, may fail to capture important features of the data. Fixed-effects models assume that the returns to urban migration are homogeneous regardless of a person's migration trajectory. As a result, these estimators overlook the important variation in consumption outcomes associated with different migration histories, potentially resulting in flawed estimates of the key policy-relevant parameters.

Fourth, to address this limitation, we turn to our group random coefficient model, which allows for heterogeneous returns across different migration histories. Our analysis reveals a consistent negative relationship between comparative and absolute advantage. When we extrapolate the estimates to non-migrants, we find significantly greater potential returns for individuals who have never migrated—particularly those remaining

in rural areas. This pattern is remarkably consistent across the three countries that we study, indicating a pattern of labor misallocation that may signal the existence of untapped opportunities for enhancing welfare through policy interventions that reduce migration barriers. One way to interpret our findings is that migration acts as a "pro-poor" mechanism: rural individuals with the lowest baseline consumption experience the most significant gains from moving to urban centers.

Our work contributes to two strands of the literature. First, we add to the evidence on the magnitudes and sources of sectoral labor productivity gaps in developing countries.[1] A central debate in this literature is whether earnings or consumption gaps imply that productivity and welfare would increase if workers were able to reallocate to more productive sectors, or whether they simply reflect self-selection of heterogeneous workers among sectors. Our findings provide a way to reconcile diverging estimates of returns to rural-urban migration and occupational mobility from agriculture to non-agriculture sectors.

Several recent studies using microdata to estimate the returns to rural-urban migration (Alvarez, 2020; Hamory, Kleemans, Li and Miguel, 2021; Herrendorf and Schoellman, 2018) find that the average rural-urban migration returns for many migrant populations are relatively small—especially when compared to earlier results that used national accounts data or cross-sectional analyses (see e.g., Gollin *et al.* 2014; Young 2013). One implication of these results obtained using microdata is that efficient sorting of workers based on comparative advantage can explain rural-urban earnings gaps, which suggests limited opportunities for welfare-enhancing policy interventions. While our panel data results are similar to these studies, we show that the average returns estimated using fixed effects hide substantial heterogeneity.

Another set of papers explores the role of misallocation and barriers to sectoral mobility and uncover evidence consistent with the notion that rural non-migrants face external constraints or costs that keep them from relocating to urban labor markets. Adamopoulos, Brandt, Leight and Restuccia (2022) use data from China to examine the interaction between misallocation and selection, finding that distortionary policies disproportionately affect more productive farmers, making them less likely to work in agriculture, which in turn leads to lower agricultural productivity overall. Gai, Guo, Li, Shi and Zhu (2024) focus in on migration costs as the chief barrier, also in China, finding that reduced migration barriers would increase productivity and GDP alike. Pulido

[1] See Donovan and Schoellman (2023) for a recent review of the role of labor market frictions in the agricultural productivity gap and Lagakos (2020) for a review of the evidence for urban-rural migration.

and Święcki (2021) explicitly incorporate barriers to mobility into a selection model and find that they act as significant productivity constraints on both sectors.[2] Similarly, the estimates in Bryan, Chowdhury and Mobarak (2014), based on experimentally-induced seasonal migration, suggest that urban migration increases consumption by 33 percent.

A key innovation in our paper is our ability to extrapolate the returns to migration to non-migrant subpopulations. When we impose additional assumptions on the form of heterogeneity, we show that returns to non-migrants are consistent with the evidence that finds evidence of important barriers to mobility. There are some similarities between our approach and that in Alvarez-Cuadrado, Amodio and Poschke (2023), who study the alignment of absolute and comparative advantage in African agriculture. Leveraging households who are involved in both the agricultural and non-agricultural sectors, they find that absolute and comparative advantage are negatively correlated in African agriculture, suggesting that self-selection may not be the key driver of agricultural productivity gaps between sub-Saharan African countries and higher-income economies. Like Alvarez-Cuadrado *et al.* (2023), we are interested in the relationship between absolute and comparative advantage, but our methodological approach differs from theirs in several key ways: first, rather than focusing on the sign of the relationship between absolute and comparative advantage, we use this relationship to extrapolate the returns to non-switcher subpopulations. Second, given our focus on rural-urban migration, we rely on sectoral switches rather than infra-marginal decisions for identification. Third, we track individuals' choices over time, as opposed to households.[3]

The second key literature that we contribute to is the vast literature on micro-economic policy evaluation, examining models with heterogeneous effects and endogenous regressors. We build on the generalized Roy models previously used by research in labor and development economics and adapt them to our context, the study of heterogeneity in the returns to rural-urban migration.[4] Our empirical strategy builds

[2]Relatedly, a counterfactual simulation in Bryan and Morten (2019), based on a structural model that incorporates sorting and agglomeration effects, suggests that removing barriers to mobility would increase productivity by 22 percent. They further argue that this is likely a lower bound on the gains from removing migration barriers, as their main analysis excludes self-employed individuals, who likely have an even greater variance in earnings. Even in a developed-country context with smaller spatial gaps, Heise and Porzio (2023) estimate a 5 percent gain in aggregate output per worker from removing spatial frictions in Germany, with gains of 17 percent in the lower-productivity East, similar in magnitude to the estimate in Bryan and Morten (2019).

[3]An extensive literature has shown that household decisions are often the result of complex negotiations or bargaining within the household, implying that household decisions may reflect this bargaining process rather than comparative advantage. As examples, see Vermeulen (2002) for a survey of household collective models and Chen (2013) for an application of such models in the context of migration in a developing country. Additionally, the aggregate nature of household-level data may mask individual heterogeneity if household members have a comparative advantage in different sectors.

[4]Lemieux (1998) develops a panel data estimator that accounts for two-sided non-random selection

on recent work in the econometrics literature (Verdier, 2020; Tjernström *et al.*, 2026) aiming to flexibly estimate the returns to switcher subpopulations and extrapolating these returns to non-switchers.

Returns for groups like non-migrants in our study represent a potential parameter of interest for policymakers and a technical challenge for researchers. Heckman and Vytlacil (1999) propose a way to estimate returns for inframarginal groups by leveraging marginal treatment effects (MTE).[5] Estimates for these populations may differ sharply from those obtained based on marginal individuals, like switcher populations. The approaches used in the MTE literature approaches require exogenous policy variation or another type of instrument, while our approach instead relies on imposing structure on the form of comparative advantage.[6]

2 Model and Identification

We study an economy where individuals choose between working in a rural or urban labor market, based on their skills and preferences. As is common in the literature, we motivate our empirical strategy with a generalized Roy (1951) model.[7] In the classical Roy model, people sort across sectors solely based on income or consumption. Our generalized Roy model adopts a standard generalization that allows location choices to also depend on non-pecuniary factors. In the context of migration, the non-pecuniary component of utility captures proximity to family, local amenities, or other idiosyncratic factors that affect location choices but are not reflected in consumption.

2.1 Consumption and Location Choice

The model has three main components. We first describe how consumption depends on worker productivity across rural and urban locations. We then decompose productivity into absolute and comparative advantage to characterize sorting and returns to migration. Finally, we introduce utility shocks and derive the worker's location choice rule.

and differential skill rewards across sectors, and applies it to the study of unions' effects on wages. Suri (2011) uses a similar model to estimate the returns to hybrid seed adoption for different farmer subpopulations.

[5] See also Heckman and Vytlacil (2005), Heckman and Urzua (2010), and Cornelissen, Dustmann, Raute and Schönberg (2016).

[6] See Gai *et al.* (2024) for a recent application that uses policy variation in the context of rural-urban migration in China.

[7] See for example Bazzi, Gaduh, Rothenberg and Wong 2016; Alvarez 2020; Lagakos and Waugh 2013; Pulido and Święcki 2021.

2.1.1 Consumption and Productivity Across Sectors

The rural and urban labor markets, indexed by $l = R, U$, demand different skills and compensate these skills differently. For worker i at time t, who works in location l, let y_{it}^l denote the systematic component of log consumption. We model this object as

$$y_{it}^U = \beta_t^U + x_{it}'\gamma^U + \theta_i^U \tag{1}$$
$$y_{it}^R = \beta_t^R + x_{it}'\gamma^R + \theta_i^R \tag{2}$$

where x_{it} is a vector of observable characteristics, β_t^l captures the average log consumption in sector l at time t, and θ_i^l is a time-invariant unobservable that captures worker i's productivity in sector l. The difference between these two sector-specific unobservables, $\theta_i^U - \theta_i^R$, represents person i's comparative advantage in favor of urban relative to rural work.

2.1.2 Comparative Advantage and Productivity Decomposition

Following Lemieux (1998) and Suri (2011), and building on the correlated random effects framework of Chamberlain (1984), we project the time-invariant, sector-specific unobservables onto comparative advantage. We define b_U and b_R as coefficients from the linear projection of θ_i^l onto $\theta_i^U - \theta_i^R$, assuming zero means. Specifically, we write

$$\theta_i^U = b_U(\theta_i^U - \theta_i^R) + \tau_i \tag{3}$$
$$\theta_i^R = b_R(\theta_i^U - \theta_i^R) + \tau_i \tag{4}$$

where τ_i captures absolute advantage that affects a worker's productivity in both locations. This decomposition isolates the part of productivity that drives sorting across locations from the part that raises consumption regardless of where a person works. By construction, τ_i is orthogonal to comparative advantage.

We can interpret the projection coefficients b_U and b_R as measuring how strongly a worker's comparative advantage, $\theta_i^U - \theta_i^R$, maps onto productivity in the urban and rural sectors, respectively. These coefficients depend on the dispersion of productivity within each sector and on the covariance between urban and rural productivity. When urban and rural productivities are highly correlated, workers who perform well in one location also tend to perform well in the other, so comparative advantage plays a smaller role in shaping relative productivity. When the correlation is low, productivity becomes more location-specific, and comparative advantage matters more for sorting across locations. Similarly, when productivity varies more in one sector than in the other, that sector

places greater weight on comparative advantage, making outcomes there more sensitive to differences in workers' skills.

Formally,

$$b_U = \frac{\sigma_U^2 - \sigma_{UR}}{\sigma_U^2 + \sigma_R^2 - 2\sigma_{UR}}, \tag{5}$$

$$b_R = \frac{\sigma_{UR} - \sigma_R^2}{\sigma_U^2 + \sigma_R^2 - 2\sigma_{UR}}, \tag{6}$$

where $\sigma_l^2 = \text{Var}(\theta_i^l)$ and $\sigma_{UR} = \text{Cov}(\theta_i^U, \theta_i^R)$.

