The Macroeconomic Effects of Lifting Barriers to Migration

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Abstract

Many economic studies have identified barriers to migration which can distort labor allocation and productivity, but comparing the macroeconomic importance of each barrier is complicated by variation in study design and sampling. We build and estimate a dynamic general-equilibrium model of rural–urban migration which nests several of the key frictions emphasized in the literature. We discipline the model using large-scale data from Kenya, the site of several recent migration experiments. We show that the model reproduces the results of these experiments well in most cases. We proceed to estimate the long-run treatment effects of each intervention, the macroeconomic effects of scaling each intervention to the national level, and a decomposition of the urban–rural income gap into each migration friction.

Keywords: internal migration, urban–rural income gap, general equilibrium model

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1 Introduction

Large gaps in income between rural and urban areas persist in many low-income countries.[1] A growing body of microeconomic evidence points to multiple frictions that can prevent rural households from migrating to cities—monetary costs of migration, information frictions, urban employment risk, and borrowing constraints—and identifies large monetary returns to relaxing those frictions through targeted interventions (Bryan, Chowdhury, and Mobarak 2014; Akram, Chowdhury, and Mobarak 2017; Baseler 2023; Barnett-Howell et al. 2025; Miner 2025). However, comparing or aggregating results across studies is not straightforward because of differences in sampling, intervention design, and intervention cost. Furthermore, we lack a unified quantitative framework to measure the aggregate importance of each barrier to migration, to understand how these frictions interact in general equilibrium, and to evaluate the macroeconomic consequences of scaling up experimental interventions.

We take a step toward filling this gap by building and estimating a quantitative general-equilibrium model of internal migration tailored to randomized controlled trial (RCT) evidence from Kenya. Kenya is the site of several recent experiments that intervene on a broad set of potential migration frictions, and restricting our focus to one country reduces the complexity in modeling sampling variation across studies. The model is designed to nest the main channels emphasized in this experimental work, and to be rich enough to reproduce their results within a single structural environment. We discipline the model using evidence from large cash transfers in Egger et al. (2022), unemployment-insurance and small cash-transfer treatments in Miner (2025), and information interventions in Barnett-Howell et al. (2025). We then use the estimated model to (i) evaluate the long-run effects of each intervention, (ii) evaluate the macroeconomic effects of scaling up each intervention to a national level, (iii) decompose the rural–urban income gap into contributions from different frictions.

Our framework is a dynamic heterogeneous agent model with incomplete markets in the spirit of Aiyagari (1994) with self-selection into location and occupation in the spirit of Roy (1951). A continuum of infinitely lived heterogeneous households chooses consumption, savings, and location between a rural region and an urban region. Borrowing is limited by a borrowing constraint. Urban workers face job-finding and separation shocks, allowing us to model the value of unemployment insurance. Migration to the city imposes a utility cost which is dependent on past urban experi-

1. See Lagakos (2020) for an overview.

ence. Urban experience accumulates stochastically while in the city and can depreciate when returning to the countryside, as in Lagakos, Mobarak, and Waugh (2023). Rural households underestimate their potential urban income, as in Barnett-Howell et al. (2025). Finally, a monetary migration cost picks up all other forces precluding rural–urban migration.

A central design objective of the model is to represent several experiments within a single structural environment. We start by estimating the model using the simulated method of moments, targeting a set of moments from observational and experimental data in Kenya. Next, we map the sampling strategy, treatments, and outcome measurement from six existing randomized interventions conducted in Kenya to their approximate analogs in the model. We explicitly reproduce three classes of interventions. First, an unconditional cash transfer, as trialled by Egger et al. (2022) and Miner (2025). Second, an unemployment insurance benefit trialled by Miner (2025). Third, an information treatment that updates rural households' beliefs about urban incomes, as in Barnett-Howell et al. (2025). We test the model's ability to replicate the treatment effects on migration and economic outcomes observed in each RCT. Overall, the model matches migration effects well for all interventions. It matches income or consumption gains well in the Egger et al. (2022) cash transfer and two out of three Barnett-Howell et al. (2025) information treatments. However, it generates sizable income gains in the two Miner (2025) treatments and one out of three Barnett-Howell et al. (2025) information treatments, where the experiments find little or no effect.

We then use the estimated model for three counterfactual exercises. First, we trace out treatment effects beyond the horizons observed in the experiments. The model predicts that the migration and income gains from the information treatment and unemployment insurance continue to build for several years, while the effects of one-time cash transfers fade as the transfer is spent. Second, we use the model to predict the effects of rolling the experimental interventions out at national level in general equilibrium. Scaling the information treatments nationally raises the urban share by 1–3 percentage points, while scaling unemployment insurance raises it by 25 percentage points; no experimental intervention substantially lowers the urban-rural income gap when rolled out nationally. Third, we decompose the baseline urban-rural gap into shares attributable to different frictions by shutting down one friction at a time. Eliminating information frictions has little effect. Relaxing financial frictions modestly narrows the gap but sharply reduces the urban share of population, suggesting that rural-to-urban migration is an important self-insurance tool in the absence of functioning financial markets. Eliminating residual migration costs reduces the gap by two-thirds while more than doubling the urban share, implying that forces not explicitly represented in the model are the dominant barriers to migration.

Our paper contributes to the emerging synthesis of development macroeconomics and microeconomic evidence from randomized controlled trials (see Buera, Kaboski, and Townsend (2023) for an overview). RCTs provide credible identification of causal effects in specific contexts, while structural models help interpret these findings, understand mechanisms, quantify general equilibrium effects, and extrapolate findings to broader populations. We follow this tradition by using a rich set of empirical moments to discipline a dynamic general equilibrium model and use it to interpret experimental evidence. Doing so helps us bridge the gap between reduced-form estimates of specific migration barriers[2] and the macroeconomic question of how these barriers jointly determine aggregate productivity and the spatial distribution of labor.[3]

Second, we contribute to the literature on the obstacles to and gains from internal migration by providing a unified framework that rationalizes findings from multiple distinct experimental interventions. Previous studies have paired a specific experiment with a model tailored to that intervention (Meghir et al. 2022; Lagakos, Mobarak, and Waugh 2023; Miner 2025; Barnett-Howell et al. 2025). In contrast, we build a single environment capable of reproducing the treatment effects of unconditional cash transfers, unemployment insurance, and information provision simultaneously. This approach allows us to assess the factors that can explain the disparate findings across experiments and provides a platform for comparing the effectiveness of different policy levers in a consistent setting.

Our work is most closely related to Lagakos, Mobarak, and Waugh (2023) and Meghir et al. (2022), who build models to interpret migration subsidy experiments by Bryan, Chowdhury, and Mobarak (2014). Like them, we build a dynamic general equilibrium model of migration. We contribute by incorporating additional frictions—information frictions and unemployment risk—and by seeking to simulate several

2. Beyond the experiments we study in Kenya, see, for example, De Janvry et al. (2015), Akram, Chowdhury, and Mobarak (2017), Beam (2016), Beam, McKenzie, and Yang (2016), Cai (2020), Shrestha (2020), and Baseler et al. (2025).

3. For examples in this literature, see Lagakos and Waugh (2013), Gollin, Lagakos, and Waugh (2014), Herrendorf and Schoellman (2018), Bryan and Morten (2019), Morten (2019), Lagakos et al. (2020), Tombe and Zhu (2019), and Morten and Oliveira (2024).

recent randomized controlled trials at once. Furthermore, we explicitly focus on the general-equilibrium implications of scaling these interventions to the national level and decompose the rural-urban income gap into the specific contributions of various frictions.

