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The Welfare Effects of Encouraging Rural-Urban Migration
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ABSTRACT

This paper studies the welfare effects of encouraging rural-urban migration in the developing world. To do so, we build a dynamic incomplete-markets model of migration in which heterogenous agents face seasonal income fluctuations, stochastic income shocks, and disutility of migration that depends on past migration experience. We calibrate the model to replicate a field experiment that subsidized migration in rural Bangladesh, leading to significant increases in both migration rates and in consumption for induced migrants. The model's welfare predictions for migration subsidies are driven by two main features of the model and data: first, induced migrants tend to be negatively selected on income and assets; second, the model's non-monetary disutility of migration is substantial, which we validate using using newly collected survey data from this same experimental sample. The average welfare gains are similar in magnitude to those obtained from an unconditional cash transfer, though migration subsidies lead to larger gains for the poorest households, which have the greatest propensity to migrate.

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1. Introduction

Differences in income per capita across countries are largely accounted for by differences in total-factor productivity (TFP) (see, e.g., Hall and Jones, 1999; Caselli, 2005). Misallocation of factors of production across firms, sectors or regions within an economy may underlie these TFP differences (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009).[1] One potentially large source of misallocation is an inefficient distribution of workers across space (Restuccia, Yang, and Zhu, 2008; Vollrath, 2009; McMillan and Rodrik, 2011; Hnatkovska and Lahiri, 2013; Bryan and Morten, 2015). This is highlighted by the large observed gaps in productivity and wages between rural and urban workers (Young, 2013; Gollin, Lagakos, and Waugh, 2014). Such gaps also create a development puzzle: Why do large shares of the population in many developing countries continue to live in rural areas when urban areas within those same countries offer much higher wages? If those wage gaps reflect misallocation, then encouraging workers to move out of less-productive rural areas could yield substantial productivity and welfare gains.

An alternative view is that such gaps could simply reflect differences in worker skills (Lagakos and Waugh, 2013; Young, 2013; Herrendorf and Schoellman, 2016; Hicks, Kleemans, Li, and Miguel, 2017). Urban residents may be more educated (Young, 2013; Herrendorf and Schoellman, 2016), or have more city-specific skills, and, thus, rural workers would not necessarily replicate the higher wages that city-dwellers earn when they migrate. So the observed spatial distribution of people may already be efficient.

However, a series of field experiments in Bangladesh (Bryan, Chowdhury, and Mobarak, 2014; Akram, Chowdhury, and Mobarak, 2017) show that paying small travel subsidies to induce rural Bangladeshis to migrate to urban areas leads to substantial gains in income and consumption over multiple years. These experimental results again raise the possibility that workers may indeed be spatially misallocated, and that encouraging migration would improve productivity and welfare. However, this evidence is not dispositive, because it may simply be the case that rural residents dislike moving, or have strong preferences for rural amenities (Harris and Todaro, 1970; Morten, 2013; Brueckner and Lall, 2015; Munshi and Rosenzweig, 2016) that are not captured by the income and consumption outcomes reported in the experiments. Rural residents may also be reacting to the treatment for reasons other than their desire to arbitrage any permanent rural-urban productivity differences. For example, if credit or insurance markets are incomplete in rural areas, the subsidy may induce

[1] Channels for misallocation emphasized in the recent literature include financial frictions (Buera and Shin, 2013; Midrigan and Xu, 2014; Moll, 2014); information frictions (David, Hopenhayn, and Venkateswaran, 2016); adjustment costs (Asker, Collard-Wexler, and De Loecker, 2015); heterogeneous markups (Peters, 2016); entry frictions (Yang, 2016); delegation frictions (Akcigit, Alp, and Peters, 2016); size-dependent policies (Guner and Xu, 2008); and regional differences in tax rates (Fajgelbaum, Morales, Serrato, and Zidar, 2015), among others.

the desperate poor to migrate only when they need to smooth adverse rural income shocks. Without a richer model of migration that allows for (unmeasured) disutility associated with relocation, or migration motives created by uninsured income shocks in rural areas, the relationship between these experimental results and the extent of spatial labor misallocation remains unclear.

To better understand what these migration experiments teach us about spatial misallocation, we confront the experimental data with a dynamic model of migration that is rich enough to characterize the welfare effects of policies that encourage rural-urban migration. In our model, households are heterogeneous in their degree of permanent productivity advantage in the urban area (Roy, 1951), and they choose to locate in either an urban region or a rural region. They face deterministic seasonal income fluctuations and stochastic income shocks, both of which are endemic to developing economies, including Bangladesh, where these experiments took place. Markets are incomplete, and agents insure themselves through a buffer stock of savings, as in Bewley (1977), Aiyagari (1994) and Huggett (1996), and following a large literature in macroeconomics (see, e.g., Heathcote, Storesletten, and Violante, 2009; Kaplan and Violante, 2010). Households can migrate either permanently or temporarily across locations, as in Kennan and Walker (2011), and face both a monetary cost of migration and a non-monetary disutility from migration that depends on past migration experience.

We discipline this model quantitatively using high-quality experimental data, which is an important methodological innovation relative to the prior literature. In particular, we replicate the results of the randomized controlled trial (RCT) described in Bryan, Chowdhury, and Mobarak (2014) within our model, and we use simulated method of moments to match the model's outcomes to the experimental data. The main moments of the experiment that we target are ones generated based by purely random variation: (i) the increase in the seasonal migration rate resulting from the subsidy, which was 22 percent; (ii) the consumption increase for those induced to migrate, which was 30 percent; and (iii) the increase in seasonal migration one year later, *after the subsidies were removed*, which was nine percent.

Matching these moments helps us isolate the characteristics of workers who are near the margin, which would be induced to migrate when an encouragement is provided, relative to those who are already migrating regularly or are permanently located in cities. The model implies that workers near the margin must be negatively selected on productivity and assets because the experimental local average treatment effect (LATE) of migration on consumption is large, while the naive OLS estimate is much smaller, suggesting a downward selection bias in OLS. From the migration and re-migration patterns in the data, the calibrated model implies that the non-monetary disutility associated with migration must be high for new

migrants (who are induced by the experiment), and that it is temporarily mitigated once those migrants gain some experience (such as a connection with an urban landlord).

When viewed through the lens of our model, the consumption gains from migration observed in Bryan, Chowdhury, and Mobarak (2014) are not due to permanent productivity gaps between urban and rural residents. Our model could - but does not - suggest that workers who would otherwise be very productive in cities are misallocated in rural areas. In our calibrated model, most workers with a strong permanent comparative advantage in the urban area are already living there.[2] The migration subsidies address a very different form of misallocation: Very poor workers who have faced a spate of bad shocks sometimes need to move to a better labor market temporarily to insure themselves. The travel cost acts as a constraint exactly in those periods, when those households have been forced to draw down their savings. This is when migration subsidies are very valuable: when the marginal utility of consumption is very high. Such workers benefit from an opportunity to go to the city, but they are typically not highly productive there. The average productivity gains that migration subsidies generate are, thus, positive, though substantially lower than those implied by Hsieh and Klenow (2009) for capital misallocation in Indian and Chinese manufacturing, or factor misallocation across farms found by Adamopoulos and Restuccia (2014), Restuccia and Santaeulalia-Llopis (2016) and Adamopoulos, Brandt, Leight, and Restuccia (2016).

The welfare gains from encouraging migration do stem from reducing misallocation of workers across space, but those with the least productive options in rural areas benefit most. Our model points to a specific reason that many rural workers seem willing to forgo substantially higher consumption levels offered by cities: the non-monetary disutility associated with moving. To highlight this point, we use our model to simulate the effects of a surprise reduction in disutility once migrants arrive in the city. We show that the welfare gains from migration subsidies in this scenario are three times larger than in our baseline case. Given the significant role it plays in our interpretation, we next empirically investigate the source of this disutility. We conduct new discrete-choice experiments in which the same experimental sample of households used to calibrate the model are asked to choose between hypothetical migration options varying in wage rates, unemployment risk, housing options at destination, and frequency of visits home to see family. This exercise points to substantial disutility associated with bad housing conditions at the destination. Offering improved housing with a proper indoor latrine increases migration propensity by 17.4 percentage points. This effect size is equivalent to the effect of increasing migration wages by 21 percent. As our model

[2] In addition, the experiment induces those with the lowest income and assets to seasonally migrate, not those with higher productivity and larger buffer stocks of savings. Moreover, the unconditional transfers induce relatively small increases in migration in the model and in the data, rather than large increases, as would be predicted by a model of misallocation due to credit constraints.

predicts, migrants seem to care a lot about non-monetary attributes of the experience. Importantly, these data show that the source of disutility is a policy-relevant parameter: If policy makers invest in improving slum housing conditions and public services in cities, this will allow for more rural-urban migration, which will, in turn, reduce misallocation and raise overall income and productivity levels.

Finally, we use the calibrated model to quantify the welfare gains from subsidizing rural-urban migration, and compare the distributional consequences of that policy against those of counterfactual development policies that are popular in developing countries: unconditional cash transfers and rural "workfare" programs, such as India's massive rural employment guarantee (NREGA), which provide payments to workers conditional on their staying in rural areas. We find that the conditional migration subsidies are better than alternatives at targeting the neediest households because they create an *ordeal*: Only the most hard-pressed who have faced recent negative shocks in the village would be induced by the subsidy to incur a disutility cost and migrate to the city. The gains from a one-time migration subsidy are about 1.0 percent in consumption-equivalent welfare in perpetuity for the poorest quintile (and 1.2 percent in perpetuity for migrants), whereas replacing those subsidies with a budget-neutral unconditional transfer program raises welfare in this group by 0.9 percent in consumption equivalents. Moreover, the requirement to migrate is sensible because the characteristic that needs to be targeted – recent negative income shocks – is not directly observable by a policy maker (unlike, say, household assets, which are often targeted in means-tested programs). The rural workfare program produces the lowest overall welfare gains (around 0.6 percent), since it discourages rural-urban migration across the board, despite the fact that urban areas offer better income opportunities, on average.