To simplify notation, we define

$$\theta_i \equiv b_R(\theta_i^U - \theta_i^R),$$

which is a rescaled measure of comparative advantage that captures both the worker's relative productivity across locations and the extent to which the rural sector rewards that advantage.

We also define

$$\phi \equiv \frac{b_U - b_R}{b_R},$$

which measures how much more important comparative advantage is for urban productivity than for rural productivity in the economy.[8] The parameter ϕ is larger when urban productivity varies more across workers or when skills transfer poorly between rural and urban locations, so that relative skill differences matter more in the urban sector. Conversely, ϕ is smaller when productivity varies more in the rural sector or when urban and rural productivities are highly correlated, in which case comparative advantage affects outcomes more symmetrically across locations. As a result, ϕ governs how strongly returns to urban location increase with workers' comparative advantage.

Using these definitions, we can rewrite the systematic components of log consumption as

$$y_{it}^U = \beta_t^U + x_{it}'\gamma^U + (1+\phi)\theta_i + \tau_i, \tag{7}$$

$$y_{it}^R = \beta_t^R + x_{it}'\gamma^R + \theta_i + \tau_i. \tag{8}$$

The term τ_i shifts consumption levels equally across locations, while θ_i governs how relative returns differ between urban and rural work. When $\phi > 0$, comparative advantage enters more strongly in the urban sector, so the returns to urban location

[8]The definition requires $b_R \neq 0$, which we assume throughout.

rise with θ_i. In that case, workers with lower rural consumption gain relatively less from migrating. When $\phi < 0$, comparative advantage matters more in rural locations, and the gains from urban migration are larger for workers with lower rural consumption.

2.1.3 Utility and Location Choice

We allow for factors other than consumption to affect migration decisions by modeling location choice as a function of utility. In addition to consumption, utility depends on non-monetary factors like proximity to family and local amenities. We capture these with a time- and location-specific idiosyncratic shock, ν_{it}^l. A person's utility from working in location l at time t is therefore $V_{it}^l = y_{it}^l + \nu_{it}^l$. These shocks generate variation in location choices even when a person's observable characteristics and productivity remain unchanged.

We assume that ν_{it}^l is independently and identically distributed across individuals, time periods, and locations. This assumption ensures that utility shocks generate transitory movements across locations without introducing persistence or correlation with past choices. It also implies that ν_{it}^l is orthogonal to the unobserved components of consumption, which simplifies the mapping from the model to the empirical specification. Under this assumption, migration decisions respond to temporary, idiosyncratic factors that do not reflect systematic differences in productivity across sectors.

An important consequence of this assumption is that the period-by-period location choice rule derived below is equivalent to the solution of a fully forward-looking dynamic optimization problem. Two conditions deliver this equivalence: the i.i.d. assumption ensures that future utility shocks are independent of the current location choice, so there is no informational option value; and the time-invariant productivity assumption (equations 1–2) ensures that payoffs do not depend on past locations, so there is no state dependence in returns. Together, these eliminate any channel through which today's choice affects future welfare, reducing the dynamic problem to a sequence of static comparisons. If non-pecuniary factors were instead persistent—or if migration experience altered productivity—the interpretation of trajectories as reflecting comparative advantage would be less precise.

Workers choose their location for period t by comparing expected utility across locations. At the end of each period, a worker observes current consumption and utility shocks and forms expectations over future shocks. She chooses the urban location in period t if her expected utility in the urban sector exceeds expected utility in the rural sector. Following Lemieux (1998), we assume that the average rural-urban consumption

gap,

$$\beta \equiv \beta_t^U - \beta_t^R, \tag{9}$$

is constant over time, while allowing the level of average consumption in each location to vary over time. Abstracting away from covariates, or equivalently assuming that observable characteristics affect consumption symmetrically across locations, we can rewrite the urban choice rule as[9]

$$E\left[V_{it}^U\right] > E\left[V_{it}^R\right] \iff \beta + \phi\,\theta_i + E\left[\nu_{it}^U - \nu_{it}^R\right] > 0. \tag{10}$$

2.2 Empirical Model

Let $D_{it} = 1$ indicate that worker i works in the urban location at time t, and $D_{it} = 0$ otherwise. Observed log consumption equals the systematic component described in the model plus an idiosyncratic error term

$$y_{it} = y_{it}^l + \varepsilon_{it}, \tag{11}$$

where $l \in \{R, U\}$ denotes location and ε_{it} captures transitory shocks to consumption.

Because D_{it} is binary, we can write observed consumption as a random coefficient model in which the return to urban location varies across workers. In particular, combining the sector-specific consumption equations yields

$$y_{it} = \beta^R + \theta_i + \tau_i + (\beta + \phi\theta_i)D_{it} + x_{it}'\gamma^R + D_{it}x_{it}'(\gamma^U - \gamma^R) + \varepsilon_{it}, \tag{12}$$

where β^R suppresses the time subscript from equations (1)–(2) because in estimation, period effects absorb the time-varying level of average consumption.

The worker-specific return to urban location is therefore $\Delta_i \equiv \beta + \phi\theta_i$, which depends on comparative advantage. Since θ_i also affects location choices through the decision rule derived above, the return to urban location is correlated with D_{it}. This places the model in the class of correlated random coefficient (CRC) models.

We assume that observable characteristics affect consumption symmetrically across locations, so that $\gamma^U = \gamma^R$. Under this restriction, equation (12) simplifies to:

$$y_{it} = \beta^R + \theta_i + \tau_i + (\beta + \phi\theta_i)D_{it} + x_{it}'\gamma + \varepsilon_{it}. \tag{10'}$$

Equation (10′) makes clear that heterogeneity in the returns to urban location arises

[9] Covariates x_{it} do not appear in the decision rule because under the symmetric covariate assumption ($\gamma^U = \gamma^R$), their contribution cancels in the urban-rural comparison.

from comparative advantage. Workers with different values of θ_i face different gains from working in the urban sector, and these gains are correlated with observed migration choices. This highlights a central identification challenge. Because returns to urban location vary across workers and are correlated with location choices, average returns cannot be recovered from comparisons of urban and rural outcomes without additional structure. In particular, without further restrictions, returns are only identified for workers who switch locations over time, and counterfactual returns for non-migrants remain unidentified.

In the remainder of this section, we show how this challenge can be addressed by aggregating workers into migration histories and imposing economically motivated restrictions that link returns across subpopulations.

2.2.1 Unrestricted Group Random Coefficient Model

The correlated random coefficient (CRC) model in equation (10′) allows worker-specific returns to urban location that are correlated with location choices. To take this model to the data, we follow Tjernström *et al.* (2026) and aggregate the CRC model over discrete migration histories, which yields a group random coefficient (GRC) representation. In what follows, we suppress covariates and period effects for clarity; these re-enter the estimation as described above.

In the GRC framework, we group workers by their observed sequence of location choices over time, which we refer to as migration trajectories. Different trajectories reflect systematic differences in workers' ability or comparative advantage, to the extent that location choices respond to relative productivity and utility. As a result, observed migration histories provide a natural way to partition workers into subpopulations with different average outcomes and returns. Each trajectory has its own average consumption level and return to urban location. The unrestricted specification places no structure on how these trajectory-specific average returns vary across migration histories.

Because the location indicator D_{it} is binary and the panel has finite length, our data contain a finite number of migration trajectories. We can summarize each worker's observed sequence of location choices by $\underline{d}_i \equiv (D_{i1}, \ldots, D_{iT})$. These trajectories take values in the finite set $\mathcal{D} = \{0,1\}^T$, which we use to index subpopulations of workers with the same migration history.

We distinguish between switcher trajectories, $\mathcal{D}_S = \left\{\underline{d} \in \mathcal{D} : 0 < \sum_{t=1}^{T} D_{it} < T\right\}$, and non-switcher trajectories, $\mathcal{D}_{NS} = \mathcal{D} \setminus \mathcal{D}_S$. The latter consist of the always-urban trajectory $d_T = \left\{\underline{d} \in \mathcal{D} : \sum_{t=1}^{T} D_{it} = T\right\}$, and the always-rural trajectory

$d_N = \left\{ \underline{d} \in \mathcal{D} : \sum_{t=1}^{T} D_{it} = 0 \right\}$.

Without additional restrictions, the CRC model implies the following unrestricted GRC representation for any $t \geq 2$.[10]

$$y_{it} = \sum_{\underline{d} \in \mathcal{D} \setminus \{d_T\}} \mu_{\underline{d}} \, \mathbb{1}\{\underline{d}_i = \underline{d}\} + \sum_{\underline{d} \in \mathcal{D}_S} \Delta_{\underline{d}} \, D_{it} \, \mathbb{1}\{\underline{d}_i = \underline{d}\} + \kappa_{d_T} \, D_{it} \, \mathbb{1}\{\underline{d}_i = d_T\} + \varepsilon_{it}. \quad (13)$$

Here, $\mu_{\underline{d}}$ denotes average rural consumption for workers following trajectory $\underline{d}$. In this unrestricted model, average returns to urban location, $\Delta_{\underline{d}}$, are non-parametrically identified only for switcher trajectories. For non-switchers, we cannot identify counterfactual outcomes. For always-rural workers, the data identify only average rural consumption, μ_{d_N}. For always-urban workers, we cannot separately identify μ_{d_T} and Δ_{d_T} and instead only recover average urban consumption, which we denote by $\kappa_{d_T} \equiv \mu_{d_T} + \Delta_{d_T}$. This limitation motivates the additional structure introduced in the next subsection.

2.2.2 Restricted Group Random Coefficient Model

To identify returns to urban location for non-migrants, we impose a linear comparative advantage (LCA) restriction that links heterogeneity in migration returns to differences in workers' comparative advantage. This restriction follows Suri (2011) and builds on the linear correlated random coefficient framework in Lemieux (1998).

The LCA restriction assumes that the return to urban location varies linearly with a worker's comparative advantage:

$$\Delta_i = \beta + \phi \, \theta_i. \quad (14)$$

Since comparative advantage also determines average rural consumption in the model, the LCA restriction implies a linear relationship between average returns and average rural consumption across migration trajectories. As a result, variation in outcomes among switchers identifies the relationship between returns and comparative advantage, which in turn allows us to extrapolate returns for non-migrants. Since τ_i does not affect location choices, trajectory-specific differences in $\mu_{\underline{d}}$ identify differences in average comparative advantage.