The rest of the paper is organized as follows. Section 2 presents the model. Section 3 describes the estimation of model parameters. Section 4 describes how we map existing RCTs in Kenya into the model. Section 5 presents the main quantitative findings on the decomposition of the rural–urban income gap and the general-equilibrium effects of different policies. Section 6 concludes.

2 Model

In this section, we develop a model of internal migration. The model is designed to capture the key frictions that can impede rural-to-urban migration, as identified by recent experimental evidence.

To be useful for our purposes of matching and interpreting RCT evidence, the model needs to include several features. First, model households must be heterogeneous along several dimensions, to allow for selection into migration and different sampling strategies across experiments. Second, households need to face a borrowing constraint and the means of self-insuring against risk, to capture the liquidity channel emphasized by cash transfer experiments. Third, households need to face urban unemployment risk, to capture the role of unemployment insurance. Fourth, households need to have imperfect beliefs about urban earnings, to capture the effects of information interventions. Finally, the model needs to be rich enough to reproduce several distinct experiments within a single structural environment, so that we can compare the mechanisms and cost-effectiveness of different interventions in a consistent setting.

2.1 Households

The model is populated by a continuum of infinitely lived heterogeneous households who make consumption, savings, and migration decisions between a rural (denoted by R) and urban (denoted by U) region. Each period, a household chooses its next period location $l' \in \{R, U\}$ and assets a'.

Preferences and Experience. Households have CRRA preferences over adjusted, or *effective*, consumption, and discount the future at rate $\beta \in (0,1)$. A household's period utility is

$$u(c,l,x) = \frac{\tilde{c}^{1-\sigma} - 1}{1-\sigma},$$

where $\sigma > 0$ is the coefficient of relative risk aversion and $\tilde{c}$ denotes effective consumption:

$$\tilde{c} = \frac{c}{1 + m_u \cdot \mathbb{1}(l = U,\, x = 0)}.$$

Here $m_u \geq 0$ is a migration disutility parameter, and $x \in \{0,1\}$ indicates urban experience. Whenever an inexperienced household $(x = 0)$ resides in the urban area $(l = U)$, they perceive their consumption as reduced by a factor of $1 + m_u$. This utility cost persists until the household acquires urban experience, or returns to the rural area. This modeling decision captures a dislike for the urban area which fades with experience there, for example reflecting psychological or cultural adjustment costs.

Urban experience $x \in \{0,1\}$ evolves stochastically. An inexperienced household $(x = 0)$ residing in the urban area gains experience $(x' = 1)$ with probability π_x each period. Once acquired, experience is permanent as long as the household remains in the city. An experienced household $(x = 1)$ that resides in the rural area loses its experience $(x' = 0)$ with probability π_{-x} per period.[4]

Employment. In the rural sector, all workers are employed in every period. In the urban sector, workers face employment risk (Harris and Todaro 1970). An employed urban worker $(e = 1)$ separates from their job with probability λ_s each period, transitioning to unemployment $(e' = 0)$. An unemployed urban worker $(e = 0)$ finds a job with probability λ_f, transitioning to employment $(e' = 1)$. Rural-to-urban migrants arrive unemployed but can find a job with probability λ_f immediately. Unemployed urban workers receive a flat unemployment benefit b.

Endowments. Households supply one unit of labor inelastically in the region where they reside, but are heterogeneous in their productivity levels z_R and z_U. Each period, each household draws two idiosyncratic productivity shocks ϵ_R and ϵ_U for rural and urban work from a normal distribution with standard deviations $\sigma_{\epsilon,R}$ and

4. Our modeling of migration experience and the disutility of migration is largely borrowed from Lagakos, Mobarak, and Waugh (2023). It also has a parallel in Meghir et al. (2022), who model a "migration asset" that can be acquired while in the city.

$\sigma_{\epsilon,U}$, and correlation ρ_ϵ between the two shocks. Productivities z_R and z_U follow a bivariate first-order autoregressive process in logs, with persistence parameters ρ_R and ρ_U:

$$\log z'_R = \rho_R \log z_R + \epsilon'_R,$$
$$\log z'_U = \rho_U \log z_U + \epsilon'_U,$$

where the shocks are jointly normally distributed,

$$\begin{pmatrix} \epsilon'_R \\ \epsilon'_U \end{pmatrix} \sim \mathcal{N}\left(\mathbf{0}, \begin{pmatrix} \sigma^2_{\epsilon,R} & \rho_\epsilon \, \sigma_{\epsilon,R} \, \sigma_{\epsilon,U} \\ \rho_\epsilon \, \sigma_{\epsilon,R} \, \sigma_{\epsilon,U} & \sigma^2_{\epsilon,U} \end{pmatrix}\right).$$

Income and Migration Cost. Labor income depends on location and employment status:

$$y(e, l, z_R, z_U) = \begin{cases} w_R \, z_R & \text{if } l = R, \\ w_U \, z_U & \text{if } l = U \text{ and } e = 1, \\ b & \text{if } l = U \text{ and } e = 0, \end{cases} \tag{1}$$

where w_R and w_U are the rural and urban wages, respectively.

Migration from the rural area to the city requires paying an additive monetary cost $m_c > 0$ in the period before the move, while a move from the city back to the rural area is free. We assume that urban households are myopic about moving costs: while rural households account for m_c when making migration decisions, urban households do not anticipate that they will have to pay m_c if they return to the rural area and then migrate to the city again. This assumption allows m_c to deter rural-to-urban moves while still permitting substantial return migration, which helps the estimated model match the urban population share without absorbing all successful migrants into the city in the stationary equilibrium.

Assets and the Borrowing Constraint. Households hold assets a that earn a return r. Each period, they choose how to allocate their income between consumption c and next period's assets a'. They face a borrowing constraint $a' \geq \underline{a}$, potentially inhibiting households from financing moving costs m_c or supporting themselves while they search for a job in the city.

The household's budget constraint is

$$c + a' + \mathbb{1}(l = R, l' = U) \cdot m_c = (1 + r)\, a + y(e, l, z_R, z_U),$$

Understatement of Urban Income. Each household faces a time-invariant information friction $\gamma \in (0, 1]$. While making decisions from the rural area, the household perceives the urban wage as $\tilde{w}_U = \gamma\, w_U$ rather than the true wage w_U. This misperception reduces the household's perceived return to urban employment and discourages migration, as documented in Baseler (2023) and Barnett-Howell et al. (2025).[5]

In the household's dynamic optimization problem, γ enters as a fixed parameter that scales perceived urban wage income. The household does not anticipate that its beliefs will be revised, capturing the idea that information about urban labor markets is difficult to acquire in rural areas. When a household with $\gamma < 1$ migrates to the city, it discovers the true urban wage and is "surprised" by the higher income. If the household later returns to the rural area, it reverts to its misperceived beliefs (but does not anticipate this reversion while in the city).

Formally, define the household's perceived income as

$$\tilde{y}(e, l, z_R, z_U, \gamma) = \begin{cases} w_R\, z_R & \text{if } l = R, \\ \gamma\, w_U\, z_U & \text{if } l = U \text{ and } e = 1, \\ b & \text{if } l = U \text{ and } e = 0, \end{cases}$$

so that the true income function (1) corresponds to the special case $\gamma = 1$.