In terms of methodology, our work follows the seminal papers by Todd and Wolpin (2006) and Kaboski and Townsend (2011), which discipline dynamic structural models using quasi-experimental evidence rather than non-experimental moments, as is most common in macroeconomics. Our paper builds on these by estimating our structural model directly using variation induced by an RCT, in which concerns about endogeneity are even less present. In this sense, our quantitative work is similar to that of Buera, Kaboski, and Shin (2014), who use a macro model to help interpret the general-equilibrium effects of unconditional asset transfer programs, and Greenwood, Kircher, Santos, and Tertilt (2013), who build a general equilibrium model of the AIDS epidemic to complement the many related RCTs.

2. The Migration Experiments: A Summary

In this section, we summarize the experimental results (Bryan, Chowdhury, and Mobarak, 2014; Akram, Chowdhury, and Mobarak, 2017) that motivate our modeling and calibration

choices. The setting for both experiments are rural, rice-growing areas in the Rangpur region of Bangladesh, home to around ten million people. Like many other agrarian societies, these areas experience a "lean season" called *Monga* during the three-month period between planting and harvest, when farmers mostly wait for the crop to grow, and labor demand falls. Landless laborers experience a drop in wages and employment opportunities as a result, and incomes fall by an estimated 50 percent or more, on average (Khandker, 2012). To cope, some households migrate to towns and cities during the lean season in search of employment.

In the first experiment, reported in Bryan, Chowdhury, and Mobarak (2014), 19 poor households were randomly sampled from each of 100 randomly selected villages in two districts in the Rangpur region. "Poor" was defined as households with almost no land holdings (less than 50 decimals of land) and that reported having missed meals during the previous lean season. These households fall in roughly the lower half of the asset distribution. In August 2008, 68 villages were randomly assigned to treatment and 32 to control. In the 19 households in each of the treatment villages, subsidies encouraged one household member to migrate during the lean season. There were no subsidies in the control villages.[3] The travel subsidy was worth about 800 Taka ($11.50), which is sufficient to pay for round-trip bus fare plus a few days of food, and is equivalent to about seven to ten days of rural wages during the lean season.

All 1900 sample households were surveyed in December 2008 (post-treatment) and June 2009 about their migration and consumption during the 2008 lean season. The random assignment of migration subsidies produced three important outcomes that will inform our modeling choices:

1. While 36 percent of households in control villages sent a seasonal migrant during the lean season, 58 percent of households in treatment villages did.

2. In an intent-to-treat comparison, consumption per household member was seven percent higher across all households in treatment villages relative to all households in control villages. Using the randomized treatment assignment as an instrumental variable for migration, the local average treatment effect (LATE) indicates that the migration led to about 30 - 35 percent higher consumption per household member. Migrants reported taking jobs such as rickshaw driving and construction work, which raised their house-

[3]The 32-village control group is comprised of a pure control (16 villages), and an information treatment (16 villages in which general information about migration possibilities were offered, but without any travel subsidy), which looks indistinguishable from the control group in terms of the migration response. The 68-village treatment group is comprised of travel subsidies in the form of a grant (37 villages) or a zero-interest loan (31 villages). The grant and loan treatments produced very similar outcomes, so, for simplicity, we combine them and refer to them as the "the treatment group"and compare their outcomes to those of the combined control group.

hold incomes. There is clear evidence that this was not simply an effect of households consuming the transfer. Actual migration activity was monitored closely, and most of the subsidy was used towards bus fare. The LATE effect on consumption is also large relative to the size of the transfer.

3. The treatment and control groups were surveyed a year later, in December 2009, though neither group received any additional treatment. Interestingly, re-migration rates during the next lean season (2009) remained nine percentage points higher in the treatment group, and this was statistically significant. The one-time intervention resulted in repeat migration, but not everyone that was induced chose to re-migrate. Subsequent results in 2011 and 2013 show elevated, but decaying migration rates in the treatment group.

The second experiment (Akram, Chowdhury, and Mobarak, 2017) was conducted in 2014 on a larger scale, with migration offers extended to 5,792 poor, landless households. The authors measure income and show that the migration offers led to significant increases in income, of a magnitude consistent with the 30-35 percent consumption increases observed in 2008. The new experiment also finds repeat migration effects of that one-time transfer during 2015-16, similar to the re-migration observed in 2009. Notably, the main experimental results from 2008-09 that we target our model to are replicated in this new experiment, which was almost five times as large. Consistent results are observed across four years of data collection.

Important for our model, this new experimental design adds random variation to the *proportion* of the landless population across 133 villages that were provided migration subsidy offers simultaneously. This labor-market-level variation created labor supply shocks of different magnitudes in different villages, which provides an experimental estimate of the wage elasticity of labor supply. We use this estimate to inform the general-equilibrium effect of emigration in the village-of-origin labor market in our model.

3. Model of Migration

To examine the implications of these behaviors for spatial misallocation, our model of migration allows for heterogeneity in permanent productivity levels in the urban area across workers. Each worker chooses her (rural or urban) location in each period, given monetary and non-monetary (utility) migration costs that depend on past migration experience. Agents face deterministic seasonal income fluctuations and stochastic income shocks, and they use a single asset to self-insure. For simplicity, we focus on a stationary distribution of the model in which the fraction of workers in each region and other aggregate variables remain constant in each period, as does the distribution of workers by state.

3.1. Economic Environment

Preferences. Households are infinitely lived and maximize expected discounted utility

$$\sum_{t=0}^{\infty} \beta^t u(c_t) \bar{u}^{x_t}, \tag{1}$$

where $u(c_t) = c_t^{1-\alpha}/(1-\alpha)$, α is the coefficient of relative risk aversion; β is the discount factor; and c_t is household consumption. The variable $\bar{u}$ captures the non-monetary costs of migration, and $x_t \in \{0, 1\}$ is an indicator variable representing whether or not the household is an "inexperienced migrant."

Inexperienced migrants experience disutility $\bar{u}$ if they locate in the urban area in period t, whereas experienced migrants experience no such disutility. After each period in the urban area, inexperienced migrants become experienced with probability $1 - \lambda$. This is meant to capture any way in which rural-urban migrants become accustomed to being in urban areas by, for example, developing a network of friends or potential employers. Experienced migrants can become inexperienced again after returning to the rural area. In each period in the rural area, the probability that an experienced migrant will become inexperienced again is $1 - \mu$.[4]

The motivation behind these modeling choices is twofold. First, we want to model the fact that migrants dislike certain aspects of migrating to an urban area (see the discussion in Section 6). However, we also want to model the idea that one's utility from a location improves as one becomes accustomed to living there.

Endowments. Households supply one unit of labor inelastically, with efficiency units that vary across time and across locations, as in Roy (1951). Households differ in permanent productivity z in the urban area, which is drawn from a Pareto distribution:

$$z \sim 1 - z^{-\theta},$$

where the shape parameter θ controls the variance in urban productivity. Here, a lower θ implies more variability in urban productivity. Households are identical in rural permanent productivity, and this value is normalized to one. Thus, the vector $\{1,\ z\}$ describes a household's permanent productivity in the rural and urban areas.[5]

[4]This formulation is related to, but distinct from, locations being "experience goods" in migration models, as in Kaplan and Schulhofer-Wohl (2017). In our model, households know for certain what the migration disutility is, but that disutility may fall after they move and remain low for some time even after they return.

[5]The assumption on one-sided selection is validated by the empirical observation that we see very low variance in the level of consumption in rural areas. Moreover, this assumption eases the computational burden, allowing us to introduce transitory shocks and behaviorial responses to them.

Households experience idiosyncratic transitory shocks to their endowments. Denoting s_t as the current shock, this shock evolves according to an AR(1) process:

$$\log s_{t+1} = \rho \log s_t + \epsilon_{t+1} \quad \text{with} \quad \epsilon_{t+1} \sim \mathcal{N}(0, \sigma_s),$$

where ρ is the autocorrelation parameter and σ_s is the standard deviation of the shocks.

To allow for this shock to have a differential impact on earnings (and risk) across locations, we assume that the household-specific, transitory component on efficiency units is s for the rural area and s^γ for the urban area. Thus, the vector $\{s,\ zs^\gamma\}$ describes a household's endowments (both permanent and transitory) for the rural and urban areas.

The parameter γ governs differential risk across locations. In particular, if $\gamma > 1$, this formulation will imply that shocks have a larger impact on incomes in the urban area than in the rural area. Hence, the urban area will be riskier than the rural area. The benefit of this modeling choice is that it allows us to reduce the dimensionality of the state space to focus on just one shock (versus multiple shock processes across locations). Still, it captures the old idea in economics that differential risk in urban and rural areas may be a deterrent to migration, as well as a source of urban-rural average income differences (Harris and Todaro, 1970).

Production. There is one homogeneous good produced in both locations by competitive producers. Locations differ in the technologies they operate. The rural technology is

$$Y_r = A_r^i N_r^\phi, \tag{2}$$

where N_r are the effective labor units working in the rural area, $0 < \phi < 1$, so that there is a decreasing marginal product of labor in the rural area, and A_r^i is rural productivity indexed by season i. Seasonality is modeled with the rural area experiencing deterministic, seasonal fluctuations. Specifically, rural productivity takes two values: $i \in \{g, \ell\}$ with productivity values satisfying $A_r^g > A_r^\ell$, where, if current rural productivity is A_r^g, then the economy transits to productivity state A_r^ℓ in the next period. Superscript g is for "growing" season, and superscript ℓ is for "lean" season.