We do not restrict the sign of this relationship; instead, we allow the data to determine whether returns to migration increase or decrease with comparative advantage.

[10] The restriction to $t \geq 2$ reflects the use of the first period to establish baseline trajectory membership. In estimation, we include all available periods and absorb initial-period effects through period indicators.

Our estimation strategy follows Tjernström *et al.* (2026), who show how to implement this restriction within a GRC framework using GMM. For a chosen baseline switcher trajectory $\underline{d}_0 \in \mathcal{D}_S$, we can write the restricted GRC model as:

$$\begin{aligned} y_{it} = & \sum_{\underline{d} \in \mathcal{D} \setminus \{d_T\}} \mu_{\underline{d}} \, \mathbb{1}\{\underline{d}_i = \underline{d}\} + \Delta_{\underline{d}_0} D_{it} \\ & + \sum_{\underline{d} \in \mathcal{D}_S \setminus \{\underline{d}_0\}} \phi(\mu_{\underline{d}} - \mu_{\underline{d}_0}) \, D_{it} \, \mathbb{1}\{\underline{d}_i = \underline{d}\} \\ & + \Big(\mu_{d_T} + \phi(\mu_{d_T} - \mu_{\underline{d}_0}) \Big) \, D_{it} \, \mathbb{1}\{\underline{d}_i = d_T\} + \varepsilon_{it}. \end{aligned} \tag{15}$$

for some baseline trajectory $d_0 \in \mathcal{D}_S$.[11]

The relationship in the LCA restriction forms the basis of how we identify returns to non-migrants in our model. Taking expectations of equation (14) within migration trajectories implies that for any two switcher trajectories $\underline{d} \neq \underline{d}'$ with distinct average rural consumption, average returns satisfy:

$$\phi = \frac{\Delta_{\underline{d}} - \Delta_{\underline{d}'}}{\mu_{\underline{d}} - \mu_{\underline{d}'}}, \quad \mu_{\underline{d}} \neq \mu_{\underline{d}'}. \tag{16}$$

If the LCA parameter, ϕ, is positive, then urban location has higher returns for the people with higher average consumption in the rural market. Conversely, a negative ϕ would suggest that those who have the lowest rural consumption would receive the highest incremental consumption gains from migrating to the urban market. We can refer to these two scenarios as migration being either "pro-rich" (positive ϕ) or "pro-poor" (negative ϕ).

Before turning to estimation, we collect below the assumptions that underlie identification:

(A1) Location-specific productivities θ_i^U and θ_i^R are time-invariant.

(A2) Non-pecuniary utility shocks ν_{it}^l are i.i.d. across individuals, time, and locations, so that migration trajectories reflect comparative advantage rather than shock persistence.

(A3) The average rural-urban consumption gap β is constant over time.

(A4) Observable characteristics affect consumption symmetrically across locations ($\gamma^U = \gamma^R$).

[11] The always-urban group ($\underline{d}_i = d_T$) receives a separate composite coefficient in the last line because these workers have $\sum_t D_{it} = T$ and are not in $\mathcal{D}_S$. Their trajectory-specific return is therefore parameterized directly rather than through the switcher summation.

(A5) The linear comparative advantage restriction $\Delta_i = \beta + \phi\,\theta_i$.

We estimate the restricted model in Eq. (15) using two-step efficient Generalized Method of Moments (GMM), as in Tjernström *et al.* (2026). Let ε_{it} denote the residual from equation (15). The moment conditions are

$$E[\varepsilon_{it} \cdot z_{it}] = 0, \tag{17}$$

where the instrument vector z_{it} consists of trajectory indicators $\mathbb{1}\{\underline{d}_i = \underline{d}\}$, the urban indicator D_{it}, interactions $D_{it} \cdot \mathbb{1}\{\underline{d}_i = \underline{d}\}$ for each switcher trajectory, and the covariate vector x_{it}. The number of moment conditions exceeds the number of parameters, and we test the overidentifying restrictions using Hansen's J-statistic. Standard errors are clustered at the individual level.

While the key identifying variation comes from the switchers in the balanced panel, we also include observations that appear in a subset of panel waves in our estimation. We include an "unbalanced" dummy variable that takes a value of one for individuals with at least one missing round of data, as well as the interaction between the "unbalanced" dummy and the urban indicator.[12] Appendix A shows results using the balanced panel.

3 Data

We use longitudinal data from three developing countries—Indonesia, China, and Tanzania—to understand selection and heterogeneity in the returns to migration and test the model's predictions. For each country, we draw on data collected in household surveys designed to collect information on the living standards of people in settings where informal employment, home production, and rural work are prevalent. Our data include detailed information on tens of thousands of individuals across multiple geographies and time periods, and provide rich information on demographic characteristics, place of residence (rural or urban), and comprehensive measures of consumption.

Table 1 provides an overview of our data sources. For Indonesia, we use data from all five waves of the Indonesia Family Life Survey, which was collected between 1993 and 2015.[13] For China and Tanzania, we use data that was generously made available by

[12] Since unbalanced individuals lack complete trajectories, all trajectory indicators equal zero for them. They therefore do not contribute to identifying the trajectory-specific parameters $\mu_{\underline{d}}$ or the slope ϕ. They only help estimate the covariate coefficients γ and the unbalanced level effects. This inclusion is valid under two assumptions: (i) attrition is independent of ε_{it} conditional on D_{it} and x_{it}, and (ii) covariate effects on consumption are common across balanced and unbalanced individuals.

[13] We organize and cleaned the Indonesia data from the raw IFLS data files, following Kleemans and Magruder (2018), Hamory *et al.* (2021) and Kleemans (2023).

Table 1: Overview of Data Sources

	Indonesia	China	Tanzania
Data source	Indonesia Family Life Survey (IFLS)	China Family Panel Study (CFPS)	National Panel Survey (NPS)
Number of waves	5	4	3
Years included	1993, 1997/98, 2000, 2007/08, 2014/15	2010, 2012, 2014, 2016	2008/09, 2010/11, 2012/13
Observations	77,744	129,466	34,527
Individuals	34,399	49,398	15,667
Rural/Urban Stayers	92.9%	93%	92%
Ag/Non-Ag Stayers	89%		

Lagakos, Marshall, Mobarak, Vernot and Waugh (2020), and that comes from the China Family Panel Study (4 waves) and the Tanzania National Panel Study (3 waves).[14] For all countries, we restrict the data to individuals aged 16 and above with non-missing information on urban/rural status and total consumption.[15] Sections 3.1, 3.2, and 3.3 provide more detail on each of these datasets.

The bottom of Table 1 highlights the proportion of individuals that never migrate between rural and urban areas. In all three countries, more than 90% of individuals always stay in their rural or urban area. We see similar numbers for sectoral switchers who switch between agriculture and non-agriculture in Indonesia. When we limit the sample to a balanced panel, the proportions of non-migrants fall to 59.6% in Indonesia, 91.8% in China, and 85.5% in Tanzania (see tables A.1, A.2, and A.3 for details).

Figure 1 examines these migration patterns in more detail. The figure shows the proportion of the sample, in each country, that we observe following different aggregated migration histories. In all three datasets, we observe that non-migrants—both always-urban and always-rural—constitute the largest subpopulations. For those who migrate, the most common pattern is a single move from rural to urban. In Indonesia, this is followed by multiple moves, with more of these occurring for individuals who we first observe in an urban location. In Tanzania, one-time urban-to-rural migration is more

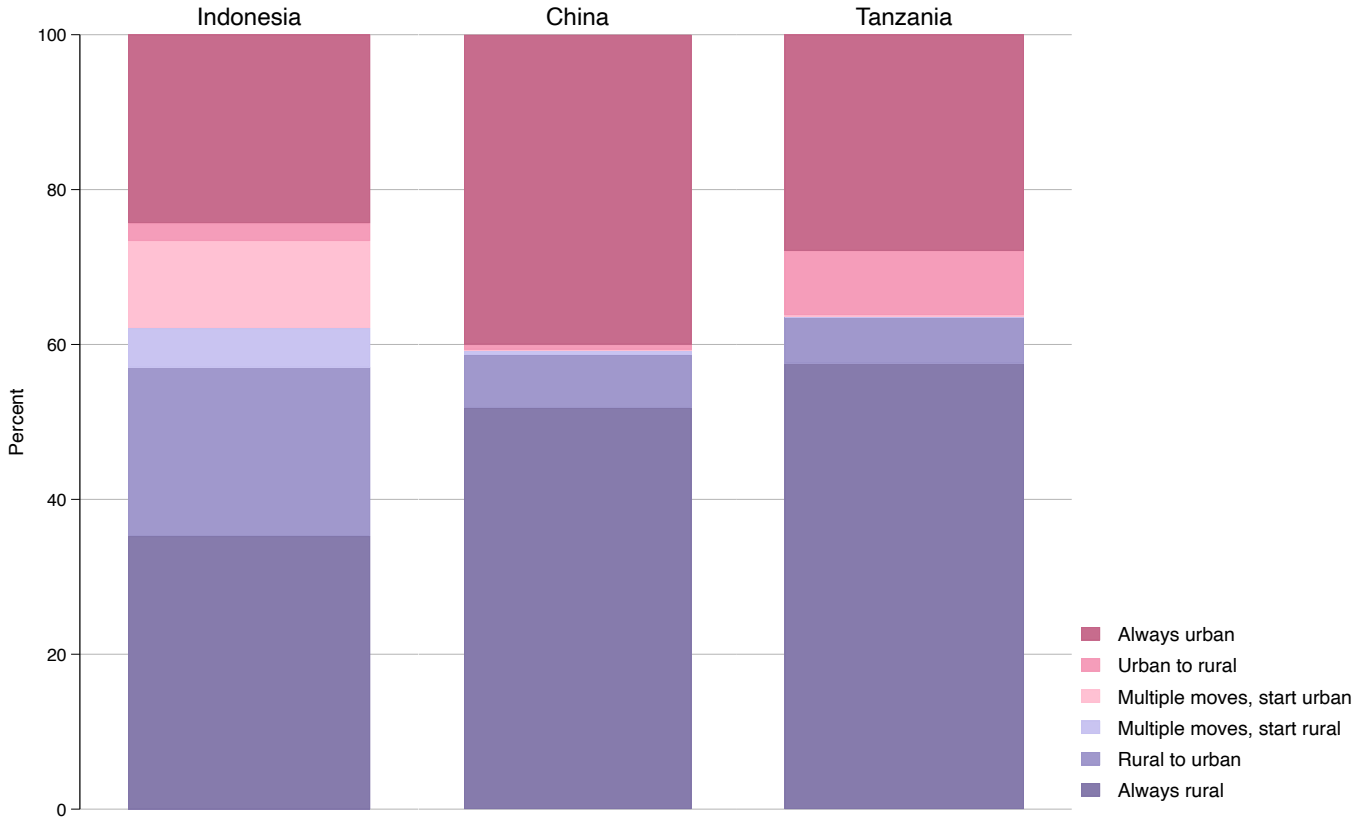
[14] Lagakos *et al.* (2020) also use data from South Africa, Ghana, and Malawi. We exclude the South Africa sample because of data quality concerns, and we do not use data from Ghana and Malawi because these data cover only 2 waves, while we need at least 3 waves to test our overidentification assumption. We are grateful to David Lagakos, Samuel Marshall, Mushfiq Mobarak, Corey Vernot, and Michael Waugh for sharing their data.