2.2 Production

A representative firm in each region operates a Cobb-Douglas technology with constant returns to scale:

$$Y_l = A_l\, K_l^{\alpha}\, L_l^{1-\alpha}, \quad l \in \{R, U\},$$

where A_l is region-specific total factor productivity, K_l is the capital stock, L_l is effective labor measured in efficiency units, and α is the capital share. Firms operate in

5. Our modeling choice is borrowed from Barnett-Howell et al. (2025).

competitive factor markets, so factor prices equal marginal products:

$$w_l = (1-\alpha)\, A_l \left(\frac{K_l}{L_l}\right)^{\alpha}, \tag{2}$$

$$r + \delta = \alpha\, A_l \left(\frac{K_l}{L_l}\right)^{\alpha-1}, \tag{3}$$

where δ is the depreciation rate of capital. Capital is perfectly mobile across regions, so the net return to capital r is equalized. With constant returns to scale and competitive markets, firm profits are zero.

2.3 Equilibrium

State Space. A household's individual state is the vector $s = (a, z_R, z_U, l, x, e, \gamma)$, comprising assets, rural productivity, urban productivity, current location, urban experience, employment status, and the information friction parameter. The control variables are $p = (a', l')$: next-period assets and next-period location.

Recursive Formulation. The household's problem can be written recursively.

A rural household chooses whether to remain in the rural area ($l' = R$) or migrate to the city ($l' = U$):

$$V_R(a, z_R, z_U, x, \gamma) = \max\left\{V_{R\to R}(a, z_R, z_U, x, \gamma),\ V_{R\to U}(a, z_R, z_U, x, \gamma)\right\}.$$

The value of remaining in the rural area is

$$V_{R\to R} = \max_{a' \geq \underline{a}} \left\{u(c, R, x) + \beta\, \mathbb{E}\left[V_R(a', z'_R, z'_U, x', \gamma)\right]\right\}$$

subject to $c + a' = (1+r)\, a + \tilde{y}(1, R, z_R, z_U, \gamma)$, where the expectation is over the next-period productivity endowments (z'_R, z'_U) and urban experience x'. The value of migrating to the urban area is

$$V_{R\to U} = \max_{a' \geq \underline{a}} \left\{u(c, R, x) + \beta\, \mathbb{E}\left[V_U(a', z'_R, z'_U, x', e', \gamma)\right]\right\}$$

subject to $c + a' + m_c = (1+r)\, a + \tilde{y}(1, R, z_R, z_U, \gamma)$, where the expectation is over the next-period productivity endowments (z'_R, z'_U), urban experience x', and employment status e'.

An urban household with employment status e chooses whether to remain or return to the countryside:

$$V_U(a, z_R, z_U, x, e, \gamma) = \max\left\{V_{U\to U}(a, z_R, z_U, x, e, \gamma),\ V_{U\to R}(a, z_R, z_U, x, e, \gamma)\right\}.$$

The value of staying in the urban area is

$$V_{U\to U} = \max_{a'\geq \underline{a}} \left\{u(c, U, x) + \beta\, \mathbb{E}\left[V_U(a', z'_R, z'_U, x', e', \gamma)\right]\right\}$$

subject to $c + a' = (1+r)\, a + \tilde{y}(e, U, z_R, z_U, \gamma)$. The expectation is over the next-period productivity endowments (z'_R, z'_U), urban experience x', and employment status e'. The value of returning to the rural area is

$$V_{U\to R} = \max_{a'\geq \underline{a}} \left\{u(c, U, x) + \beta\, \mathbb{E}\left[V_R(a', z'_R, z'_U, x', \gamma)\right]\right\}$$

subject to $c + a' + m_c = (1+r)\, a + \tilde{y}(e, U, z_R, z_U, \gamma)$. A household that moves to the rural area arrives employed, since rural employment is guaranteed.

Information Friction in the Recursive Problem. The information friction parameter γ enters the household's problem through the perceived urban wage. In the value function iteration, a household with $\gamma < 1$ perceives urban wage income as $\gamma\, w_U\, z_U$ rather than the true $w_U\, z_U$, yielding value and policy functions indexed by γ that differ from those computed under accurate information ($\gamma = 1$). Because γ is fixed within the household's problem, the household does not anticipate that its beliefs will change with location.

Crucially, households moving to the urban region never actually experience the understated urban wage. In the simulation of the stationary distribution, the value and policy functions assigned to a household depend on its current location. A rural household with $\gamma < 1$ uses $V(\cdot\,;\gamma)$, the value and policy functions solved under its own γ, and therefore underestimates urban income when evaluating whether to migrate. If such a household does migrate to the city, it is switched to $V(\cdot\,;1)$—the value and policy functions corresponding to accurate information—and is "positively surprised" by the true urban income. Conversely, an urban household with $\gamma < 1$ uses $V(\cdot\,;1)$ while in the city, and therefore does not anticipate reverting to its original misperception upon return. If the household moves back to the rural area, it is switched to $V(\cdot;\gamma)$, effectively forgetting what it learned about urban income.[6]

A similar logic is applied to migration-cost beliefs. In the simulation, rural households use the policies solved under the estimated value of m_c. Urban households, in contrast, use the policies solved under the belief that $m_c = 0$: they "forget" that rural-urban migration has a cost, making them more willing to return to the village in the future, not realizing that the migration cost might "trap" them there for a while.

General Equilibrium. A stationary recursive competitive equilibrium consists of value functions V_R and V_U; household policy functions for consumption $c(\cdot)$, savings $a'(\cdot)$, and location choice $l'(\cdot)$; factor prices $\{w_R, w_U, r\}$; aggregate quantities $\{K_R, K_U, L_R, L_U\}$; and a time-invariant distribution of households over the state space, $\mu(s)$, such that:

1. *Household optimization.* Given factor prices, the value functions and policy functions solve the household's recursive problem defined above.

2. *Firm optimization.* In each region $l \in \{R, U\}$, factor prices equal marginal products as in equations (2)–(3). Perfect capital mobility ensures that the net return r is equalized across regions.

3. *Market clearing.* Labor demand equals labor supply in each region:

$$L_R = \int_{l=R} z_R \, d\mu,$$
$$L_U = \int_{l=U,\, e=1} z_U \, d\mu.$$

Total capital demanded by firms equals total capital supplied by households through their savings:

$$K_R + K_U = \int a \, d\mu.$$

The aggregate resource constraint is

$$\int c \, d\mu + \delta(K_R + K_U) + M = Y_R + Y_U + B,$$

where $M = \int m_c \cdot \mathbb{1}(l = R, l' = U) \, d\mu(s)$ is total migration costs paid by all

6. This modeling choice captures the idea that accurate information about urban labor markets is hard to acquire in rural areas. The asymmetry between the value function iteration and the simulation is intentional: it allows the model to simulate imperfect information in a computationally cheap way, without having to model the learning process explicitly.

migrating households and $B = \int b \cdot \mathbb{1}(l = U, e = 0)\, d\mu(s)$ is total unemployment benefits. In stationary equilibrium, aggregate net investment is zero. Benefits represent a net resource injection into the economy: they are not financed by any tax on households.