The urban technology is

$$Y_u = A_u N_u, \tag{3}$$

where N_u are the effective labor units supplied by households working in the urban area. Notice that N_u and N_r do not sum to one, but are the sum across efficiency units and, thus, depend on the shock realizations and the pattern of selection across sectors.

Wages. In season i, with N_r workers in the rural area, wages per efficiency unit are

$$\omega_{r,i}(N_r) = A_r^i \phi N_r^{\phi-1} \quad \text{and} \quad \omega_u = A_u. \tag{4}$$

Agents working in a particular location receive wages that are the product of (4) and the number of their efficiency units (both in permanent and transitory terms). We denote the labor income that a household with with permanent state $\{1, z\}$ and transitory state s receives for working in location i as:

$$w_r(z, s, i) = s\omega_{r,i} \quad \text{and} \quad w_u(z, s) = zs^\gamma \omega_u, \tag{5}$$

which depends on the product of a household's permanent and transitory productivity and wages per efficiency unit in (4).

Location Options. Households have choices about where to reside and work. Those in the rural area have three options. First, they can work in the rural area. Second, they can pay the fixed cost m_T and work in the urban area for one period and return to the rural area in the next period. This is (temporary) *seasonal* migration in the model: a one-period working spell in the urban area by a rural household. Third, the household can pay the fixed cost $m_P > m_T$ and work in the urban area for the indefinite future. This is *permanent* migration: a move that enables the household to permanently live and work in the urban area.

Households residing in the urban area have similar options. They can work in the urban area, or they can pay fixed cost m_P and work in the rural area for the indefinite future. The latter option allows for rural-to-urban and then urban-to-rural moves as a household's comparative advantage, experience, and asset holdings change over time.

Asset Choices. Households can accumulate a non-state-contingent asset, a, with a gross rate of return, R. Asset holdings are restricted to be non-negative, and, thus, there is no borrowing. Furthermore, we assume that R is exogenous.

3.2. Optimization

Before describing the value functions of a household, it is important to have a complete accounting of the state space. The state variables for a household can be divided into objects that are permanent, transitory, endogenous and aggregate.

- **Permanent productivity state.** Each household is endowed with z efficiency units in the urban area and one efficiency unit in the rural area. This is the "static Roy model" aspect of the model.

- **Transitory productivity state.** Each household is subject to transitory productivity shocks, s.
- **Endogenous state variables.** There are three endogenous (individual) state variables. The first is the household's asset holdings, a. The second is a composite variable that describes the household's location and migration status. The possible states are: rural, seasonal-migrant (living in the rural area but working in the urban area for one period), and urban. The third is whether or not the household is an inexperienced migrant, x, and, thus, whether or not it suffers disutility $\bar{u}$ from locating in the urban area.
- **Aggregate state variables.** There are two aggregate state variables: the season, $i \in \{g, \ell\}$, and the number of workers in the rural area, N_r. The season determines the current and future productivity in the rural area, and jointly, the two aggregate states determine the current wage per efficiency unit as in equation (4).

We begin with the problem of a rural household. Because z is time-invariant for each household, we omit it from the formulation of the household's problem below.

Rural Households. A rural household with productivity z solves the following problem:

$$v(a, r, s, x, i, N_r) = \max \left\{ v(a, r, s, x, i, N_r, | \text{ stay}),\ v(a, r, s, x, i, N_r, | \text{ seas}),\ v(a, r, s, x, i, N_r, | \text{ perm}) \right\}, \quad (6)$$

where a household chooses among staying in the the rural area, seasonally moving, and permanently moving. Conditional on staying in the rural area, the value function is:

$$v(a, r, s, x, i, N_r | \text{ stay}) = \max_{a' \in \mathcal{A}} \left\{ u(Ra + w_r(s, i, N_r) - a') + \beta \, \mathbb{E}[v(a', r, s', x', i', N_r')] \right\}, \quad (7)$$

which says that the household chooses future asset holdings to maximize the expected present discounted value of utility. The asset holdings must respect the borrowing constraint and, thus, must lie in the set $\mathcal{A}$. Given asset choices, a household's consumption equals the gross return on current asset holdings, Ra, plus labor income from working in the rural area, $w_r(z, s, i)$, minus future asset holdings. Next period's state variables are the new asset holdings, location in the rural area, the transitory productivity shock, the experience level, the subsequent season, and the aggregate rural efficiency units in the next period. The expectation operator is defined over two uncertain outcomes: the transitory shocks and the change in experience. Recall, that if the household is experienced, it stays that way with probability π and becomes inexperienced with probability $1 - \pi$; if the household is inexperienced, then it stays inexperienced.

The value function associated with a permanent move is:

$$v(a, r, s, x, i, N_r|\text{ perm}) = \max_{a' \in \mathcal{A}} \Big\{ u(Ra + w_r(z, s, i, N_r) - a' - m_p) + \beta\, \mathbb{E}[v(a', u, s', x', i', N_r')] \Big\}.$$

While similar to the staying value function, there are several points of difference. First, the agent must pay m_p to make the permanent move, and this costs resources. Second, the continuation value function denotes that the household's location changes from the rural to the urban area.

The value function associated with a seasonal move is:

$$v(a, r, s, x, i, N_r|\text{ seas}) = \max_{a' \in \mathcal{A}} \Big\{ u(Ra + w_r(s, i, N_r) - a' - m_T) + \beta\, \mathbb{E}[v(a', seas, s', x', i', N_r')] \Big\}. \quad (8)$$

If a household decides to move seasonally, it pays the moving cost m_T, and works in the urban area in the next period. The key distinction between the permanent move and the seasonal move is that the seasonal move is for just one period. Hence, the location state variable is $seas$ and not u, as this indicates that the household is going to work in the urban area and return in the next period. The value function associated with a seasonal move while in the urban area is:

$$v(a', seas, s', x', i', N_r') = \max_{a'' \in \mathcal{A}} \Big[u(Ra' + w_u(z, s') - a'')\bar{u}^{x'} + \beta\, \mathbb{E}[v(a'', r, s'', x'', i'', N_r'')] \Big]. \quad (9)$$

There are several important points to take note of in (9). First, this household has only one choice: how to adjust its asset holdings. By the definition of a seasonal move, the household works in the urban area for one period and then returns to the rural area. Second, note how the disutility from living in the urban area appears (i.e., the presence of $\bar{u}$). Moreover, the state variable of a household's experience x determines whether or not the disutility is experienced.

Equations (8) and (9) illustrate the forces that shape the decision to move seasonally and, in turn, our inferences from the experimental and survey results. Generally, the choice to move seasonally will relate to a household's comparative earnings advantage in the urban area relative to the rural area. However, several forces may lead a household with a permanent comparative advantage in the city not to move. First, the urban disutility may prevent the household from moving, even though its comparative advantage in the urban area is expected to be high. Second, there is risk associated with the move. A household does not know s', and, hence, there is a chance that the income realization in the urban area will not be favorable. Third, the household may have limited assets that simply make a move infeasible

or not sufficient to insure against a bad outcome in the urban area.

Urban Households. Urban households face problems similar to those described above, though they choose between just two options: staying or making a permanent move. For a household with productivity level z, the problem is:

$$v(a,u,s,x,N_r,i) = \max\left\{ v(a,u,s,x,N_r,i|\text{ stay}),\ v(a,u,s,x,N_r,i|\text{ perm}) \right\}. \tag{10}$$

Conditional on staying in the urban area, the value is:

$$v(a,u,s,x,i,N_r,|\text{ stay}) = \max_{a'\in\mathcal{A}}\left\{ u(Ra + w_u(z,s) - a')\bar{u}^x + \beta\,\mathbb{E}[v(a',u,s',x',i',N_r')] \right\}. \tag{11}$$

Households staying in the urban area have several key differences from those staying in the rural area. First, their wage depends on their permanent productivity level, z, and not on the season or number of aggregate efficiency units in the rural areas. Moreover, the transitory productivity shocks may have more or less volatility relative to the rural area, as modulated by the γ parameter (see equation (5)). Third, the disutility from living in the urban area appears (i.e., the presence of $\bar{u}$), and the state variable of a household's experience x determines whether or not the disutility is experienced.

Finally, as with rural households, expectations are taken with respect to the transitory shock s and the change in experience. However, as these households are in the urban area, inexperienced households stay that way in the next period with probability λ and become experienced with probability $1-\lambda$. Experienced households retain their experience.

The value function associated with a permanent move back to the rural area is:

$$v(a,u,s,x,i,N_r|\text{ perm}) = \max_{a'\in\mathcal{A}}\left[u(Ra + w_u(z,s) - a' - m_p)\bar{u}^x + \beta\,\mathbb{E}[v(a',r,s',x',i',N_r')] \right]. \tag{12}$$

Here, the agent must pay m_p to make the permanent move. Furthermore, the continuation value function denotes the household's location changes from the urban to the rural area. After a permanent move to the rural area, experienced households keep their experience with probability π and lose it with probability $1-\pi$.

3.3. Discussion: Determinants of Migration and Location Choice

The model allows for a rich set of determinants of migration and of location choice more generally. While in the following section, we allow the data to discipline the most important determinants, it is worth discussing them informally here first.

One clear determinant of migration in the model is the season. Since the growing season has higher productivity than the lean season, rural households will be more likely to migrate (seasonally or permanently) to the urban area in the lean season, all else equal.

The permanent urban productivity level, z, which captures comparative advantage in the urban area, is another important determinant of migration. All else equal, agents with higher values of z will have stronger incentives to locate in the urban area. The migration disutility, $\bar{u}$, is also an unambiguous deterrent to migration. The higher is $\bar{u}$, the less likely it is that inexperienced households will locate in the urban area. Furthermore, those with migration experience are more likely to migrate, as these households face no disutility of locating in the urban area. Finally, both effects—permanent comparative advantage and experience will interact, as households with a stronger comparative advantage in the urban area are more likely to migrate and, hence, have experience in migrating.