[15] When studying returns to working in a non-agricultural sector rather than in agriculture, we restrict the sample to those with non-missing information on sector. We can only do that for Indonesia because we do not have sectoral data for China and Tanzania.

common than in the other two countries.

Despite spanning multiple years, these surveys are characterized by low attrition rates and represent a significant portion of the population in each country, as detailed in Sections 3.1, 3.2, and 3.3. If individuals from a household were temporarily away or unwell, enumerators made an effort to get a proxy from that household to answer questions on behalf of the missing individual. Although attrition is low, the number of observations differs across periods due to the long time span of the data and our restriction to individuals aged 16 and older. As such, individuals age into the sample over time and eventually exit the panel when they die. In Section 5, we show that our results are robust to using a balanced panel of individuals.

Figure 1: Migration Patterns



Migration patterns in Indonesia, China, and Tanzania, grouped by their migration histories as follows: those who we never observe moving in the data ("always urban" and "always rural"), those who move once ("urban to rural" and "rural to urban"), and those who move multiple times ("multiple moves, start urban" and "multiple moves, start rural").

We use consumption as our main outcome variable. For all surveys, this variable is constructed using detailed expenditure modules, in which respondents are presented with lists of items they consumed and asked to report their total expenditure for each

good. In addition to asking for total expenditure purchased, these surveys ask for the approximate value of items that were consumed by the household and that were self-produced.

We prefer consumption over income and wages for several reasons. First, in developing countries, consumption typically measures welfare better than earnings or wages, precisely because it also captures the value of home production and in-kind transfers. Second, computing earnings from wages requires information on hours worked, which tends to introduce measurement error that is correlated with sector and formality. Third, data on income and hours worked is missing for a substantial portion of observations in our data. This is the case for those who are not engaged in income-generating activities, and even among those who are, the value of income and hours worked are often missing in the data. Data is disproportionally missing for rural and agricultural workers, which introduces bias in our estimates, so we believe that results on consumption are more representative.[16]

In the sections that follow, we provide more details on the data source and variable definitions by country.

3.1 Indonesia

Indonesia is the world's fourth largest country with a population size of 275 million. Our analysis draws on data from all five waves of the Indonesia Family Life Survey (henceforth, IFLS), collected between 1993 and 2015. During this study period, Indonesia was characterized as a lower middle-income country (World Bank, 2024).

The IFLS is representative of 83 percent of the Indonesian population (Strauss, Beegle, Sikoki, Dwiyanto, Herawati and Witoelar, 2004). The IFLS is particularly suitable for studies involving migration because of intensive tracking efforts. As a result, attrition is low with re-response rates of over 90 percent between any two consecutive survey waves and 87 percent of households from the first wave were interviewed in all five waves (Strauss, Witoelar and Sikoki, 2016).[17]

In a detailed consumption module, respondents are presented with lists of items and asked to report the value they consumed during a reference period. For all 37 food items

[16]The likelihood that income data is missing varies a lot by country: In Indonesia, income is missing for 34 percent of observations while in China and Tanzania, income is missing for 55 and 60 percent of observations, respectively. We believe that this variation is in part due to differences in data collection, which reaffirms our preference to use consumption as our main outcome variable.

[17]Please refer to Kleemans and Magruder (2018), Hamory *et al.* (2021), and Kleemans (2023) for more details on the IFLS data. Unlike Hamory *et al.* (2021), we do not use recall data between survey waves, because consumption is only collected at the time of the survey.

the reference period is the past week. For 9 non-food items, such as toiletries, utilities and transportation, respondents are asked about consumption in the past month. For 11 less frequently consumed items, such as clothing, furniture, education and health services, respondents are asked about the past year. For all items, respondents are asked for the value of both purchased and self-produced items.

We construct province-level spatial price deflators using poverty lines published by Statistics Indonesia (Badan Pusat Statistik, BPS). BPS calculates separate poverty lines for urban and rural areas within each of Indonesia's 34 provinces, representing the monthly per-capita expenditure required to obtain 2,100 calories per day plus basic non-food necessities. These poverty lines reflect local prices and consumption patterns, effectively functioning as spatial price indices.

We define the spatial price index for province p and area type $a \in \{\text{urban}, \text{rural}\}$ as:

$$S_{pa} = \frac{Z_{pa}}{Z_{\text{ref}}} \tag{18}$$

where Z_{pa} denotes the BPS poverty line for area a in province p, and Z_{ref} is the poverty line for urban Jakarta, our reference region. Since province-level poverty lines are available only from 2013 onward, we use the September 2014 poverty lines to construct S_{pa}, matching the IFLS5 survey period. To adjust for inflation across survey waves, we then apply the national Consumer Price Index (CPI) published by BPS.[18]

Real consumption for individual i in province p, area a, and survey year t is then:

$$C_{ipat}^{\text{real}} = \frac{C_{ipat}^{\text{nom}} \times \text{CPI}_{2014}}{S_{pa} \times \text{CPI}_t} \tag{19}$$

where $C_{i,p,a,t}^{\text{nom}}$ denotes nominal consumption expenditure and CPI_t is the national consumer price index in year t.

Our measure of urban residence is survey-based: respondents indicating they live in a 'village' are classified as rural, and those who report living in a 'town' or 'city' are considered urban. As discussed in Section 2, we believe our model assumptions are more likely to hold when studying returns to rural-urban migration than returns to sectoral shifts out of agriculture into non-agricultural sectors. Nevertheless, we repeat our analysis for sectoral choice in Indonesia, the only country that consistently provides these data. We define sectoral choice in the IFLS based on whether an individual

[18]The 1997–98 Asian financial crisis produced differential inflation across regions and between urban and rural areas. However, IFLS2 was fielded in late 1997 before the most severe price dislocations, and IFLS3 in 2000 after relative price stabilization. The spatial component of our deflator, which captures persistent cross-regional price differences, is more consequential for welfare comparisons than short-run crisis-induced deviations from the national CPI trend.

reports that their primary employment in agriculture or in a non-agricultural sector. Results for sectoral choice are reported in the Appendix.

Table 2: Summary Statistics Indonesia

	All	Rural	Urban	Difference t-test
Location		52.6%	47.4%	
Log Consumption	12.02	11.84	12.23	-0.39***
	(0.79)	(0.77)	(0.76)	
Log Income	14.88	14.64	15.15	-0.50***
	(1.15)	(1.15)	(1.08)	
Female	0.52	0.51	0.53	-0.01***
	(0.50)	(0.50)	(0.50)	
Age (years)	39.37	39.78	38.91	0.88***
	(14.95)	(15.36)	(14.48)	
Education (years)	8.05	6.79	9.45	-2.65***
	(4.65)	(4.45)	(4.46)	
Household Size	4.71	4.61	4.82	-0.21***
	(2.12)	(2.01)	(2.24)	
Observations	93,038	48,972	44,066	
Individuals	29,716			
Non-switchers	92.9%			

Summary statistics for Indonesia for the unbalanced panel across all five waves. Source: IFLS. The table reports means and standard deviations (in parentheses) based on individual-year pairs. See section 3 for further details. All variables have the same number of observations, except for income, which is missing for some observations. Income has 61,300 observations.

Table 2 shows summary statistics from Indonesia. The units of observation in this table are individual-year pairs of which there are 93,038 in the data. These come from 29,716 unique individuals, 92.9 percent of whom never switch between rural and urban locations. Columns 2 and 3 show that consumption and income are higher for observations in urban areas than in rural areas (3.3% and 3.5%, respectively). There are also significant differences in the demographic characteristics shown, which we will use as our main control variables in our analysis. Individuals in urban areas are, on average, almost one year younger and have received an additional 2.7 years of education.

3.2 China

We use Chinese data from four waves of the China Family Panel Study (henceforth, CFPS) that were collected biannually from 2010 to 2016 (Institute of Social Science Survey, 2015). During this time period, China was the most populous country in the world with over 1.3 billion inhabitants and characterized as an upper middle-income country (World Bank, 2024). The survey is representative of 95 percent of the Chinese population. The initial survey included 16,000 households living in 25 provinces and re-contact rates were 85.3 percent in 2012 and and 89.7 percent in 2014. (Lagakos *et al.*, 2020).

The consumption variable in the CFPS is based on 31 non-food categories of items consumed. Food consumption is divided into two aggregate categories only: purchased items and self-produced food. Purchased and self-produced food consumption includes the value of foods, snacks, beverages, cigarettes, and alcohol that were consumed by members of the household, regardless of whether the consumption occurred inside or outside of the household. The CFPS identifies areas as either urban neighborhoods or villages, which we use to assign urban and rural status, respectively. We use cleaned data files that were generously made available by Lagakos *et al.* (2020).

To account for spatial and temporal price differences, we adjust nominal consumption using the provincial spatial price deflators constructed by Brandt and Holz (2006). These deflators price a fixed national basket of goods and services across provinces, separately for urban and rural areas, providing consistent purchasing power comparisons across regions. The deflators are benchmarked to a 1990 base year and extended forward and backward using provincial consumer price indices. We use the updated series available from Holz's website, which maintains the original methodology while incorporating recent price data.