4. *Stationary distribution.* The distribution μ is a fixed point of the transition operator T induced by household policy functions and the exogenous stochastic processes:

$$\mu = T(\mu).$$

The transition operator incorporates the information friction described above: a household with permanent friction parameter γ follows different policy functions depending on its current location. Define the effective friction as

$$\gamma^{\text{eff}}(\gamma, l) = \begin{cases} \gamma & \text{if } l = R, \\ 1 & \text{if } l = U. \end{cases}$$

The operator T evaluates each household's policy functions at $\gamma^{\text{eff}}(\gamma, l)$, so that rural households use value and policy functions solved under their own γ, while urban households use those solved under accurate information.

3 Estimation

We discipline the model using estimates from the extant literature, Kenyan national accounts data, and Kenyan microdata collected by Barnett-Howell et al. (2025).

3.1 Assigned Parameters

Table 1 summarizes the parameters that are fixed directly rather than estimated through the simulated method of moments. Those parameters are:

Period length (t). We set one model period to six months, approximately the mean duration of a post-treatment migration event in Barnett-Howell et al. (2025). A longer period would compress migration and job-search dynamics too aggressively, while a shorter period would limit the availability of moments in the data.

Table 1: Assigned Parameters

Parameter	Value	Source
t	6 months	—
β	0.98	Standard discount factor for a six-month period.
σ	2.00	Lagakos, Mobarak, and Waugh (2023).
α	0.64	Capital share implied by a Kenyan labor share of 0.36 from ILOSTAT.
δ	0.051	Standard annual depreciation rate of 0.10 converted to a six-month period.
A_R	1.00	Rural TFP normalization.
λ_s	0.06	Six-month urban job separation hazard measured for migrants measured by Barnett-Howell et al. (2025).
λ_f	0.42	Six-month urban job finding hazard.
m_u	0.34	Income share inexperienced migrants are willing to forgo in order to return to the rural area, measured by Barnett-Howell et al. (2025).
π_x	0.45	Share of initially rural-preferring migrants who switch to an urban preference within six months after migrating, Barnett-Howell et al. (2025).
π_{-x}	0.68	Share of initially urban-preferring return migrants who switch back to a rural preference within six months, Barnett-Howell et al. (2025).
γ	0.56	Average expected Nairobi income reported by rural households as a share of actual Nairobi income, Barnett-Howell et al. (2025).
b	0.00	No formal unemployment insurance in Kenya.
$\underline{a}$	0.00	No borrowing allowed at baseline.

Discount factor (β). We set the discount factor to $\beta = 0.98$, which is the six-month counterpart to the conventional annual value of 0.96.

Risk aversion (σ). The coefficient of relative risk aversion is fixed at $\sigma = 2$, following Lagakos, Mobarak, and Waugh (2023).

Capital share (α). We set the capital share in both regional production functions to $\alpha = 0.64$, corresponding to Kenya's labor share of 0.36 reported by ILOSTAT.

Depreciation (δ). The depreciation rate is fixed at $\delta = 0.051$, which is the six-month equivalent of a standard annual depreciation rate of 10 percent.

Rural productivity normalization (A_R). We normalize rural TFP to $A_R = 1$. Since only relative productivity differences matter for the spatial allocation decisions in the model, this normalization leaves urban productivity A_U free to capture the empirically relevant urban productivity premium.

Labor market transitions (λ_s, λ_f). The urban job separation and job-finding rates are set to $\lambda_s = 0.06$ and $\lambda_f = 0.42$ using six-month transition hazards observed for migrants in the survey conducted by Barnett-Howell et al. (2025).

Migration disutility (m_u). The utility cost of migration for inexperienced migrants is fixed at $m_u = 0.34$. Empirically, this comes from a question in the survey conducted by Barnett-Howell et al. (2025) asking urban migrants what rural income would make them willing to return home. Among migrants who prefer the village, the implied compensating differential is 34% of income. We interpret this as a consumption-equivalent disutility from urban life for inexperienced migrants.

Experience transitions (π_x, π_{-x}). We set the per-period probability of gaining urban experience to $\pi_x = 0.45$ and the probability of losing it after returning to the rural area to $\pi_{-x} = 0.68$. In the data, π_x is measured as the share of rural-to-urban migrants that initially prefer the village (i.e. when surveyed in the village, state that they require a higher urban income to be willing to move), but switch to an urban preference after migrating (i.e. when surveyed in the city, state that they require a higher rural income to be willing to return), while π_{-x} is measured as the share of urban-preferring migrants that switch to a rural preference after moving home. Both moments are computed from panel survey data collected by Barnett-Howell et al. (2025). These moments are informative because the model's urban experience state is intended to capture exactly these transitions: households learn to navigate the city, build networks, or otherwise adapt so that the urban consumption penalty disappears. The relatively high values of both parameters suggest that migrants adapt to their new location fairly quickly.

Information friction (γ). We set the urban wage understatement parameter to $\gamma = 0.56$. This matches the finding of Barnett-Howell et al. (2025): on average, rural households underestimate Nairobi income (conditional on demographic characteristics) by 44%.

Unemployment benefit (b). The unemployment benefit is set to $b = 0$ in the baseline, as there is no formal unemployment insurance in Kenya.

Borrowing limit ($\underline{a}$). The borrowing limit is set to $\underline{a} = 0$, prohibiting all borrowing at baseline and forcing households to build up precautionary savings to self-insure against shocks and cover the cost of migration.

3.2 Estimated Parameters

The remaining parameters are estimated using the simulated method of moments. We pick a set of moments that are informative about the underlying structural parameters and then search for the parameter values that minimize the distance between the model-generated moments and their empirical counterparts. The parameter-moment mapping described below is not one-to-one, as each parameter influences all moments at once. Still, each parameter-moment pair highlights which moment is particularly sensitive to changes in that parameter and therefore provides the main source of identification for it.

Table 2: Estimated Parameters

Parameter	Value	Target moment	Moment value	
			Data	Model
A_U	1.77	Urban–rural ratio of median incomes	5.15	4.95
ρ_R	0.64	Standard deviation of log rural income	1.49	1.55
ρ_U	0.78	Standard deviation of log urban income	1.57	1.60
$\sigma_{\epsilon,R}$	1.16	Standard deviation of residual rural log income	1.14	1.19
$\sigma_{\epsilon,U}$	1.07	Standard deviation of residual urban log income	1.05	1.10
ρ_ϵ	0.03	Slope of urban vs rural log incomes	0.065	0.068
m_c	1721	Urban population share	0.320	0.328

Urban productivity (A_U). Urban TFP is estimated at $A_U = 1.77$ to match the urban–rural ratio of median incomes in Kenyan household data.

Shock volatilities ($\sigma_{\epsilon,R}$, $\sigma_{\epsilon,U}$). The shock standard deviations are estimated at $\sigma_{\epsilon,R} = 1.16$ and $\sigma_{\epsilon,U} = 1.07$, using the standard deviations of the residuals in an AR(1) regression of rural and urban log income respectively. These moments isolate the short-run components of earnings risk, leaving ρ_R and ρ_U to capture the long-run components.

Productivity persistence (ρ_R, ρ_U). The persistence parameters are estimated at $\rho_R = 0.64$ and $\rho_U = 0.78$, targeting the cross-sectional standard deviations of log rural and log urban income, respectively. The identifying logic is the same in both locations: persistent heterogeneity, rather than purely transitory shocks, must account for a large share of the earnings differences that matter for migration selection. Higher persistence makes location-specific earning ability more durable over time, so currently productive rural households expect to remain productive if they stay, while productive urban households expect their comparative advantage in the city to persist after migration.