What role do the experience gain and loss probabilities, λ and π, play in migration and location decisions? These terms mostly affect the extent of *repeat* migration. When experience is easy to obtain and hard to lose—i.e., λ is low and π is high—a subsidy to migration will induce inexperienced rural-urban migrants to repeat migrate (or to stay in the urban area) for many periods in the future. For rural households induced to migrate seasonally, the lower is π, the less likely they will be to migrate in subsequent periods since experience is lost at a faster rate.

The transitory shock, s, and asset levels, a, have ambiguous effects on migration and location choice. First, suppose that shocks are persistent, so that households with a high shock today are more likely to receive a high shock one period hence. And consider the following two cases: if γ is above or below one.

If $\gamma > 1$, the shocks are more volatile in the urban area. In this case, rural households may be more likely to migrate to the urban area after receiving a good shock. The asset holdings also play a role in this case. High values of assets allow for insurance, which may mean that households migrate in this case only when their assets are sufficiently high. One concrete story that our model allows for here is that households with high urban productivity – either because of high z or high s shocks—are "misallocated" in the rural area, due to insufficient buffer stocks of savings. If this is the case, subsidizing migration may induce these high-productivity households to migrate and to realize large consumption gains due to a better allocation of their urban-specific productivity. It is worth emphasizing that this case is more likely to occur the lower is the return to saving, R, since for higher savings rates, workers can self-finance and save their way out of these credit constraints (see, e.g., Midrigan and Xu, 2014; Moll, 2014; Donovan, 2016).

Suppose, instead, that $\gamma < 1$, so that shocks are more volatile in the rural area than in the urban area. In this case, rural households may be more likely to migrate when they have bad shocks than when they have good shocks. Since migration is costly both in monetary terms and non-monetary disutility, households may migrate only when they are sufficiently unproductive and when their assets are too low for them to insure themselves against their current low productivity. In this case, subsidizing migration may induce these low-productivity households to migrate and to realize large consumption gains to avoid bad outcomes in the rural area and reap benefits of higher average productivity in the urban area. This case is related to the findings of Gröger and Zylerberg (2016) and Kleemans (2015), who find evidence that workers use migration as a coping mechanism after bad shocks. [6]

Whether induced migrants tend to be low-productivity with low assets, or high-productivity workers with high assets, is determined by the data. More generally, the welfare effects of subsidizing migration depend on the data used to discipline the model quantitatively. In particular, the welfare gains to a migrant induced to migrate depend on the size of the transfer to the migrant and the monetary cost of migrating; the expected gains from migrating; the income risk faced by the migrant; the non-monetary disutility of migrating; and how likely households are to gain and subsequently lose their experience. We turn to this in the next section.

4. Model Parameterization and Quantification

To quantify and estimate the model, we use the simulated method of moments such that the estimated parameters match two important sources of data. The first is rural Bangladeshi households' behavior in controlled migration experiments (Bryan, Chowdhury, and Mobarak, 2014; Akram, Chowdhury, and Mobarak, 2017), which we replicate within the model. The second is a set of aggregate, cross-sectional moments that we calculate using the nationally representative Household Income and Expenditure Survey (HIES) of Bangladesh from 2010. Taken together, we are asking the model to jointly fit both the aggregate facts of the Bangladesh economy and household responses that are very well identified through controlled experimental trials.

4.1. Data

The Migration Subsidy Experiment. Rural Bangladeshi households' reactions to the migration subsidies they were offered in the Bryan, Chowdhury, and Mobarak (2014) experiment

[6] For the case of international migration, Bazzi (2017) finds that credit constraints limit emigration from poorer rural areas in Indonesia, though in more developed rural areas, those with higher permanent income shocks are less likely to migrate.

informs several key parameters of our model. We calibrate the model in an attempt to match three facts that were identified using purely random variation in that experiment: Relative to a control group not provided any intervention, (a) poor, rural households become 22 percentage points more likely to migrate when they were offered a subsidy that (roughly) fully offset the cost of travel; (b) consumption among those induced to migrate by this subsidy increased by 30 percent; and (c) treated households were nine percentage points more likely to re-migrate a year later, absent any further subsidies.[7]

These facts are observed (and matched to our model) in partial equilibrium from an experiment in which only ten percent of poor households in the village were offered migration subsidies. The scaled-up version of this experiment, in which up to 70 percent of the village population was simultaneously offered migration subsidies, is informative about the decreasing marginal product of labor that is embedded in our production function for rural areas. The Akram, Chowdhury, and Mobarak (2017) experiment shows that every ten percentage point increase in emigration raises rural wages by 2.2 percent in general equilibrium, which translates into an estimate of ϕ in the rural production function of 0.91.

Household Income and Expenditure Survey (HIES) of Bangladesh. We can discipline the model further by matching to some aggregate moments that describe key features of the rural and urban labor market conditions in Bangladesh. For that, we use large-sample nationally representative household survey data to construct estimates of the fraction of households residing in rural areas, the aggregate urban-rural wage gap, and the variance of log wages in the urban area.

The 2010 Household Income and Expenditure Survey administered by the Bangladesh Bureau of Statistics is a nationally representative survey of 12,240 households. To construct the empirical moments, we restrict attention to wage earners since the data on wage earnings are more detailed and reliable than the data on self-employed income or farm income. We also restrict attention to those aged 15 and older who worked positive hours in the last week, had positive labor earning in the last month, and had a non-missing value for rural-urban status. We compute the wage as monthly earnings divided by weekly hours multiplied by four, and we drop the top and bottom one percent of the wage distribution.

We find that 63 percent of individuals live in rural areas. The urban-rural wage gap is 1.80, similar to the the adjusted agricultural productivity gap of 2.3 reported in Gollin, Lagakos, and Waugh (2014). The variance of log wages in the urban area is computed to be 0.68.

[7] Furthermore, we also calibrate our model to naive OLS correlation between migration and consumption in these data (that do not use the experimental variation and therefore do not account for selection). Comparing the OLS correlation to the experimental estimates are informative about the nature of selection into migration.

Table 1: Pre-Assigned Parameters

Parameter	Value	Source
Time period	Half year	—
Risk aversion, α	2.0	—
Discount factor, β	0.95	—
Gross real interest rate, R	0.95	1/ gross inflation rate
Rural seasonal productivity, A_{rl}/A_{rg}	50% drop in rural inc.	Khandker (2012)
Seasonal moving costs, m_T	10% of rural consumption	Bryan et al. (2014)
Permanent moving costs, m_p	$2 \times m_T$	–
Decreasing returns in rural area, ϕ	0.91	Akram et al. (2017)

4.2. Directly Chosen Parameters

We begin by assigning some parameter values directly. These are parameters that either have a direct relationship between the model and the data, or are difficult to identify from the data.

We choose a time period of half a year, to allow us to have seasonal migration and seasonal variation in rural productivity. We set the risk-aversion parameter, α, to be two, which is within the range of commonly chosen values in the macroeconomics literature. We choose the discount factor, β, to be 0.95.

The return on assets, R, is set to 0.95 to capture the average half-yearly inflation rate in Bangladesh (around five percent). This choice is consistent with the asset composition of households' balance sheets in our experimental sample. Most asset holdings (conditional on having assets) are in cash.[8] Thus, the return on their cash holdings corresponds to the inflation rate.

Seasonal variation in rural productivity is set so that the lean season is 50 percent less productive than the growing season, consistent with estimates by Khandker (2012). The seasonal moving cost is set at ten percent of rural consumption. This is approximately the seasonal

[8]There is strong evidence that households and small business operators in the developing world face poor savings technologies and saving constraints (see, e.g., Karlan, Ratan, and Zinman, 2014). Casaburi and Macchiavello (2016) show that dairy farmers in Kenya are willing to take a 20 percent pay cut to have the milk buyer hold on to their earnings for the month instead of getting paid daily. Dupas and Robinson (2013) show that even providing rural Kenyans with a secure place to store money at home leads to substantial increases in savings and business investment.

migration cost (round-trip bus fare plus a few days of food during travel) reported in Bryan, Chowdhury, and Mobarak (2014). We set the permanent migration costs high enough such that gross flows across regions are negligible because that is true in this region over the eight years of tracking in the Bangladesh data. We find that our results are not substantially affected by this parameter value.

Finally, we set the elasticity of output with respect to labor, ϕ, to be 0.91, following the general equilibrium wage elasticity of labor estimated by Akram, Chowdhury, and Mobarak (2017). They observe that wages rise with larger labor supply shocks, because the proportion of households receiving migration subsidies varies randomly across villages. Our choice of ϕ replicates their elasticity of a 2.2 percent increase in rural wages for every ten percent increase in emigration. Table 1 summarizes these parameter values.

4.3. Parameters to Estimate

We estimate ten parameters in our model, and summarize those below:

Preference parameters. We have three parameters that interact directly with preferences: the disutility of migration, $\bar{u}$, and the probabilities of becoming experienced and inexperienced, λ and π.

Productivity Parameters. We have five parameters that determine household productivity across space and time. First is the parameter controlling aggregate productivity in the urban area, A_u, and second, the shape parameter controlling the urban productivity distribution, θ. Third, controlling transitory shocks across time is the standard deviation of transitory shocks, σ_s, and fourth, the autocorrelation of those shocks, ρ. Finally, we have the urban relative risk parameter, γ, which modulates the relative variance of these shocks across space.

Measurement Error in Income and Consumption Data. Finally, we allow for the possibility of measurement error in the income and consumption data and estimate its extent. Income and consumption in the data are clearly measured with error; hence, we do not want to force the model to ascribe all of the income and consumption variance to permanent or temporary shocks rather than to error.