Table 3 shows summary statistics based on 109,535 individual-year pairs, originating from 34,746 individuals. The share of individuals that we observe migrating between rural and urban areas is considerably lower in China than in Indonesia and Tanzania with only 4.3 percent of individuals engaging in such moves. This may partly be explained by China's Hukou system that aimed to reduce rural-urban migration during our study period, for example see Khanna, Liang, Mobarak and Song (2021). Similar to Indonesia, consumption and income are higher in urban areas. The education gap is similar to Indonesia, with individuals in urban areas having received an additional 2.7 years of education. Unlike Indonesia, household size is smaller in urban areas, and the difference in age is modest.

Table 3: Summary Statistics China

	All	Rural	Urban	Difference t-test
Location		54.2%	45.8%	
Log Consumption	10.46	10.26	10.70	-0.44***
	(0.93)	(0.90)	(0.90)	
Log Income	8.74	8.25	9.20	-0.95***
	(1.93)	(2.08)	(1.64)	
Female	0.51	0.51	0.52	-0.01***
	(0.50)	(0.50)	(0.50)	
Age (years)	46.66	46.70	46.60	0.10
	(16.57)	(16.51)	(16.64)	
Education (years)	7.38	6.16	8.83	-2.68***
	(4.92)	(4.68)	(4.80)	
Household Size	4.26	4.56	3.91	0.65***
	(1.91)	(1.98)	(1.76)	
Observations	109,535	59,354	50,181	
Individuals	34,746			
Non-switchers	95.7%			

Summary statistics for China for the unbalanced panel across all waves. Source: China survey. The table reports means and standard deviations (in parentheses) based on individual-year pairs. See section 3 for further details. All variables have the same number of observations, except for income, which is missing for some observations. Income has 49,191 observations.

3.3 Tanzania

Tanzania was a low-income country during our study period from 2008 to 2013 and currently has a population size of 65 million. Following Lagakos *et al.* (2020), we use three waves of the Tanzania National Panel Survey (henceforth, NPS), which were collected in 2008/2009, 2010/2011, and 2012/2013.

The initial sample of the NPS was nationally representative and attrition is the lowest of all three countries. Between waves 2 and 3 attrition was 3.5 percent and between waves 1 and 3, was 4.8 percent. The NPS consumption modules include 72 food items and 46 non-food items. The food consumption variable for Tanzania includes the value of all purchased or self-produced foods and non-alcoholic beverages that were consumed by the family inside or outside of the household. NPS already uses a spatial

price deflator in their data to account for different price levels between rural and urban areas. We follow the rural-urban definition provided by the NPS who define villages as rural areas and urban census enumeration areas as urban. As we did for the Chinese data, we directly use the NPS replication data provided by Lagakos *et al.* (2020).

Table 4: Summary Statistics Tanzania

	All	Rural	Urban	Difference t-test
Location		64.6%	35.4%	
Log Consumption	14.89	14.65	15.31	-0.66***
	(0.81)	(0.72)	(0.78)	
Log Income	13.80	13.25	14.49	-1.24***
	(1.93)	(1.82)	(1.83)	
Female	0.52	0.52	0.53	-0.01*
	(0.50)	(0.50)	(0.50)	
Age (years)	36.21	37.22	34.38	2.84***
	(16.84)	(17.58)	(15.23)	
Education (years)	6.69	5.69	8.50	-2.80***
	(3.97)	(3.72)	(3.75)	
Household Size	6.38	6.66	5.86	0.80***
	(4.08)	(4.46)	(3.21)	
Observations	29,864	19,282	10,582	
Individuals	11,012			
Non-switchers	88.6%			

Summary statistics for Tanzania for the unbalanced panel across all waves. Source: Tanzania survey. The table reports means and standard deviations (in parentheses) based on individual-year pairs. See section 3 for further details. All variables have the same number of observations, except for income, which is missing for some observations. Income has 12,052 observations.

We present summary statistics from Tanzania in Table 4. The NPS is smaller than our other surveys and includes 29,864 individual-year pairs from 11,012 individuals. There is more migration between rural-urban areas in Tanzania than in our samples of Indonesia and China. 11.4 percent of individuals are observed in both a rural and an urban area at some point during the panel. Similar to Indonesia and China, consumption and income is considerably higher in urban areas. Similar to Indonesia, individuals in urban areas are younger in Tanzania (by almost three years). Households are larger

in Tanzania than in Indonesia and China. Differences in education between rural and areas are remarkably similar between the three countries with urban residents having an additional 2.66, 2.67, and 2.81 years of education in Indonesia, China and Tanzania, respectively.

4 Results

4.1 Observational Returns

We start with showing results from OLS regressions, in line with Hamory *et al.* (2021). Table 5 shows results for Indonesia, China and Tanzania in Panels A, B and C, respectively. The dependent variable in all regressions is the log of per capita consumption, which is defined as total household-level consumption divided by the number of household members.

In column (1) we regress log consumption per capita on an indicator for urban location, so the coefficient on urban reflects the raw consumption gap between rural and urban areas in our data. This gap is 39 log points in Indonesia, 44 log points in China, and 66 log points in Tanzania, so average consumption differences range from 48% to 94% in favor of urban areas. In subsequent columns, we gradually add covariates. In column (2), we add time fixed effects, in column (3) we add a female indicator, and in column (4), we also add age squared. For all three countries, the rural-urban consumption gap changes little with the addition of these controls as we move from column (1) to (4).

The inclusion of education controls (years of education and years of education squared) in column (5) significantly reduces the rural-urban consumption gap. The rural-urban consumption gap decreases by 12-17 log points, consistent with the fact that urban residents are more educated than rural residents: across the three countries in our data, urban residents have almost three more years of schooling than rural ones.

In column (6), we repeat the specification in column (5), including all covariates and time fixed effects but for the sample of migrants only. In other words, this sample only includes individuals who we observe switching between rural and urban at least once in the data. For all three countries, the estimated consumption gap reduces further. In Indonesia, the consumption gaps drops by 4 log points down to 15 log points. In China, restricting the sample to migrants results in a drop of 5 log points, down to an estimated consumption gap of 2.6 log points. In Tanzania, restricting the sample to migrants reduces the consumption gap more substantially by 39 log points to 8.8 log

points.

Finally, in column (7), we show the results of a specification that includes individual fixed effects. In the Tanzanian data (Panel C), the estimated consumption gap is similar in columns (6) and (7), suggesting that limiting the identifying variation to migrants-only has a similar effect on the estimated consumption gap as the inclusion of individual fixed effects, which control for time-invariant unobserved characteristics. In Indonesia and China, the gap reduces another 6 to 9 log points, respectively, with the inclusion of individual fixed effects. The remaining consumption gap in column (7) is modest in Indonesia and Tanzania—at 8.8 and 7.2 log points, respectively—but larger in China at 17.2 log points. This may reflect the unique nature of internal migration in China under the Hukou system, which assigns Hukou status based on where individuals were born. When individuals migrate away from the area of their assigned Hukou, they often lose access to various government-provided institutions such as schooling and health care. This effectively increases the cost of migrating for those who do not hold Hukou registration in their destination and leads to distinct selection into migration, as discussed in Section 3.

Table 5: OLS Estimates of the Returns to Urban Location on log Consumption

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Indonesia							
Urban	0.388***	0.348***	0.349***	0.347***	0.190***	0.151***	0.088***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.019)	(0.008)
Observations	93,026	93,026	93,026	93,026	93,026	6,635	93,026
Individuals	29,710	29,710	29,710	29,710	29,710	1,327	29,710
Adj. R^2	0.060	0.16	0.16	0.16	0.27	0.25	0.52
Panel B: China							
Urban	0.442***	0.432***	0.432***	0.430***	0.315***	0.264***	0.172***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.026)	(0.015)
Observations	109,535	109,535	109,535	109,535	109,535	4,664	109,535
Individuals	34,746	34,746	34,746	34,746	34,746	1,166	34,746
Adj. R^2	0.056	0.089	0.089	0.12	0.15	0.13	0.52
Panel C: Tanzania							
Urban	0.660***	0.662***	0.663***	0.646***	0.475***	0.088***	0.072***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.019)	(0.016)
Observations	29,862	29,862	29,862	29,862	29,862	3,414	29,862
Individuals	11,010	11,010	11,010	11,010	11,010	1,138	11,010
Adj. R^2	0.15	0.16	0.17	0.18	0.26	0.16	0.69
Covariates			Female	& Age^2	All	All	All
Time FE		Y	Y	Y	Y	Y	Y
Individual FE							Y
Migrants only						Y	

The dependent variable is the log of total consumption per capita. Columns (2) to (7) include time (survey wave) fixed effects, column (3) adds a female indicator, column (4) adds age squared, and columns (5) to (7) add education (years of schooling, maximum across periods) and its square. Column (6) restricts the sample to migrants, i.e. those who we observe switching between rural and urban at least once in our data, and column (7) adds individual fixed effects. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4.2 Heterogeneity by Trajectory Type

Consumption gaps estimated using individual fixed effects in Table 5 represent a weighted average of the returns for different switcher types. The weights will be determined by the extent of within-individual variation in migration status and the variance of returns across individuals. Migrants with greater within-person variance and/or more frequent sectoral changes will influence the overall estimate more. In this section we start fully non-parametrically and test for heterogeneity in the returns for various switcher types as defined by their trajectories, i.e. their migration histories. If returns differ substantially between trajectory types, the fixed effects results could mask important variation in the returns across different migrant types, making it less informative about the returns to migration for any single switcher group, and likely less informative about the returns to migration for non-switchers.