Cross-location shock correlation (ρ_ϵ). We estimate the correlation between rural and urban productivity shocks at $\rho_\epsilon = 0.03$. The target moment is the slope from regressing urban log income on rural log income for observationally comparable households (each observation is a cluster formed using a k-means algorithm on survey data from Barnett-Howell et al. (2025). In the model, we use potential urban log income on potential rural log income within a household.

Monetary migration cost (m_c). The monetary migration cost is estimated at $m_c = 1721$ by matching the share of the Kenyan population living in cities. We treat this parameter as a residual migration friction in the model, capturing any reason Kenyan households may have not to migrate that the explicitly modeled and estimated costs and risks do not account for.

4 Reproducing Experiments

This section describes how we map the sampling strategies, intervention designs, and outcome measurement of Egger et al. (2022), Miner (2025), and Barnett-Howell et al. (2025) to our model, and compares model-estimated to experimental impacts on migration and economic outcomes for each intervention.

4.1 Egger et al. (2022): Cash Transfer

This paper studies the impacts of large, unconditional cash transfers on rural Kenyan households. While not explicitly focused on migration, the intervention potentially relieves liquidity constraints, a migration friction emphasized in the literature and included in our model.

4.1.1 Sampling

Experiment. The experimental sample is drawn from Siaya, a predominantly rural Kenyan county. About one-half of villages were randomized into a treatment group. Within treatment villages, eligibility for the transfer is restricted to poorer households, operationalized by requiring that households have thatched roofs, a criterion that covers about a third of the sample.

Model. The model represents this sampling choice by taking the poorest third of rural households (ranked by assets) and randomly treating half of them.

4.1.2 Treatment

Experiment. Eligible households receive a large unconditional transfer, roughly equal to 75% of mean annual household expenditure among recipients.

Model. We implement the treatment as a one-time asset transfer equal to 0.75 times mean rural annual consumption.

4.1.3 Measurement

Experiment. The endline survey was conducted 19 months after the initial transfer for the median household. The headline welfare outcome is the change in household expenditure relative to control households. The change in the migration rate is also reported.

Model. In the model, outcomes are measured after three six-month periods, or 18 months, which is close to the median experimental horizon. The migration treatment effect is measured as the difference in the share of initially rural households living in the urban region at endline between treatment and control. The consumption treatment effect is measured as the difference in consumption between treated and control households, normalized relative to average control consumption: we map this measure to the experimental definition of household expenditure change.

4.1.4 Results

In the data, the cash transfer raises expenditure by 11.6% and has no significant migration effect. In the model, the endline consumption effect is 13.7%, while the migration effect is virtually zero. The direct treatment effects therefore line up reasonably well in sign and magnitude.

Table 3: Cash transfer treatment effects in Egger et al. (2022) and the model

	Migration Rate Change		**Consumption Change**	
Treatment arm	**RCT**	**Model**	**RCT**	**Model**
Cash transfer	0.0 pp	0.0 pp	11.6%	13.7%

4.2 Miner (2025): Unemployment Insurance and Cash Transfer

This paper studies the impacts of smaller unconditional cash transfers, as well as urban unemployment insurance, on rural Kenyan households. The unemployment insurance intervention is aimed at reducing the risk of migrating—captured in our model by urban unemployment risk—by adding a wage floor in the city.

4.2.1 Sampling

Experiment. The sample for this paper is drawn from Siaya county, as in Egger et al. (2022). Within sampled villages, the experiment recruits male rural workers aged 18–30. By design, this sampling strategy targets the demographic most likely to migrate: in fact, 65% of participants had prior migration experience. The study covers about 1,300 workers in 111 villages, which corresponds to roughly 11.7 sampled workers per village.

Model. To capture the idea that the recruited young men are more migration-ready than the average rural person, we prioritize sampling experienced households in the model. We set the target sample size to 11.7% of rural households and sample rural households with prior urban experience first, then fill the remaining slots with randomly sampled inexperienced rural households.

4.2.2 Treatment

Experiment. The study includes two treatments. The first is a migration-contingent unemployment-insurance payment tied to being in Nairobi: treated respondents can claim up to 15 days of benefits equal to the average daily urban wage (about 4 USD per day, or 60 USD total). Claiming the benefit required showing up in person at a central office, making it costly for employed migrants to claim. The second treatment is a one-time unconditional cash transfer of 50 USD.

Model. We map the unemployment-insurance arm into the unemployment-benefit parameter b for treated households, with its magnitude matched to 15 days of the average urban wage. This mapping differs from the RCT in that it treats the unemployment benefit as being offered in perpetuity (15 days of average income for every 6-month period that the urban worker spends unemployed). We map the cash arm into a one-time asset transfer equal to $\frac{50}{60}$ of the unemployment insurance amount.

4.2.3 Measurement

Experiment. The main migration outcome is whether the respondent is in Nairobi at the endline survey, conducted about six months after treatment. The main economic outcome is total monthly income of the individual.

Model. We measure outcomes one model period after treatment, corresponding to the six-month experimental horizon. The migration effect is the change in the urban-residence rate from baseline to endline for treated households relative to the same baseline-to-endline change for controls. The income effect is measured with the same difference-in-differences structure, normalized by baseline treated income.

4.2.4 Results

Unemployment-insurance arm. In the experiment, unemployment insurance raises migration by 10.9 percentage points and has no significant effect on income. In the model, the same arm increases migration by 10.8 percentage points, while raising income by 120.5%. Our model therefore matches the short-run migration response closely, but generates a very large income gain that is absent in the RCT.

Cash-transfer arm. In the experiment, the unconditional cash transfer raises migration by 4.5 percentage points and again produces no detectable income effect. In the model, the cash arm raises migration by 3.0 percentage points and income by 9.1%. Our model thus matches the migration impact reasonably well, but still overstates the income response. The migration response to this cash transfer is bigger than to the much larger cash transfer in Egger et al. (2022), because the sample in Miner (2025) is more interested in migration (modeled via migration experience), and therefore more responsive to a given relaxation of liquidity constraints.

TABLE 4: Unemployment insurance and cash transfer treatment effects in Miner (2025) and the model

	Migration Rate Change		**Income Change**	
Treatment arm	**RCT**	**MODEL**	**RCT**	**MODEL**
Unemployment insurance	10.9 pp	10.8 pp	0.0%	120.5%
Cash transfer	4.5 pp	3.0 pp	0.0%	9.1%

Note: Income change excludes UI.

4.3 BARNETT-HOWELL ET AL. (2025): INFORMATION PROVISION

This paper studies the impacts of information and social network interventions on rural-urban migration in Kenya, which we use to assess the model's estimates of the importance of information frictions.

4.3.1 SAMPLING

EXPERIMENT. The experimental sample includes roughly 17,000 rural households, randomly drawn from five predominantly rural counties in Kenya. The sample is representative of the rural portions of these counties by design, but not necessarily of rural Kenya overall. Treatment is administered to about 30% of households within sampled villages.

MODEL. To mirror the experimental treated share, the model randomly assigns treatment to 30% of rural households in the panel, with the remaining rural households serving as controls. This captures the treatment intensity in the RCT, while ignoring residual differences between the five study counties and the national rural population, which are modest on several key dimensions.

4.3.2 Treatment

Experiment. The interventions provide information about labor-market conditions in Nairobi, such as typical earnings for various demographic groups. The experiment includes three main delivery arms: information provision to individual households, information provision to individual households coupled with connections to urban residents ("mentors") who can provide additional information, and information provision through group meetings in villages.