In particular, we assume that rural consumption growth (which we observe using the experimental data) satisfies:

$$\hat{g}_{c,i} = g_{c,i} + \upsilon_{r,i}, \tag{13}$$

where $\hat{g}_{c,i}$ is observed consumption growth of household i; $g_{c,i}$ is actual consumption growth; and $\upsilon_{r,i}$ is measurement error, which we assume is normally distributed with mean zero and

variance $\sigma_{c,r}$. Urban income, in turn, satisfies:

$$\log \hat{y}_i = \log y_i + \log \upsilon_{u,i}, \tag{14}$$

where y_i is observed income of household i; y_i is actual income; and $\log \upsilon_{u,i}$ is measurement error, which we assume is normally distributed with mean zero and variance $\sigma_{y,u}$.

4.4. Estimation by Simulated Method of Moments

We estimate the parameters of the model using simulated method of moments. The basic idea is to pick the parameter vector

$$\Theta = \{\bar{u}, \lambda, \pi, A_u, \theta, \sigma_s, \rho, \gamma, \sigma_{c,r}, \sigma_{y,u}\} \tag{15}$$

such that simulated moments from the model match up with moments in the data. This is analogous to the generalized method of moments estimation, but we do not have closed-form representations of model moments. Thus, we solve the model and construct moments from simulated data. The ten data moments off which we estimate the parameters are listed in Table 2 and can be divided into two basic groups: moments from the control and treatment groups (top seven); and aggregate, cross-sectional moments (bottom three).

We construct the simulated moments in the following way. For the cross-sectional moments, we solve the household's problem and construct the stationary distribution of households. From the stationary distribution, we compute the urban-rural wage gap, the percent of households that permanently live in the rural area, and the variance of log income in the urban area.

A novel feature of our estimation procedure is that we replicate the Bryan, Chowdhury, and Mobarak (2014) migration experiment directly in our model. We implement this procedure in the following way. First, we solve for optimal policies of households that are faced with a one-time, unanticipated seasonal migration opportunity without m_T. This is all done in partial equilibrium, which is appropriate given the relatively small number of experiment participants (19 households) in each village and the relatively small number of villages in the experiment.

We then randomly sample rural households from the model's stationary distribution, consistent with the sample selection criteria used by Bryan, Chowdhury, and Mobarak (2014) (see the discussion in Section 2). Specifically, they conducted their baseline survey prior to the lean season; thus, we follow the same timing in the baseline sample selection and measurement for our model. Furthermore, they selected households that were relatively poor to

start with, and we implement this in the model by selecting rural households that are in the bottom half of the asset distribution for rural residents.

Given the appropriate sample of households and their optimal policies if treated or not, we compute moments from the control and treatment groups. For the control group, we focus on several moments: variance in consumption growth; the fraction of households with zero assets prior to the lean season; the seasonal migration rate; and the slope coefficient from the projection of consumption on migration. The last moment is constructed by regressing the consumption of households in the lean season on an indicator variable if the household either migrated or did not.

For the treatment group, the moments we focus on are the increase in seasonal migration relative to the control group; the seasonal migration rate in the subsequent year (when no subsidy was given); and the local average treatment effect (LATE) of migration on consumption, as in the experiment. This last moment uses data from both the treatment and control groups, and conducts an IV regression in which consumption is regressed on (instrumented) migration, with migration instrumented by assignment to treatment in a first stage.

Table 2: Targeted Moments in Data and Model

Moments	Data	Model
Control: Variance of log consumption growth in rural	0.18	0.18
Control: Percent of rural households with no liquid assets	47	47
Control: Seasonal migrants	36	36
Control: Consumption increase of migrants (OLS)	10	10
Treatment: Seasonal migration relative to control	22	22
Treatment: Seasonal migration relative to control in year 2	9	6
Treatment: Consumption of induced migrants relative to control (LATE)	30	30
Urban-Rural wage gap	1.80	1.80
Percent in rural	63	63
Variance of log wages in urban	0.68	0.68

Note: The table reports the moments targeted using simulated method of moments and their values in the data and in the model.

4.5. Estimation Results

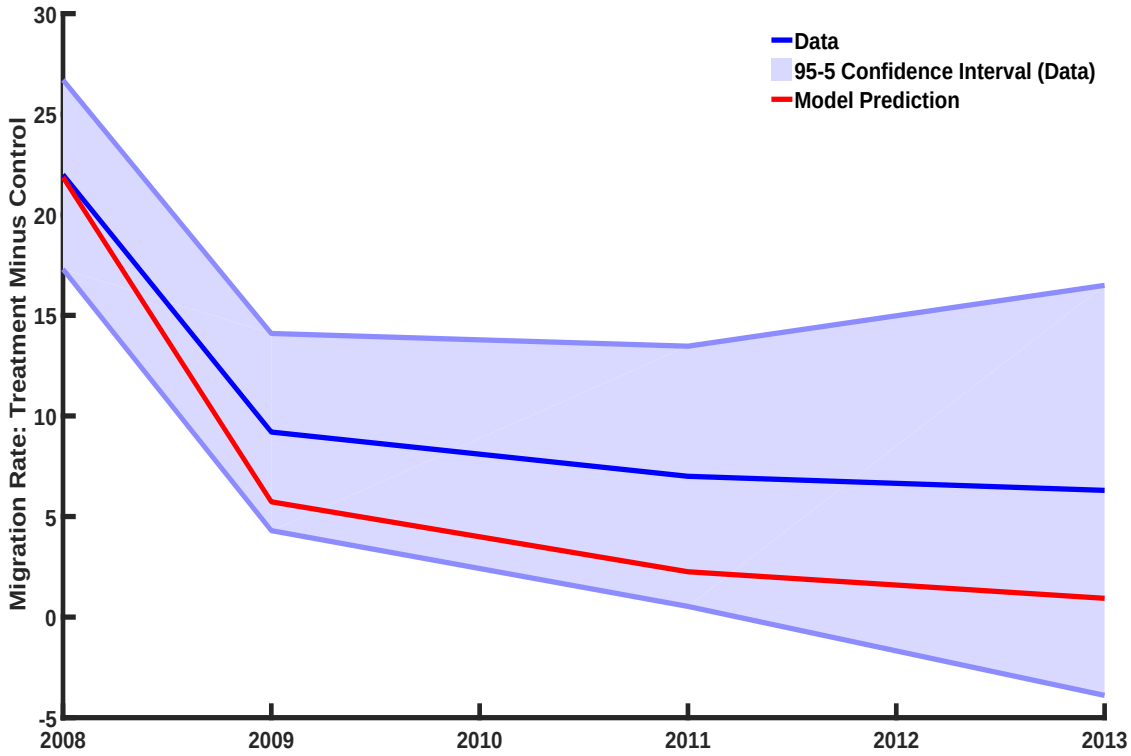


Figure 1: **Difference in Migration Rates in Treatment and Control Groups**

Table 2 presents the the data and the model moments. In general, the model's predicted moments are quite similar to its counterparts in the data. Nine of the ten moments are matched exactly, while the tenth (the return migration rate) is a bit lower in the model than in the data. Figure 1 plots the difference in migration rates between the treatment and control groups in the model and data in 2008 (the year of the experiment in the model), and for five subsequent years. As the figure shows, the model also does well in other years, capturing the declining pattern present in the data. By five years after the experiment, the difference in migration rates between the two groups is positive, but small in magnitude, in the model, at two percent, and statistically insignificant in the data.

Table 3 shows the estimated parameter values. While the next two sections discuss the economic implications and identification of these parameter values, several features of Table 3 are worth pointing out. First, the shape parameter controlling permanent differences in ability is relatively low, at around two. This implies that there is relatively large variation in permanent productivity in the urban area. Second, the urban relative risk parameter is less than one, implying that shocks in the urban area are less volatile than those in the rural area.

Table 3: Parameter Values

Parameter	Value
Migration disutility, $\bar{u}$	1.45
Probability gaining experience, $1-\lambda$	0.38
Probability losing experience, $1-\pi$	0.49
Shape parameter, urban talent, θ	2.08
Urban relative shock, γ	0.66
Productivity urban area A_u	1.45
Standard deviation of transitory shocks	0.36
Persistence of transitory shocks	0.71
Measurement error in rural consumption data	0.37
Measurement error in urban income data	0.31

Note: The table lists the parameters whose values were determined using simulated method of moments, as described in the text, and their values in the quantitative analysis.

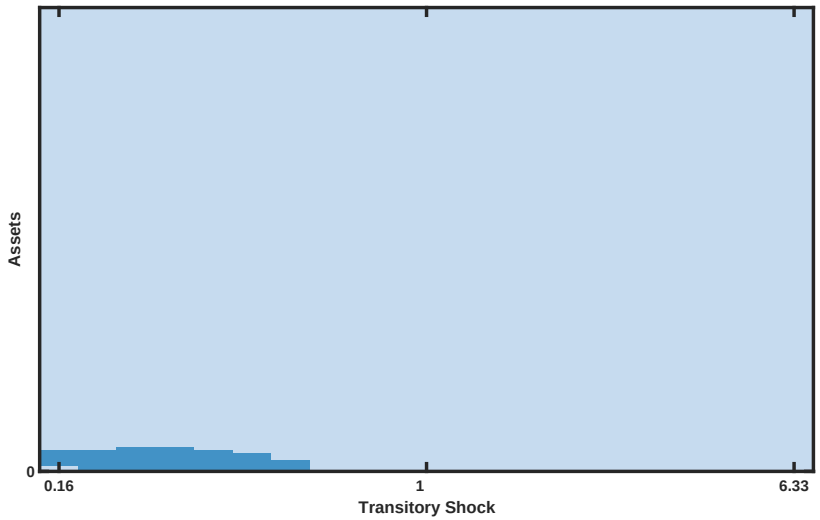
Third, the disutility of the urban area is sizeable (and positive, since the level of household utility is negative). In Section 6, we use new survey data to point to specific reasons why households suffer disutility of temporary migration. Fourth, there are non-trivial dynamics (i.e., the λ and π) in the ability to acquire and lose experience with the urban area.