Figure 2 examines the observational returns for switcher trajectories in the data. More precisely, the figure plots the Δ-coefficients from the following regression equation:

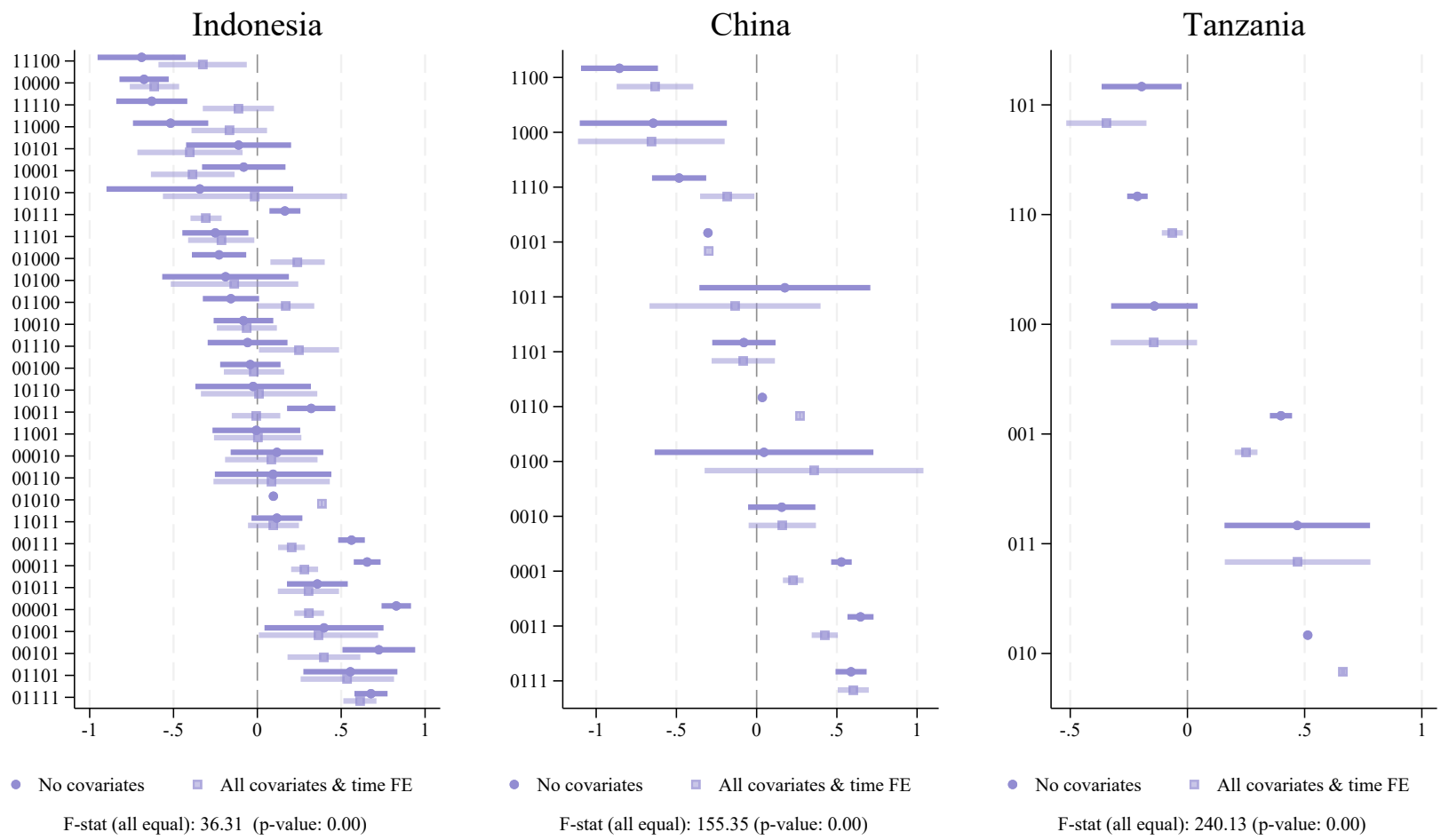
$$y_{it} = \sum_{\underline{d} \in \mathcal{D} \setminus d_T} \mu_{\underline{d}} \mathbb{1}\left\{d_i = \underline{d}\right\} + \sum_{\underline{d} \in \mathcal{D}_s} \Delta_{\underline{d}} D_{it} \mathbb{1}\left\{d_i = \underline{d}\right\} + X'\delta + \varepsilon_{it}, \tag{20}$$

where $\mathcal{D} \setminus \mathcal{D}_T$ denotes all trajectories less always-adopters, $\mathcal{D}_S$ denotes the set of switcher trajectories, and X is a vector of covariates. In other words, $\Delta_{\underline{d}}$ is the coefficient on the interaction between an indicator variable for urban location and an indicator for each switcher-trajectory, $\underline{d} \in \mathcal{D}_{\mathcal{S}}$.

The Δ-coefficients are sorted by size and the figure additionally shows their 95-percent confidence intervals. The labels on the vertical axis of each panel denote different trajectories where 1 is urban and 0 is rural. For example, 11100 on the top left represents the trajectory "urban-urban-urban-rural-rural" in Indonesia, whereas 01111 on the bottom left is the trajectory "rural-urban-urban-urban-urban".

For all countries, coefficient values cover a wide range, from negative to positive values. The F-statistic below each graph tests the null hypothesis that the Δ-coefficients for all trajectories in $\mathcal{D}_S$ are equal, which we soundly reject for all three countries. This suggests that relying on a single estimated return for all switcher types is likely to mask important heterogeneity. We now turn to the analysis of our model that adds more structure in order to leverage this heterogeneity and obtain the estimated returns for non-movers.

Figure 2: Consumption Returns to Urban Location by Country



Plot of coefficients representing the observational returns to urban location for each switcher trajectory in the data. More precisely, the figure plots the Δ-coefficients from the following regression equation: $y_{it} = \sum_{\underline{d} \in \mathcal{D} \setminus \mathcal{D}_T} \mu_{\underline{d}} \mathbb{1}\{d_i = \underline{d}\} + \sum_{\underline{d} \in \mathcal{D}_s} \Delta_{\underline{d}} D_{it} \mathbb{1}\{d_i = \underline{d}\} + X'\delta + \varepsilon_{it}$, where $\mathcal{D} \setminus \mathcal{D}_T$ denotes the full set of trajectories, excluding always-adopters, $\mathcal{D}_T$; $\mathcal{D}_S$ denotes the set of switcher trajectories, and X is a vector of covariates. In other words, $\Delta_{\underline{d}}$ is the coefficient on the interaction between indicator variable for urban location and a dummy for switcher-trajectories $\underline{d}$. The test statistics below each graph come from an F-test of the equality of the Δ-coefficients for all trajectories in $\mathcal{D}_S$.

4.3 Estimates from Restricted GRC Model

Tables 6, 7, and 8 report results from the restricted GRC model for Indonesia, China, and Tanzania, respectively. In the first row, we show the estimated returns for non-migrants, extrapolated based on returns from all switcher trajectories using the linear in comparative advantage (LCA) assumption, as detailed in Section 2.2.2. In the second row, we report the slope of the extrapolation line, ϕ. If this slope parameter is positive, it would indicate that people with higher rural consumption levels benefit more from urban migration, reflecting a "pro-rich" pattern. In contrast, a negative slope suggests that those with lower rural consumption see the greatest gains from migration, meaning that migration is "pro-poor."

For Indonesia, the estimated returns for non-migrants are fairly large in column (1) at 30 log points, and gradually reduce as we add covariates in subsequent columns. When we add controls for education and education squared in column (4), the estimated coefficient drops to 20.6 log points. Further, when we additionally control for a linear time trend in column (5), we estimate the returns to non-migrants to be 12 log points.

Comparing these results to the observational returns in Panel A of Table 5, we note that the estimated returns for non-migrants are 78 percent larger than the 6.7 log points estimated using individual fixed effects. Our results suggest that the average consumption gap between rural and urban workers controlling for observables and individual fixed effects is considerably smaller than the returns we estimate for non-migrants when we explicitly account for heterogeneity in the returns to migration.

The slope of the extrapolation line, shown as ϕ in the second row, is consistently negative in all specifications in Indonesia. This indicates that those who stand most to gain from migrating to an urban area are those with the lowest initial consumption in rural areas. This group may face constraints to migrate, for example liquidity or information constraints, and alleviating these constraints would allow them to increase consumption and benefit from migrating. We conclude that for Indonesia, migration can be seen as a pro-poor strategy.

Turning to the results from China, shown in Table 7, the estimated returns to non-migrants are strikingly similar to those of Indonesia. The returns to never-movers estimated without any controls in column (1) are 43 log points and decrease with inclusion of additional covariates. Once we include all controls and a linear time trend, the returns are 10.7 log points. Unlike for Indonesia, however, this is lower than the observational returns of 14.5 log points that we estimated in Panel B of Table 5. As explained in Section 4.1 the higher observational returns for China may be due to the Hukou system that effectively restricts rural-urban migration. We return to this in

Table 6: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in Indonesia

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.304***	0.086***	0.086***	0.091***	0.071***
	(0.054)	(0.021)	(0.021)	(0.021)	(0.018)
ϕ	-2.445***	-0.309***	-0.310***	-0.321***	-0.526***
	(0.070)	(0.087)	(0.087)	(0.086)	(0.102)
Individuals	29,697	29,697	29,692	29,692	29,692
Observations	92,450	92,450	92,439	92,439	92,439
Average Δ	0.0273	0.0029	0.0029	0.0032	0.0027
J-stat	86.5	32.5	32.4	33.3	28.2
J-stat (p-value)	0.000	0.214	0.216	0.187	0.403
Converged	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses data from the Indonesia Family Life Survey. Please refer to Section 3 for further details on the data. The dependent variable is the log of total consumption per capita. Urban is an indicator equal to one for individuals who report living in a city or town, as opposed to a village. Individuals are assigned to trajectories based on their location history across the survey waves. This table reports the extrapolated returns to migrating to an urban location for individuals who are never observed in an urban location in the data. Columns (2) to (5) include time (survey wave) fixed effects, column (3) adds a female indicator, column (4) adds age squared, and column (5) adds education (years of schooling, maximum across periods) and its square. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Section 4.3.1.

As is the case for Indonesia, the slope of the extrapolation line, ϕ, for China is consistently negative across all specifications, indicating that rural-to-urban migration is most beneficial for those with the lowest baseline consumption in rural. Therefore, migration appears to act as a pro-poor technology in China as well.