Baseline information treatment arm. Enumerators delivered a brochure and read out a script to each household in a one-on-one meeting. As a result, treated households revised their expectations of migration income upward by 4% on average compared to control.

Mentor treatment arm. This arm included the same brochure and script as the baseline information arm, but also paired each household with an experienced urban mentor offering information over the phone or in person in Nairobi. Expected migration income went up 10% in this arm.

Group treatment arm. In this arm, the same brochure and script were delivered to households in a village-wide group meeting followed by a group discussion. Expected migration income went up 12% in this arm. However, households already experienced in migrating were disproportionately responsive to this treatment arm compared to the baseline and mentor arms, possibly because they were more engaged during and after treatment. Barnett-Howell et al. (2025) use this fact to argue that the group treatment induced adverse selection on gains from migrating.

Model. We take a narrow view of each treatment's impact, mapping the treatments into the model as an increase in rural households' perceived urban earnings.

Baseline information treatment arm. Treatment raises the γ of treated households from $\gamma_{current}$ to $1.04 * \gamma_{current}$, effectively reducing the understatement of urban income and raising expected urban wage by 4%.

Mentor treatment arm. Treatment raises the γ of treated households from $\gamma_{current}$ to $1.10 * \gamma_{current}$, reflecting the 10% increase in expected migration income in this arm.

Group treatment arm. To represent the stronger impact of the group arm on experienced households, we set experienced treated households to $\gamma = 1$ and then infer the change in inexperienced households' γ that yields a 12% average treatment impact on beliefs.

4.3.3 Measurement

Experiment. The main endline outcomes are measured about 16 months after treatment. The paper measures the migration treatment effect as the difference in the share of households that sent at least one migrant to Nairobi between treatment and control. It measures the income treatment effect as the difference in mean household income at endline between treatment and control. The monetary difference is normalized relative to average baseline rural income.

Model. In the model, outcomes are measured after three six-month periods, or 18 months, which is close to the experimental horizon. The migration treatment effect is measured as the difference in the share of initially rural households living in the urban region at endline between treatment and control. The income treatment effect is measured as the difference in the change in mean household income from baseline to endline between treatment and control, normalized relative to average baseline rural income.

4.3.4 Results

Information treatment arm. In the experiment, the baseline information treatment increases migration by 1.8 percentage points and income by 6.7%. The model generates smaller effects: a 0.8 percentage point increase in migration and a 3.1% increase in income.

Mentor treatment arm. In the experiment, the mentor arm raises migration by 2.4 percentage points and income by 7.7%. The model closely matches these effects on migration (2.4 percentage points) and income (7.1%).

Group treatment arm. In the experiment, the group-delivery arm raises migration by 2.2 percentage points but generates no significant change in income. In the model, the experience-weighted group treatment increases migration by 2.4 percentage points and income by 6.9%. The migration effect is therefore very close to the RCT estimate, but the model still generates a positive income response that is absent in the experiment. Directionally, the model does capture the weaker income effect of the group arm compared to the mentor arm despite a slightly larger migration effect, but the scale of the difference is vastly understated in the model compared to the experiment.

TABLE 5: Information-provision treatment effects in Barnett-Howell et al. (2025) and the model

	Migration Rate Change		Income Change	
Treatment arm	RCT	MODEL	RCT	MODEL
Information	1.8 pp	0.8 pp	6.7%	3.1%
Mentor	2.4 pp	2.4 pp	7.7%	7.1%
Group	2.2 pp	2.4 pp	0.0%	6.9%

5 Quantitative Results

In this section we use our model to extrapolate treatment impacts beyond the horizon measured in each experiment, estimate the impacts of each intervention at a national scale, and compare the relative contribution of each model friction to the overall urban–rural income gap.

5.1 Long Run Treatment Effects

Beyond comparing shorter-run treatment effects to those measured by each RCT, our model allows us to evaluate the predicted medium- and long-run effects of each intervention. These might differ from the shorter-run effects measured in the RCTs because some treated households may not experience a shock that makes migration attractive until after the endline survey, and because households interested in migration might need time to accumulate sufficient savings to cover migration costs and the uncertainty of urban employment.

Figure 1 shows the evolution of treatment effects of the cash transfer intervention emulating Egger et al. (2022). After the endline survey 18 months after treatment, the consumption decays as the one-time transfer is spent, but does so slowly: even 15 years after treatment, consumption of treated households is 6% higher than that of control households. Furthermore, the model predicts that even though the cash transfer produced negligible migration effects at the endline, migration builds over time as more and more households experience a positive urban productivity or a negative rural productivity shock that makes migration attractive—and their significant

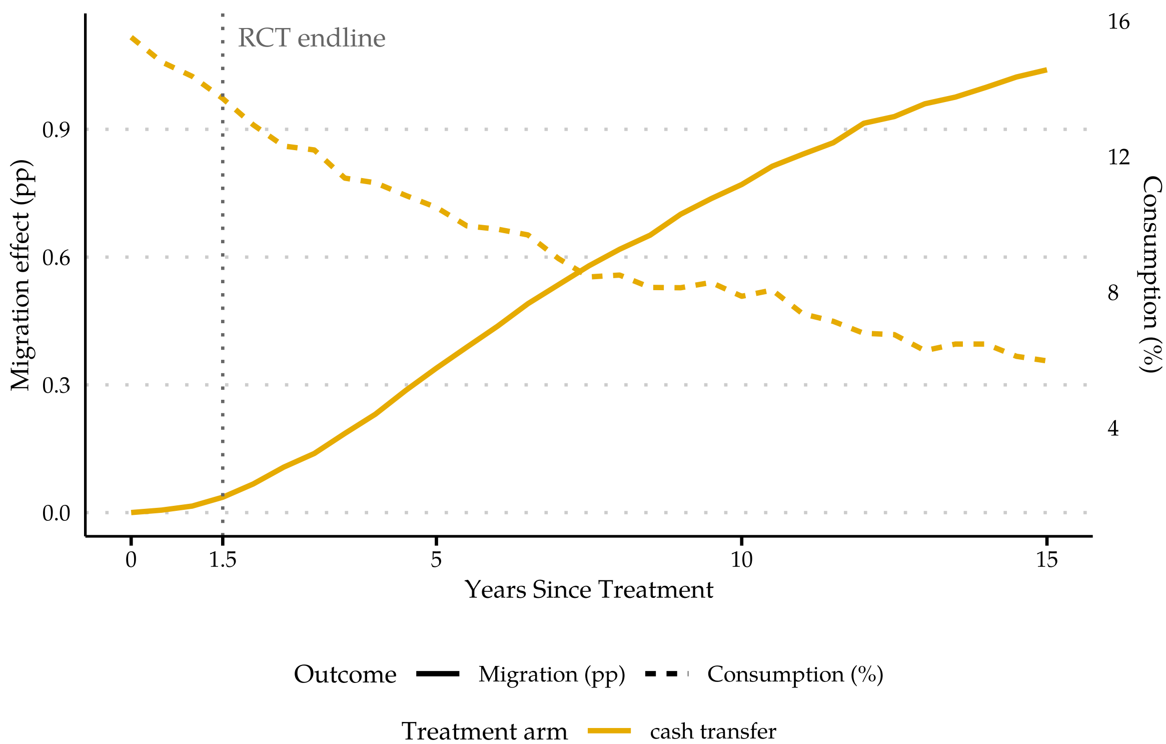


Figure 1: Treatment effects over time: cash transfer emulating Egger et al. (2022)

asset holdings allow them to cover migration costs and the uncertainty of employment. By the 15-year mark, the share of treated households living in the urban region is 1 percentage point higher than that of control households, before beginning to slowly decay.