4.6. Who Migrates? Why?

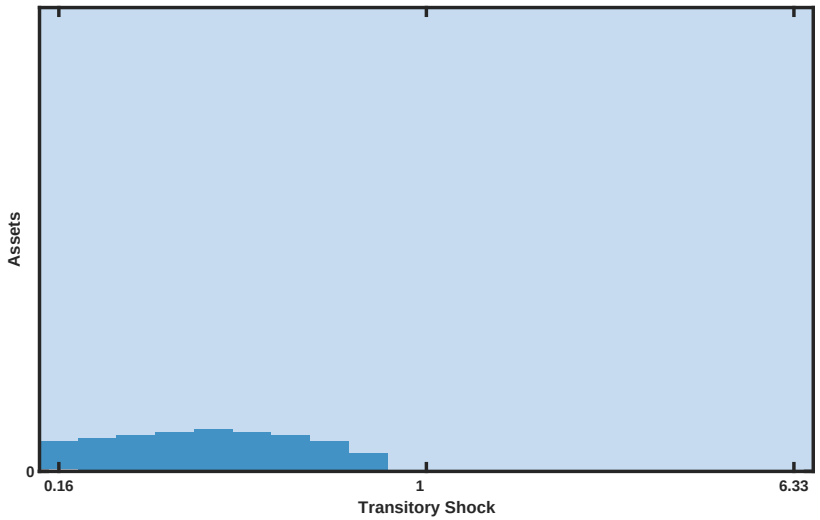
In this section, we discuss how the policy functions for location choice depend on permanent productivity, z, as well as asset holdings, a, the transitory shock, s, and experience. We focus on rural households leading into the lean season since most migration occurs then.

Figure 2 plots the moving policy functions of rural households with different levels of urban productivity, z, and migration experience, as a function of their transitory shocks and asset holdings. The x-axis represents the transitory productivity shock, and the y-axis is the asset holdings of the household. The dark blue region represents the set of a and s values such that the household seasonally moves to the urban region; in the light blue region, the household stays in the rural area.

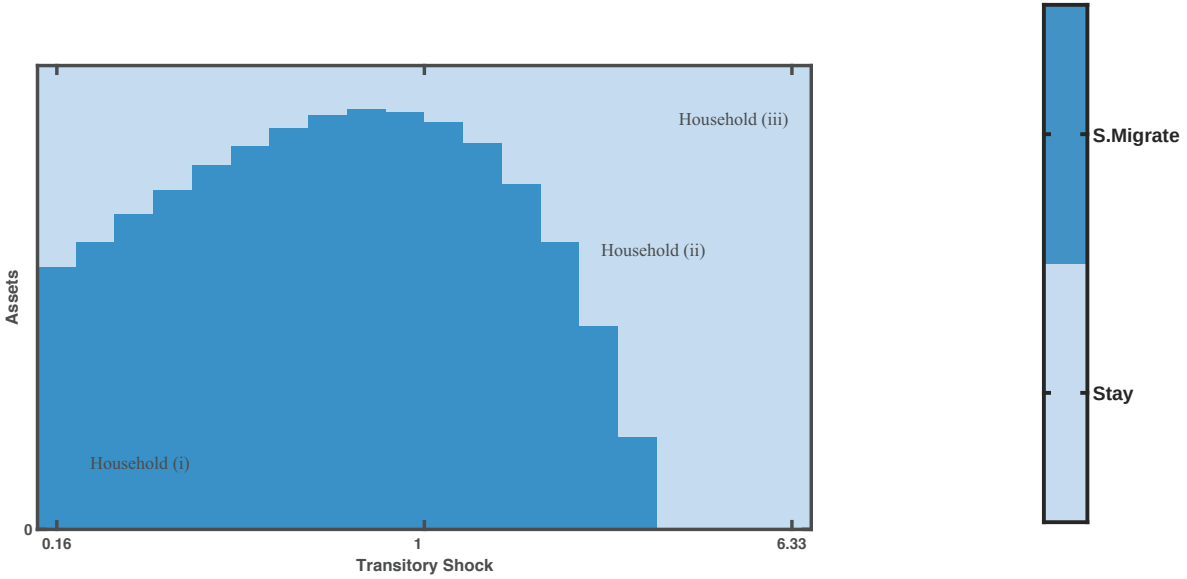
There are three take-aways from Figure 2: higher urban productivity leads to more migration, experience leads to more migration, and low-asset and low-transitory-shock households are more likely to move.



(a) **Low z, No Experience**



(b) **Moderate z, No Experience**



(c) **Moderate z, Experience**

Figure 2: Migration Policies for Households with Different Values of z and Experience

Figures 2(a) and 2(b) contrast the moving policy for low z households and moderate z households. The dark blue region in the southwest corner of Figures 2(a) and 2(b) is larger for moderate z households relative to low z households. This means that those with a stronger comparative advantage are more likely to seasonally migrate to the urban area. This observation yields the following implication about the set of households living the rural area. They are mostly households with relatively low z values, since the high z types move permanently to the city. Thus, any new policy (such as migration subsidies) directed towards workers in the rural area will be directed more towards households with low permanent productivity levels in the urban area.

Figures 2(b) and 2(c) contrast the moving policy for the same z, but different experience levels. The dark blue migration region in Figure 2(c) is larger relative to the situation with no experience. This illustrates the point, that, in the estimated model, we infer an important role for disutility of the urban area in shaping the migration choice.

Finally, Figure 2 illustrates that households with low assets and low transitory shocks are more likely to migrate. This point is seen by noting that in all cases, the dark blue migration region always originates out of the southwest corner. At first glance this may seem surprising, if our expectation is that credit constraints are the primary reason that households do not migrate. If migration costs are high and the credit constraint binds, then the migration region would originate from the northeast corner in Figure 2, because this is where the constraint would be alleviated.[9]

In contrast, the data and model suggest that households use migration as a coping mechanism in response to bad shocks. Per our discussion in Section 3.3, if migration is costly both in monetary terms and in non-monetary disutility, households migrate only when they are sufficiently unproductive and when their assets are too low for them to insure themselves against their current low productivity. Thus, migrating households are *negatively* selected on transitory shocks and assets. As we discuss in our welfare evaluation in Section 5, the observation that migration is being used as a coping mechanism implies that migration subsidies are a way to target poor and needy households.

4.7. Identification

In this section, we discuss how the experimental and cross-sectional moments help identify the parameters of the model. To do so, we start with the benchmark calibration and then compute the elasticity of each targeted moment to each parameter.

[9]Credit constraints prevent migration for a very small part of our parameter space, seen in Figure 2(a) in the lower left corner, representing the few households with very low permanent productivity in the urban area, no assets, and the lowest shock realizations.

Table 4: Elasticities of Targeted Moments to Parameters

	θ	$\bar{u}$	λ	π	γ	A_u	σ_s	ρ
Migration, Control	**3.2**	**-7.8**	-0.5	**1.1**	**-1.2**	**2.4**	-0.5	0.9
Migration, Treatment - Control	**1.6**	**-1.2**	0.3	-0.0	-0.3	**2.6**	**1.2**	**-1.5**
Migration, Treatment - Control, year two	**2.5**	**-1.1**	**-1.0**	**1.0**	0.6	**3.5**	**1.3**	**-1.3**
Consumption, OLS	**-2.9**	**2.4**	-0.6	**1.0**	**3.3**	**-1.6**	-0.6	0.7
Consumption, LATE	0.2	**1.4**	0.0	-0.0	-0.1	0.5	-0.2	0.8
Urban-Rural wage gap	**-1.3**	-0.1	0.1	0.0	0.3	-0.3	-0.4	0.2
Percent in rural	-0.7	-0.8	-0.0	0.2	0.2	**-1.5**	-0.4	0.4
Fraction of households with no assets	0.1	-0.2	0.1	-0.1	-0.2	-0.7	**-2.7**	**5.3**

Note: This table reports the elasticities of each targeted moment to each parameter. Elasticities are calculated by computing the percent increase in each moment to a one percent increase in each parameter, starting from the calibrated parameters of the model. For expositional purposes, elasticities greater than one in absolute value are printed in bold.

Table 4 presents the elasticity of each targeted moment to each parameter. That is the percent increase in each moment to a one percent increase in each parameter. For expositional purposes, we put in bold any elasticity greater than one in absolute value. It is useful to discuss the results in Table 4 one parameter at a time, as well as the moments that are most sensitive to the change in parameters.

Permanent productivity in the urban area: θ. All three migration rates – of the control group, the treatment group, and the treatment group in year two—are very sensitive to the extent of permanent productivity differences. The intuition here is that θ controls how many households potentially have a comparative advantage in the urban area—i.e., how many "marginal households" there are. Or in the context of Figures 2(a) and 2(b), θ controls how many moderate z households there are relative to low z households. As $\theta \to \infty$, there are no differences in comparative advantage, and (at least in permanent terms) all households are on the margin. Thus, there will be a greater response to the migration subsidy.

Our identification argument about the parameter controlling permanent comparative advantage is distinct from the more typical approaches in Lagakos and Waugh (2013), Hsieh, Hurst, Jones, and Klenow (2013), and Burstein, Morales, and Vogel (2015). These approaches

exploit the mapping from heterogeneity in productivity to cross-sectional variation in labor earnings. The novel feature of our approach is the use of migration rates and experimentally induced migration to help identify this parameter.