In our Tanzanian data, the estimated returns to non-migrants are much larger, as shown in Table 8. Without covariates, the returns are 78 log points and unlike for Indonesia and China, our estimates are not very sensitive to adding covariates in columns (2) to (4). Once we control for all our covariates and a time trend in column (5), the returns for non-migrants remain high at 37 log points, around three times the average observational returns that we estimate with fixed effects in Table 5. As is the case in the two other countries, we estimate a consistently negative slope coefficient, ϕ, which again is consistent with rural-urban migration having greater benefits for the

Table 7: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in China

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.424***	0.090***	0.090***	0.104***	0.098***
	(0.021)	(0.028)	(0.028)	(0.023)	(0.021)
ϕ	-0.898***	-0.073	-0.073	-0.161	-0.205
	(0.056)	(0.134)	(0.134)	(0.117)	(0.134)
Individuals	34,746	34,746	34,746	34,746	34,746
Observations	109,535	109,535	109,535	109,535	109,535
Average Δ	0.0201	0.0034	0.0034	0.0039	0.0038
J-stat	98.9	17.1	17.1	18.3	17.5
J-stat (p-value)	0.000	0.029	0.029	0.019	0.025
Converged	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses data from the China Family Panel Survey. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in Tanzania

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.539***	0.301***	0.304***	0.301***	0.270***
	(0.036)	(0.039)	(0.039)	(0.039)	(0.033)
ϕ	-0.998***	-0.515***	-0.523***	-0.534***	-0.719***
	(0.064)	(0.091)	(0.092)	(0.093)	(0.124)
Individuals	11,012	11,012	11,012	11,012	11,012
Observations	29,864	29,864	29,864	29,864	29,864
Average Δ	0.0098	0.0117	0.0117	0.0117	0.0121
J-stat	63.0	6.7	6.5	6.7	3.8
J-stat (p-value)	0.000	0.084	0.089	0.084	0.280
Converged	N	Y	Y	Y	Y
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses data from the National Panel Survey from Tanzania. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

poorest individuals in rural areas.

4.3.1 Hukou Restrictions and J-test Rejection in China

As we estimate the restricted GRC model using GMM, we can test the validity of our overidentifying restrictions (and, thereby, the empirical support for assumption A5) using Hansen's J-test. Overidentifying restrictions arise when the number of moment conditions exceeds the number of estimated parameters, and the J-test checks whether these moment conditions hold jointly.[19]

When the J-test fails to reject, we interpret the LCA restriction as providing a reasonable approximation to the heterogeneity structure, supporting extrapolation to non-switchers. When the test rejects, however, the linear relationship required for such extrapolation lacks empirical support, and estimates of Δ_{d_N} and Δ_{d_T} from the restricted model should be interpreted with caution. The China results reject the null, suggesting that at least one maintained assumption fails, but the test does not identify which assumptions fail.

Several potential sources of misspecification could generate rejection. First, the linear relationship between returns and comparative advantage may not hold: if returns vary nonlinearly with θ_i, perhaps due to threshold effects or institutional discontinuities, the constant-slope restriction fails. Second, serial correlation in non-pecuniary shocks (ν^l_{it}) would violate the independence assumption underlying identification. This could arise if institutional constraints in period t predict constraints in $t+1$.

We investigate whether China's hukou system generates the institutional discontinuities that produce J-test rejection. Rural hukou holders who migrate to urban areas face barriers to formal employment, housing, and social services that urban hukou holders do not face. These constraints create scope for parameter heterogeneity: if the slope ϕ differs across hukou status, pooling both populations and estimating a single ϕ forces a common slope onto distinct data-generating processes, producing moment condition violations that manifest as J-test restrictions.

To test this, we estimate the restricted GRC model separately for rural and urban hukou holders, with results reported in Tables 9 and 10. Neither subsample rejects the J-test at conventional significance levels, yet the estimated slope estimates differ substantially. This pattern supports the hypothesis that pooling causes misspecification in Table 7. The LCA restriction approximates the heterogeneity structure well within each regime, but the pooled model fails because it imposes a common slope across

[19] Specifically, the LCA restriction constrains trajectory-specific returns to satisfy $\Delta_{\underline{d}} = \beta + \phi(\mu_{\underline{d}} - \mu_{\underline{d}_0})$, generating overidentifying restrictions testable via the Hansen J-statistic.

regimes with different return-generating processes.

These results together suggest that the LCA framework remains useful for characterizing heterogeneous returns to migration, but institutional context determines the relevant parameters. Extrapolating returns to non-migrant populations in China requires accounting for the institutional regime they face. Rural hukou holders who have not migrated confront different barriers than urban hukou holders, and counterfactual returns should be extrapolated using group-specific estimates of ϕ.

Table 9: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in China, Rural Hukou First

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.168**	0.074**	0.074**	0.105***	0.106***
	(0.074)	(0.036)	(0.036)	(0.025)	(0.023)
ϕ	-0.894***	0.130	0.129	-0.039	-0.039
	(0.070)	(0.193)	(0.193)	(0.151)	(0.153)
Individuals	25,491	25,491	25,491	25,491	25,491
Observations	80,742	80,742	80,742	80,742	80,742
J-stat	86.0	10.9	10.9	12.6	12.6
J-stat (p-value)	0.000	0.210	0.209	0.125	0.125
Converged	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses data from the China Family Panel Survey. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5 Robustness

In this section, we present results for the restricted GRC model, estimated using the balanced panel. Since sample attrition can be correlated with aging, employment, and migration trajectories, we believe that it is important to examine whether our results are robust to restricting the sample to a balanced panel. Tables 11, 12, and 13 show the results for Indonesia, China, and Tanzania, respectively. The results for China and Tanzania, shown in Tables 12 and 13, are nearly identical to those obtained in the full sample.

Table 10: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in China, Urban Hukou First

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	-0.027	0.042	0.044	0.002	-0.127
	(0.146)	(0.117)	(0.117)	(0.116)	(0.125)
ϕ	-1.324***	-0.805***	-0.806***	-0.830***	-0.989***
	(0.165)	(0.162)	(0.162)	(0.160)	(0.147)
Individuals	9,024	9,024	9,024	9,024	9,024
Observations	28,264	28,264	28,264	28,264	28,264
J-stat	3.8	9.0	9.2	8.6	6.9
J-stat (p-value)	0.585	0.108	0.101	0.128	0.231
Converged	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses data from the China Family Panel Survey. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 11: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in Indonesia, Balanced Panel

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.304***	0.051**	0.051**	0.051**	0.040**
	(0.054)	(0.023)	(0.023)	(0.023)	(0.019)
ϕ	-2.445***	-0.214**	-0.212**	-0.212**	-0.322***
	(0.071)	(0.095)	(0.096)	(0.096)	(0.121)
Individuals	3,284	3,284	3,284	3,284	3,284
Observations	16,391	16,391	16,391	16,391	16,391
J-stat	86.6	23.4	23.5	23.5	23.1
J-stat (p-value)	0.000	0.662	0.656	0.656	0.677
Converged = 1	1	1	1	1	1
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses the balanced panel from the Indonesia Family Life Survey. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 12: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in China, Balanced Panel

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.424***	0.106***	0.106***	0.103***	0.100***
	(0.021)	(0.027)	(0.027)	(0.023)	(0.020)
ϕ	-0.896***	-0.099	-0.099	-0.155	-0.229*
	(0.056)	(0.130)	(0.130)	(0.119)	(0.134)
Individuals	14,214	14,214	14,214	14,214	14,214
Observations	56,855	56,855	56,855	56,855	56,855
J-stat	98.9	19.3	19.3	18.9	18.5
J-stat (p-value)	0.000	0.013	0.013	0.016	0.018
Converged = 1	1	1	1	1	1
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses the balanced panel from the China Family Panel Survey. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 13: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in Tanzania, Balanced Panel

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.539***	0.295***	0.298***	0.289***	0.267***
	(0.036)	(0.040)	(0.040)	(0.040)	(0.033)
ϕ	-0.998***	-0.501***	-0.508***	-0.501***	-0.710***
	(0.064)	(0.093)	(0.093)	(0.097)	(0.122)
Individuals	7,842	7,842	7,842	7,842	7,842
Observations	23,526	23,526	23,526	23,526	23,526
J-stat	63.0	7.4	7.3	7.9	2.9
J-stat (p-value)	0.000	0.060	0.063	0.048	0.405
Converged = 1	0	1	1	1	1
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses the balanced panel from the Tanzanian National Panel Survey. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The results for Indonesia, shown in Table 11, are also similar to those estimated with the unbalanced panel, albeit slightly attenuated. In particular, the estimated returns to urban migration for non-migrants fall to 7 log points once we include all controls and a time trend. This estimate is very similar to the one that we obtain using fixed effects in the unbalanced panel (column 7 in Table 5). However, a more appropriate comparison would be the fixed-effects model estimated on a balanced panel (see column 7 in Table A.4), which are much smaller at 3 log points.

The length of the time period over which the Indonesian data were collected leads to a drastic reduction in the available sample size, which is why our preferred estimates are those with the full sample. Comparing the summary statistics across the full and balanced samples, with the latter reported in Table A.1, we can see that the age profile of respondents differs quite substantially across the two samples. In the full sample, rural respondents are on average around one year younger than their urban counterparts. In contrast, this difference is reversed in the full sample, with urban respondents being nearly two years older. This may reflect different mortality patterns, which would also skew attrition patterns, reinforcing our preference for the full sample.

6 Conclusion

In this paper, we aim to reconcile divergent estimates on the returns to rural-urban migration in developing countries by accounting for the role of selection and heterogeneity in returns to migration. Motivated by a multi-period Roy model, we formulate a correlated random coefficient model that allows for location-specific skills and heterogeneous returns. We use a person's migration history as the relevant dimension of heterogeneity, which we interpret as a person's revealed preference for location and that is conveniently observable in the data. Then, we build on Suri (2011), Lemieux (1998), and Tjernström *et al.* (2026) to leverage a linear relationship between returns to migration and comparative advantage that allows us to extrapolate the returns identified from migrant sub-populations to non-migrants. The group of non-migrants plays a central role in debates on misallocation, whereby non-migrants may reside in areas where they do not live up to their economic potential. Moreover, this group is of specific interest to policymakers determining whether to promote migration as a development strategy.