Figure 2 shows the evolution of treatment effects of the cash transfer and unemployment insurance interventions emulating Miner (2025). By the endline survey 6 months after treatment, almost all of the migration effects and income gains from the cash transfer have been realized. Afterward, both effects slowly decay as the one-time transfer is spent. In contrast, migration and income impacts of unemployment insurance build over time, with about two-thirds of the gains realized by the endline survey. This behavior is consistent with additional rural households experiencing a positive urban productivity (or a negative rural productivity) shock pushing them to migrate and take advantage of the unemployment benefit.

Figure 3 shows the evolution of treatment effects of the information interventions emulating Barnett-Howell et al. (2025). By the endline survey 18 months after treatment, roughly three-quarters of the migration and income gains from the information

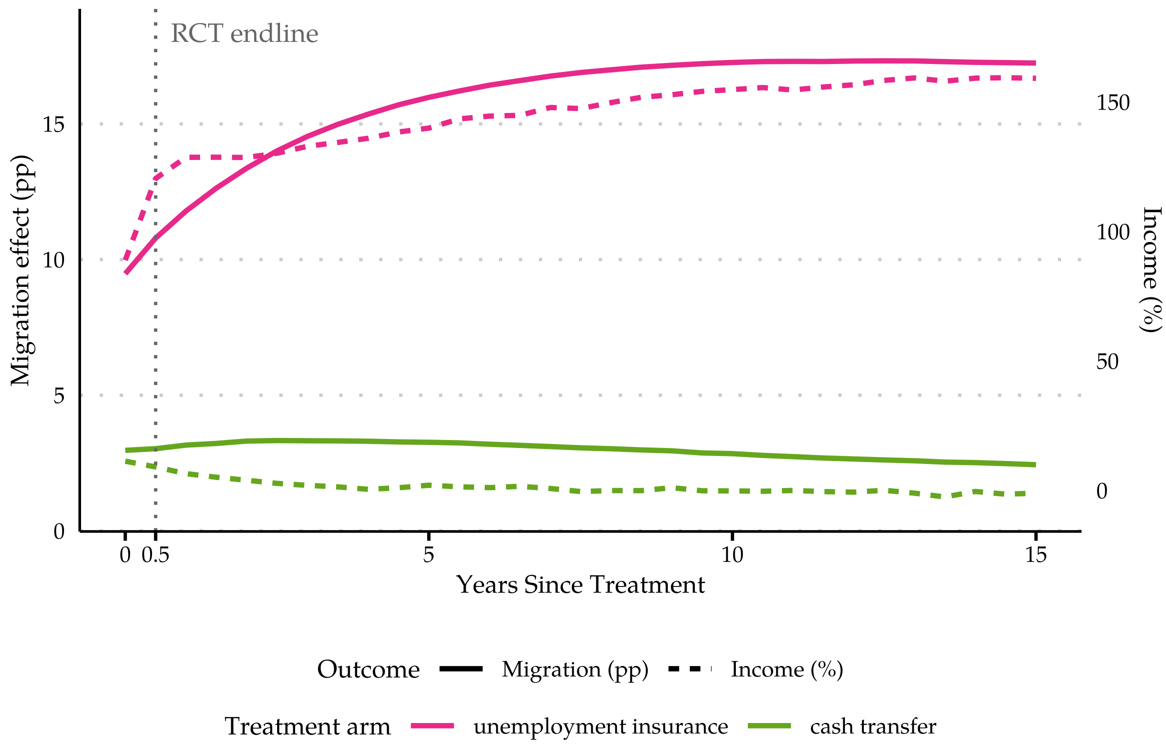


Figure 2: Treatment effects over time: unemployment insurance and cash transfer emulating Miner (2025)

treatment have been realized. These gains continue to grow for a few years as more and more households experience positive urban productivity or negative rural productivity shocks that make migration attractive. Later, some of the advantage of the treatment is eroded as more and more of the control households experience shocks that make migration attractive even for them: once a control household ends up in the city, it learns the true urban income and behaves like a treated household as long as they remain in the city.

5.2 National Rollout

We next use the model to estimate the effects of scaling each intervention to the national level, accounting for general equilibrium effects of migration through labor and asset markets. To assess the effects of a national rollout in the model, we apply the treatment to all model households and re-solve for the new stationary distribution and general equilibrium.

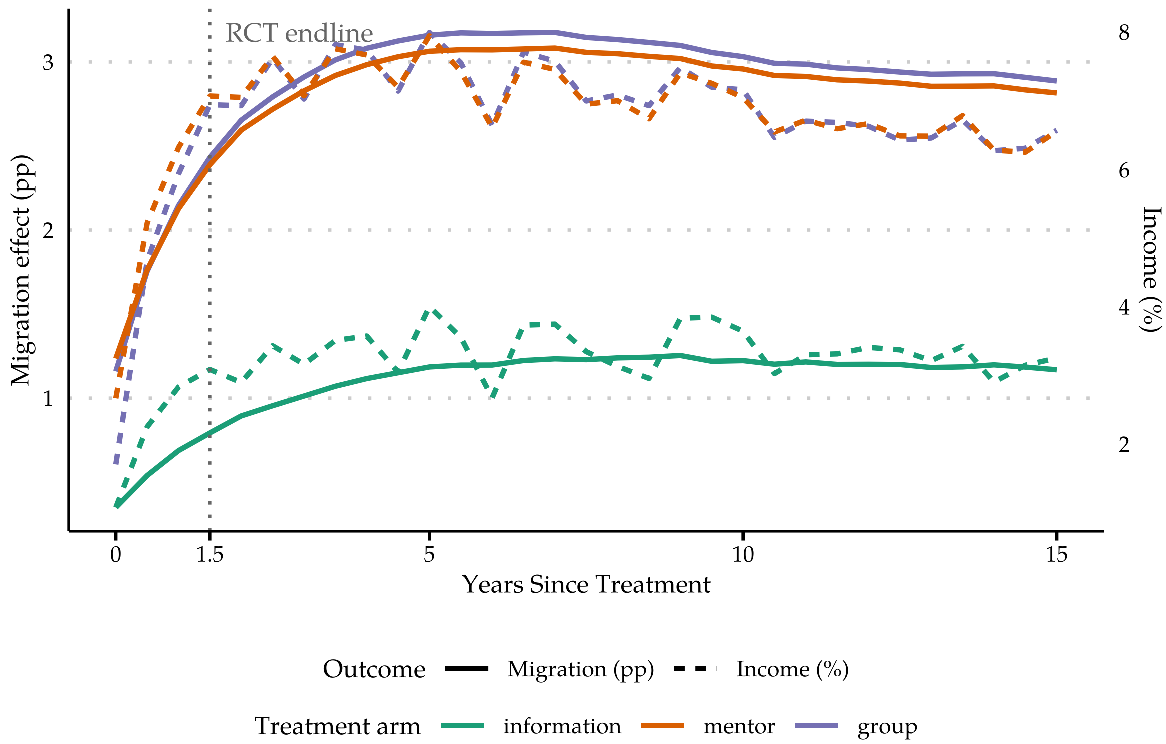


Figure 3: Treatment effects over time: information provision emulating Barnett-Howell et al. (2025)

Table 6: Counterfactual outcomes of rolling out Barnett-Howell et al. (2025) and Miner (2025) treatments nationally

Scenario	Urban Share	URPG
Baseline	32.8%	4.945
Barnett-Howell et al. (2025): Individual	33.5%	4.940
Barnett-Howell et al. (2025): Mentor	35.6%	4.928
Miner (2025): Unemployment insurance	58.1%	5.046

Table 6 shows that the information interventions boost the urban share by 1–3 percentage points. The unemployment insurance rollout has a much larger effect on the urban share. All interventions do little to change the income gap. This suggests that unemployment insurance can be a potent tool of encouraging rural-to-urban migration while preserving high urban incomes.