Disutility in the urban area $\bar{u}$ and the dynamics of experience, λ and π. As in the previous discussion, disutility affects the three migration rates as well. Intuitively, if the urban area is an unattractive place to live, then households will not migrate in general, and they will also not migrate in response to a migration subsidy. The comparison of Figures 2(b) and 2(c) illustrates this point clearly.

However, how does one distinguish differences in comparative advantage from disutility? The key insight is that the LATE effect of migration on consumption is very responsive to $\bar{u}$, with all other parameters having little or no effect. This implies that the consumption gains of those who are *experimentally induced* are identifying the size of the disutility of migration to the urban area. The intuition is that when the non-monetary disutility from migration is larger, households need a larger consumption gain from migration to induce them to migrate in equilibrium. Put differently, for lower non-monetary disutility values, most rural households would not pass up large consumption gains from migration; they would already be migrating, and the LATE of migration on consumption for those households would be smaller.

The dynamics of acquiring and losing experience are pinned down by migration rates and, especially, by the subsequent re-migration response in the years after the initial treatment. If it is easy to acquire experience, and if experience depreciates less, then there is more re-migration in subsequent years.

Urban Relative Volatility: γ. The moment most informative about this parameter is the OLS effect of consumption on migration. This implies that γ is being identified from the extent to which migrants are positively or negatively selected on transitory shocks. The intuition is as follows. When γ is smaller, households induced to migrate are more likely to be those with lower transitory shocks and few asset holdings. If these households migrate, therefore, they are more likely to be those with the relatively lowest productivity draws in the urban areas. This, in turn, leads to a lower OLS coefficient of consumption migration, since those deciding to migrate have relatively lower consumption levels.

Urban Productivity: A_u. Urban productivity affects urban wages and, hence, migration rates and the percent of households that permanently locate in the rural and urban areas. As Table 4 suggests, it is the last moment that is key here. That is, varying urban productivity provides us a degree of freedom to ensure that rural and urban populations in the model reflect the data.

Transitory shock process: ρ and σ_s. The asset distribution is informative about these parameters. This follows from intuitive properties of precautionary savings motives in incomplete market economies. If the variance of the shocks is high, then there is a stronger motive to hold more assets. If the shocks are more persistent, then the shocks are less insurable, and, hence, it is more likely that one ends up with no assets.

4.8. Non-Targeted Moments

How does the model fare in predicting non-targeted moments? We answer this question by examining several features of the data: consumption growth and migration rates by the initial distribution of consumption; variances of consumption growth by migration status; and the effects of unconditional cash transfers.

We focus on these non-targeted moments for the following reasons. The first two sets of moments speak to households' heterogeneous responses to the treatments. These responses are of interest since our welfare results suggest important heterogeneity in how the gains from migration are distributed across the population.

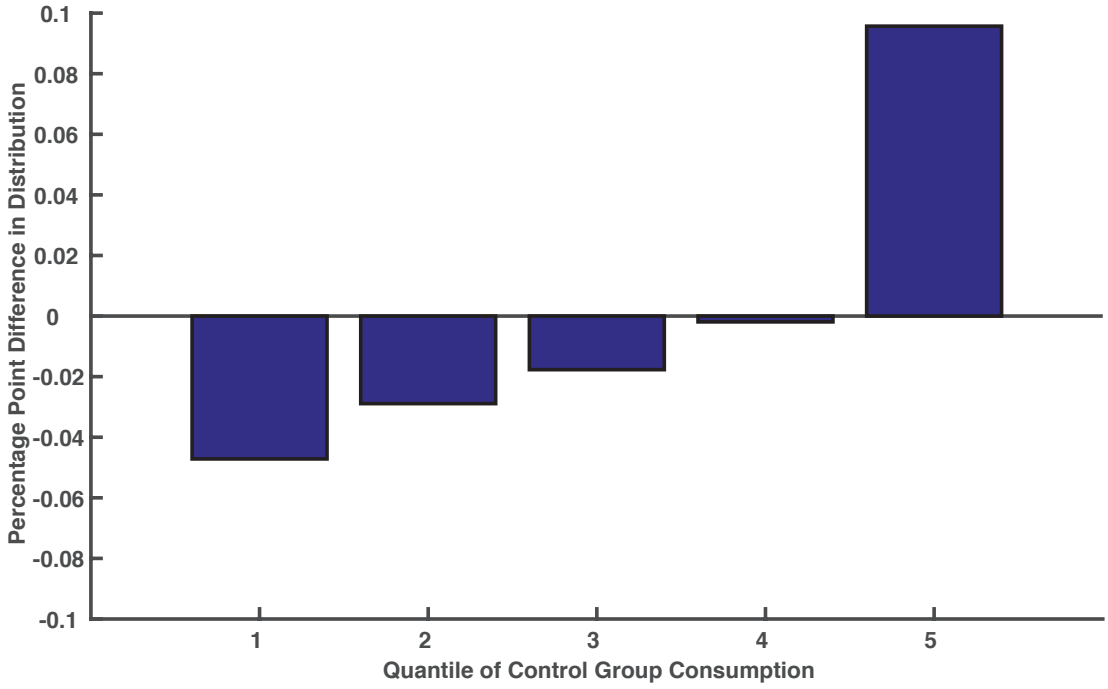
The later sets of moments – variance of consumption growth and the effects of unconditional transfers – speak to potential sources of "misallocation" in the model. These are, migration risk, as in Harris and Todaro (1970), and credit constraints that limit migration.

the role that relaxing credit effects the migration decision.

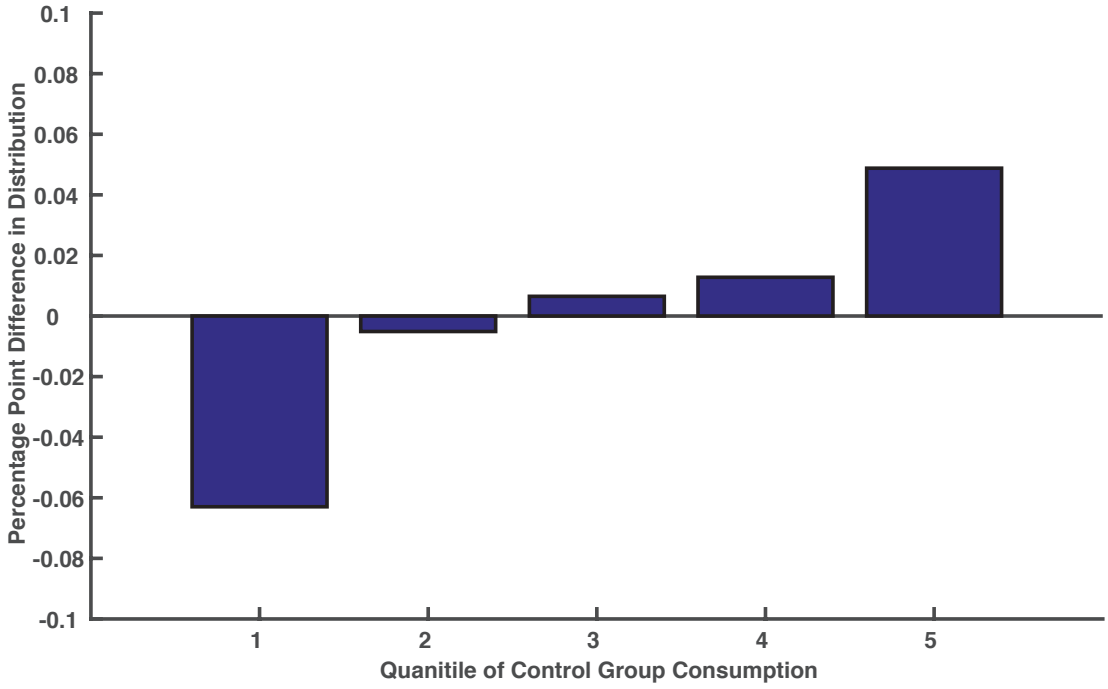
Consumption Growth and Migration Rates by Initial Consumption Level. A key prediction of the model is that the migration transfers affect poorer households relative to richer households. Our observations regarding Figure 2 imply that migrating households are negatively selected on transitory shocks and assets.

To assess the model's predictions, Figure 3 plots the difference between the distribution of consumption for the treatment group and the control group. In other words, the figure plots the percentage point difference between the treatment and control group's consumption levels by quintile of the initial (control group) distribution.

As Figure 3 shows, the biggest differences between the treatment and control distributions in the data (upper panel) come from the lowest and highest quintiles. The lowest quintile has around five percentage points less weight in the treatment than in the control distribution, and around ten percentage points higher weight in the highest quintile. The reason is that the experiment tended to raise the consumption of the poorest households the most. The model (lower panel) does quite well in matching these patterns. The lowest quintile of the model consumption distribution has around six percentage points less density in the



(a) **Data**



(b) **Model**

Figure 3: **Difference in Treatment and Control Consumption Distribution**

treatment group than in the control group, while the highest quintile has around five percent more. In both the model and data, the second, third and fourth quintiles have more modest differences between the treatment groups, though the model modestly underpredicts these differences. Overall, the model does fairly well at capturing the difference between the consumption distributions in the treatment and control groups.

Figure 4 plots the migration rates in the treatment and control groups and their difference by quintile of the consumption distribution. In the data (upper panel), migration rates are higher in the treatment group for all five quintiles, by a larger margin in the lowest quintile than in the rest. In the model (lower panel), migration rates are also higher in the treatment group for all five quintiles, with the largest difference coming in the lowest quintile. The model somewhat overpredicts the difference in migration rates for the fourth quintiles, and underpredicts the consumption difference for the fifth quintile. As these moments were untargeted, we conclude that the model provides quite a good fit to the broad patterns of migration by consumption level.