We test our model using detailed survey data from three developing countries, Indonesia, China and Tanzania. In line with the existing literature, we confirm the existence of large cross-sectional consumption gaps between rural and urban areas. The

gap narrows when we use the panel component of the data and include demographic controls, a time trend, and especially when we include individual fixed effects. We then estimate our Group Random Coefficient model and test its assumptions. Results show a distinct pattern of the relationship between absolute and comparative advantage that is remarkably consistent across the three countries: individuals with the lowest consumption in rural areas stand most to gain from migrating to urban areas. As such, migration can be seen as a pro-poor technology but individuals with the lowest consumption may face barriers to migrate, which might be due to borrowing, liquidity, or information constraints. We conclude that individuals are inefficiently sorted across space and that promoting migration would reduce misallocation and, thereby, increase overall growth.

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Appendix

A Additional Results: Balanced Panel

Table A.1: Summary Statistics Indonesia, Balanced Panel

	All	Rural	Urban	Difference t-test
Location		55.2%	44.8%	
Log Consumption	12.00	11.82	12.21	-0.39***
	(0.80)	(0.80)	(0.76)	
Log Income	14.92	14.73	15.16	-0.43***
	(1.13)	(1.14)	(1.07)	
Female	0.50	0.48	0.52	-0.04***
	(0.50)	(0.50)	(0.50)	
Age (years)	43.45	42.59	44.52	-1.93***
	(12.16)	(12.19)	(12.03)	
Education (years)	7.57	6.63	8.72	-2.09***
	(4.40)	(4.27)	(4.28)	
Household Size	4.72	4.65	4.79	-0.14***
	(1.99)	(1.90)	(2.10)	
Observations	16,420	9,059	7,361	
Individuals	3,284			
Non-switchers	59.6%			

Summary statistics for Indonesia for the balanced panel across all five waves. Source: IFLS. The table reports means and standard deviations (in parentheses) based on individual-year pairs. See section 3 for further details. All variables have the same number of observations, except for income, which is missing for some observations. Income has 12,510 observations.

Table A.2: Summary Statistics China, Balanced Panel

	All	Rural	Urban	Difference t-test
Location		56.2%	43.8%	
Log Consumption	10.39	10.21	10.63	-0.43***
	(0.92)	(0.89)	(0.89)	
Log Income	8.60	8.08	9.13	-1.05***
	(1.91)	(2.06)	(1.58)	
Female	0.52	0.51	0.53	-0.01***
	(0.50)	(0.50)	(0.50)	
Age (years)	49.28	49.34	49.20	0.13
	(14.61)	(14.38)	(14.91)	
Education (years)	6.92	5.70	8.49	-2.79***
	(4.78)	(4.46)	(4.73)	
Household Size	4.12	4.39	3.77	0.62***
	(1.81)	(1.87)	(1.67)	
Observations	56,855	31,968	24,887	
Individuals	14,214			
Non-switchers	91.8%			

Summary statistics for China for the balanced panel across all waves. Source: China survey. The table reports means and standard deviations (in parentheses) based on individual-year pairs. See section 3 for further details. All variables have the same number of observations, except for income, which is missing for some observations. Income has 25,530 observations.

Table A.3: Summary Statistics Tanzania, Balanced Panel

	All	Rural	Urban	Difference t-test
Location		64.5%	35.5%	
Log Consumption	14.85	14.61	15.29	-0.68***
	(0.81)	(0.71)	(0.79)	
Log Income	13.86	13.29	14.55	-1.26***
	(1.92)	(1.81)	(1.83)	
Female	0.52	0.52	0.52	-0.00
	(0.50)	(0.50)	(0.50)	
Age (years)	37.88	39.07	35.72	3.35***
	(16.58)	(17.16)	(15.24)	
Education (years)	6.59	5.55	8.48	-2.93***
	(4.03)	(3.75)	(3.83)	
Household Size	6.27	6.49	5.86	0.63***
	(4.06)	(4.43)	(3.22)	
Observations	23,526	15,165	8,361	
Individuals	7,842			
Non-switchers	85.5%			

Summary statistics for Tanzania for the balanced panel across all waves. Source: Tanzania survey. The table reports means and standard deviations (in parentheses) based on individual-year pairs. See section 3 for further details. All variables have the same number of observations, except for income, which is missing for some observations. Income has 9,760 observations.

Table A.4: OLS Estimates of the Returns to Urban Location on log Consumption, Balanced Sample

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Indonesia							
Urban	0.392***	0.335***	0.335***	0.331***	0.194***	0.151***	0.031*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.019)	(0.017)
Observations	16,420	16,420	16,420	16,420	16,420	6,635	16,420
Individuals	3,284	3,284	3,284	3,284	3,284	1,327	3,284
Adj. R^2	0.059	0.14	0.14	0.15	0.26	0.25	0.53
Panel B: China							
Urban	0.425***	0.416***	0.416***	0.415***	0.287***	0.264***	0.142***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.026)	(0.022)
Observations	56,855	56,855	56,855	56,855	56,855	4,664	56,855
Individuals	14,214	14,214	14,214	14,214	14,214	1,166	14,214
Adj. R^2	0.053	0.080	0.080	0.11	0.14	0.13	0.52
Panel C: Tanzania							
Urban	0.684***	0.688***	0.688***	0.670***	0.489***	0.088***	0.065***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.019)	(0.016)
Observations	23,526	23,526	23,526	23,526	23,526	3,414	23,526
Individuals	7,842	7,842	7,842	7,842	7,842	1,138	7,842
Adj. R^2	0.16	0.18	0.18	0.19	0.27	0.16	0.69
Covariates			Female	& Age^2	All	All	All
Time FE		Y	Y	Y	Y	Y	Y
Individual FE							Y
Migrants only						Y	

This table repeats the analyses of Table 5 using the balanced panel. Please refer to Section 3 for further details on the data and to the notes of Table 5 for additional information on the variables. The dependent variable is the log of total consumption per capita. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

B Additional Results: Non-agricultural Sector

Table B.5: Summary Statistics Indonesia

	All	Rural	Urban	Difference t-test
Non-Agricultural		33.9%	66.1%	
Log Consumption	12.05	11.75	12.20	-0.46***
	(0.79)	(0.74)	(0.78)	
Log Income	14.89	14.41	15.09	-0.68***
	(1.14)	(1.15)	(1.08)	
Female	0.44	0.43	0.45	-0.02***
	(0.50)	(0.49)	(0.50)	
Age (years)	39.94	43.40	38.16	5.24***
	(13.61)	(15.02)	(12.45)	
Education (years)	7.97	5.54	9.22	-3.67***
	(4.63)	(3.92)	(4.47)	
Household Size	4.65	4.55	4.70	-0.15***
	(2.07)	(1.98)	(2.12)	
Observations	93,038	46,797	69,289	
Individuals	29,716			
Non-switchers	92.9%			

Summary statistics for Indonesia for the unbalanced panel across all five waves. Source: IFLS. The table reports means and standard deviations (in parentheses) based on individual-year pairs. See section 3 for further details. All variables have the same number of observations, except for income, which is missing for some observations. Income has 61,300 observations.

Table B.6: OLS Estimates of the Returns to Non-Agricultural Sector on log Consumption

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Indonesia							
Non-agricultural employment	0.388***	0.348***	0.349***	0.347***	0.190***	0.151***	0.088***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.019)	(0.008)
Observations	93,026	93,026	93,026	93,026	93,026	6,635	93,026
Individuals	29,710	29,710	29,710	29,710	29,710	1,327	29,710
Adj. R^2	0.060	0.16	0.16	0.16	0.27	0.25	0.52
Covariates			Female	& Age^2	All	All	All
Time FE		Y	Y	Y	Y	Y	Y
Individual FE							Y
Migrants only						Y	

This table repeats the analyses of Table 5 for non-agricultural employment, which is an indicator equal to one for individuals who report working in the non-agricultural sector. Please refer to Section 3 for further details on the data and to the notes of Table 5 for additional information on the variables. The dependent variable is the log of total consumption per capita. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B.7: Restricted GRC Estimates of the Returns to Non-Agricultural Sector on log Consumption in Indonesia

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.304***	0.086***	0.086***	0.091***	0.071***
	(0.054)	(0.021)	(0.021)	(0.021)	(0.018)
ϕ	-2.445***	-0.309***	-0.310***	-0.321***	-0.526***
	(0.070)	(0.087)	(0.087)	(0.086)	(0.102)
Individuals	29,697	29,697	29,692	29,692	29,692
Observations	92,450	92,450	92,439	92,439	92,439
J-stat	86.5	32.5	32.4	33.3	28.2
J-stat (p-value)	0.000	0.214	0.216	0.187	0.403
Converged = 1	1	1	1	1	1
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table repeats the analyses of Table 6 for non-agricultural employment, which is an indicator equal to one for individuals who report working in the non-agricultural sector. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. The dependent variable is the log of total consumption per capita. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

C Additional Results: Hukou Status

Table C.8: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in China, Only Rural Hukou

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	0.436***	0.075**	0.075**	0.098***	0.100***
	(0.047)	(0.032)	(0.032)	(0.025)	(0.023)
ϕ	-0.286***	0.089	0.088	-0.021	-0.033
	(0.104)	(0.176)	(0.175)	(0.151)	(0.152)
Individuals	23,989	23,989	23,989	23,989	23,989
Observations	75,748	75,748	75,748	75,748	75,748
J-stat	84.5	9.7	9.7	10.9	11.0
J-stat (p-value)	0.000	0.287	0.286	0.208	0.200
Converged	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses data from the China Family Panel Survey. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C.9: Restricted GRC Estimates of the Returns to Urban Location on log Consumption in China, Only Urban Hukou

Dep. var: log(consumption)	(1)	(2)	(3)	(4)	(5)
Δ_{never}	-0.087	0.015	0.020	-0.033	-0.153
	(0.158)	(0.130)	(0.130)	(0.129)	(0.142)
ϕ	-1.276***	-0.793***	-0.794***	-0.818***	-0.985***
	(0.137)	(0.156)	(0.156)	(0.154)	(0.175)
Individuals	8,366	8,366	8,366	8,366	8,366
Observations	26,155	26,155	26,155	26,155	26,155
J-stat	2.6	7.7	7.9	6.9	6.3
J-stat (p-value)	0.759	0.174	0.163	0.230	0.281
Converged	Y	Y	Y	Y	Y
Time FE		Y	Y	Y	Y
Covariates			Female	& Age^2	All

This table uses data from the China Family Panel Survey. Please refer to Section 3 for further details on the data and to the notes of Table 6 for additional information on the variables. We report robust standard errors, clustered at the individual level, in parentheses. Stars denote: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.