5.3 Urban-Rural Income Gap Decomposition

Finally, we use the model to decompose the fivefold urban–rural productivity gap (URPG) at baseline into the contributions of each of the various frictions. Instead of simply reproducing the trialed interventions as they seek to partially address various obstacles to migration, we shut down each friction in the model entirely. Shutting each friction one at a time (and re-solving for the new stationary general equilibrium) allows us to isolate the contribution of each friction to the urban–rural income gap.

Table 7 and Figure 4 shut down one friction at a time while keeping the remaining frictions fixed. The percentage labels in the figure report the share of the excess gap above income parity, URPG $-$ 1, accounted for by each counterfactual.

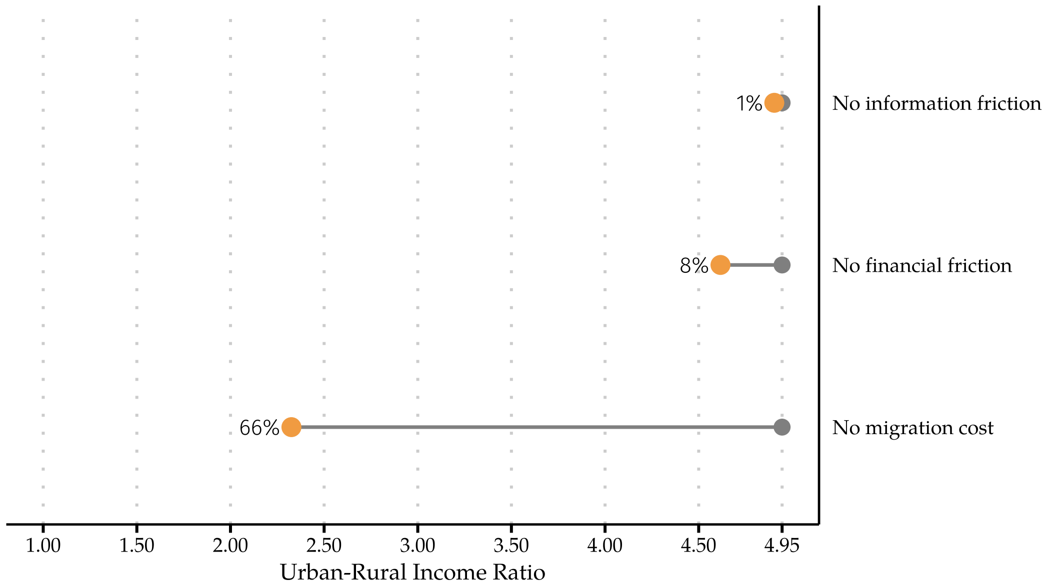
Table 7: Results of shutting down one friction at a time

Scenario	Urban Share	URPG
Baseline	32.8%	4.945
No information friction	32.9%	4.904
No financial friction	1.2%	4.616
No migration cost	72.9%	2.325

Shutting down the information friction so that rural households do not underestimate potential urban income (setting $\gamma = 1$ for everyone) modestly reduces the urban-rural income gap from 4.945 to 4.904. It raises the urban share slightly, at 32.9% rather than 32.8%.

Relaxing the financial friction (allowing households to borrow against future income by setting $\underline{a} = -\infty$) has a curious effect: the urban share collapses from 32.8% to 1.2%, while the urban-rural income gap falls to 4.616. This result suggests that much of the rural-to-urban migration in the current equilibrium is merely a way to insure against bad rural income shocks in the absence of credit. Once households are able to borrow to ride out bad rural income shocks (such as poor harvest), most choose to stay in the rural region. This result echoes the findings of Lagakos, Mobarak, and Waugh (2023) and Meghir et al. (2022), who develop models of migration disciplined by the Bryan, Chowdhury, and Mobarak (2014) RCT and argue that in large part, rural-to-urban migration plays the role of informal insurance for rural households.

Finally, eliminating the migration cost (setting $m_c = 0$) has the most transformative effect, reducing the urban-rural income gap to 2.325 and raising the urban



Note. Each scenario shuts down one friction at a time, re-solving the model in general equilibrium in each case. The plot shows the baseline urban-rural income gap levels and the counterfactual levels when each friction is removed. The percentage labels report the share of the excess gap above parity, URPG − 1, accounted for by each friction.

Figure 4: Urban–rural income gap after shutting down each friction

share to 72.9%. This result suggests that, through the lens of the model, residual migration costs (migration obstacles unexplained by the explicitly modeled information frictions, inexperience, borrowing constraints, and unemployment risk) are the dominant barrier to migration. After disciplining these explicit frictions with empirical moments, the model still struggles to explain why so few people live in the city despite a huge premium earned there: during estimation, this puzzle is resolved through a high residual migration cost m_c. One interpretation of this result is that travel costs—those paid upon migrating to the city but which do not enter migrants' responses about compensating differentials between rural and urban life—are very large. Another is that, while we estimate a fast transition rate from inexperience to experience for new migrants, the rate may be much slower for non-migrants (or they may perceive it to be slower than it truly is). In this case, the disutility of urban life would play a larger role in migration decisions than we estimate.

6 Conclusion

This paper uses a unified quantitative framework to interpret recent experimental evidence on internal migration and to compare the macroeconomic importance of several barriers emphasized in that literature. We find that relaxing liquidity constraints, improving information, and reducing urban employment risk can each increase migration, but with different dynamic and aggregate consequences.

At the same time, our estimates leave an important puzzle unresolved. The frictions we explicitly model—borrowing constraints, unemployment risk, an urban-specific disutility that declines with urban experience, and income misperceptions—appear too small to explain Kenya's low migration rate on their own. To match observed urbanization, the model requires a sizable residual migration cost, suggesting that the main force holding households back is still not fully understood. One possibility is literal travel or relocation costs such as initial job search costs, though these seem unlikely to account for the magnitude of the residual friction by themselves.

In our view, a more plausible interpretation is that prospective migrants overestimate the non-pecuniary difficulty of urban life. Individuals may expect loneliness, disorientation, cultural mismatch, or inability to navigate city labor and housing markets, and therefore assign a large utility cost to moving. Yet once they migrate, many adapt more quickly than anticipated, consistent with the relatively rapid transition from inexperience to experience estimated in the data. Such an interpretation would be consistent with evidence from psychology and behavioral economics that individuals often overestimate the lasting emotional costs of major life changes and underestimate their capacity to adapt once those changes occur (Wilson and Gilbert 2003, 2005). We see attempts to better measure and test this mechanism as a promising direction for future research.

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