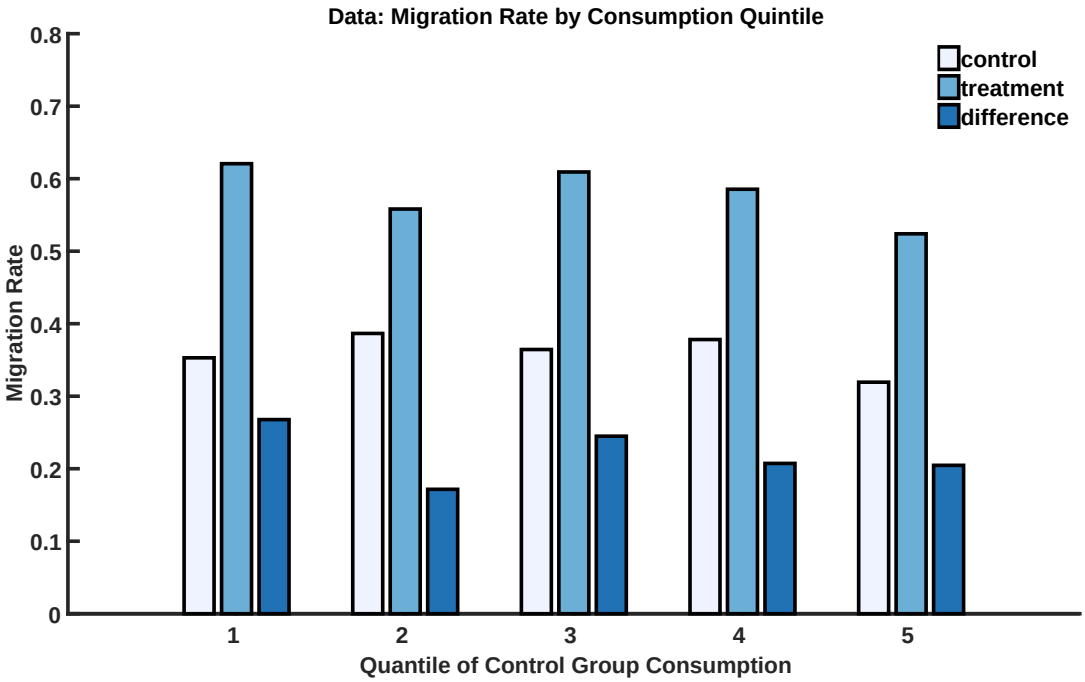
Variance of Consumption Growth. We turn next to the variance of consumption growth. These second moments are important because they are informative about the risk facing households that choose to migrate (or not). Table 5 lists the variance of log consumption growth for households that stay and those that migrate, in both the data and the model. In the data, the control group (upper panel) has log consumption growth variance of 0.39 for stayers and marginally higher variance, at 0.43, for those that migrate. The model is similar, with 0.41 for the stayers and 0.43 for the migrants. The treatment group (lower panel) in the data is somewhat similar to the control group, and, again, the model matches the similar but marginally higher log consumption variance of the migrants.[10]

Table 5: Variance of Log Consumption Growth

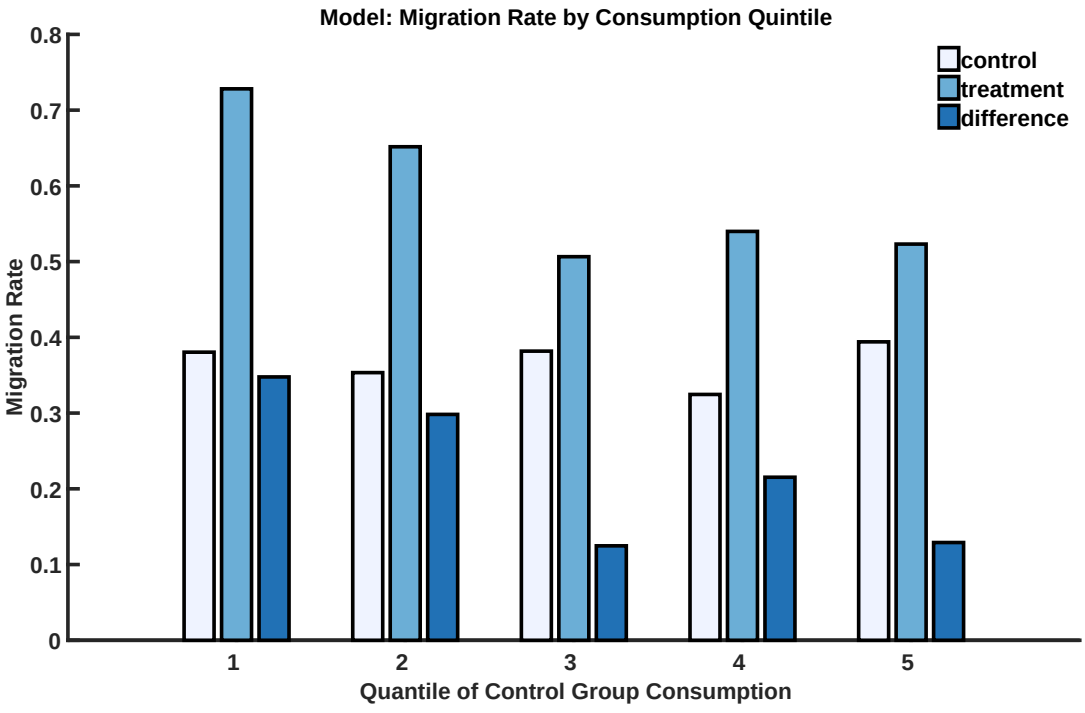
Control Group			Treatment Group		
	Stay	Migrate		Stay	Migrate
Data	0.39	0.43	Data	0.41	0.43
Model	0.41	0.43	Model	0.40	0.42

Note: The table reports variance of log consumption growth from before the lean season to afterwards. The top panel is for the control group, and the bottom panel is for the treatment group. The columns represent the set of households that stay (do not send a migrant) versus those that migrate (do send a migrant).

[10]The fact that consumption variances for movers and stayers is so similar is consistent with the findings of Kleemans (2015) for Indonesian migrants.



(a) Data



(b) Model

Figure 4: **Migration Rate by Consumption Quintile**

It is worth discussing how our model correctly predicts higher consumption growth variance for migrants than for non-migrants, even though it features higher transitory shock variance in the rural area ($\gamma < 1$). The reason is as follows. The model's prediction is that households with relatively low transitory shocks and asset levels do more temporary migration, all else equal. In the calibrated model, these temporary migrants see large gains in income and hence consumption, since they are largely "hand-to-mouth." This tends to increase consumption growth variance for migrants. In the aggregate, this force leads to larger consumption growth variance for migrants, even though migrants face lower income risk at the individual level.

Unconditional Transfers. One potential source of misallocation in the model comes from households that would prefer to migrate but cannot do so due to credit frictions. One way to help reduce misallocation from credit frictions would be to offer these households *unconditional* transfers. How do agents respond to unconditional transfer in the model, and how does that compare with the data?

To answer this question, we simulate the effects of offering unconditional transfers in the model, such that the total cost of the unconditional transfers is equal to the cost of the conditional migration transfer program studied thus far. We find that unconditional transfers induce a negligible increase in migration of less than one percent. As it turns out, the Bryan, Chowdhury, and Mobarak (2014) experiment offered an unconditional transfer to some households in 2011, and found that those offers produced no statistically significant change in migration, consistent with our model's prediction. Our model is able to simultaneously rationalize responses to both the conditional transfer (which is a targeted moment) and the unconditional transfer (which was not targeted in our calibration).

5. Measuring the Welfare Effects of Rural-Urban Migration

The model matches the salient features of the data, including a number of non-targeted moments. Thus, we have confidence in the model's interpretation of the experimental evidence and the magnitudes of its main forces. In this section, we use the model to measure the welfare implications of encouraging migration through conditional migration transfers. We begin by presenting the welfare gains overall, and then we go beneath the surface to look at heterogeneous effects and the role that different mechanisms play in shaping the gains.

We compute welfare as the consumption-equivalent welfare metric used in macroeconomics since Lucas (1985) and extensively thereafter. This metric computes the percent increase in consumption, p, that makes the household indifferent between a p-percent consumption increase in perpetuity and being offered the conditional migration transfer.

Table 6: **Consumption-Equivalent Welfare Gains by Income Quintile**

		Conditional Migration Transfer			Unconditional Transfer	
		Welfare	Welfare | Migr.	Migr. Rate	Welfare	Migr. Rate
Income Quintile	1	1.01	1.17	85.8	0.88	46.0
	2	0.35	0.59	59.1	0.46	35.5
	3	0.21	0.43	48.8	0.34	32.8
	4	0.13	0.30	40.9	0.26	28.7
	5	0.07	0.20	35.8	0.18	28.5
Average		0.35	0.65	56.0	0.42	36.0

Note: The table reports the (lifetime) consumption-equivalent welfare gains from the conditional migration transfers relative to an unconditional transfer program costing the same total amount. The numbers in the table are the average percent increase in consumption each period that would make the households indifferent between the consumption increase and the transfers.

Table 6 reports the overall average welfare gains by quintile of the income distribution for the treated population. As a frame of reference, we also report the welfare gains from an unconditional transfer system costing the same total amount. This is equivalent to giving a smaller amount of the consumption good to a larger number of households, without any conditions, and only to households in the rural area.[11]

On average, the welfare gains for the conditional migration transfer and the unconditional transfer program are similar in magnitude. However, the welfare gains for the conditional transfer are systematically larger for the poorest households. For the poorest quintile, the gains are about 15 percent larger for the migration transfers (1.01 percent versus 0.88 percent) unconditionally, and about 33 percent higher for those who migrate (1.17 percent versus 0.88 percent). As the third data column shows, the higher welfare gains for the poorest households come from their substantially higher migration rates in response to the conditional transfers. For households in the second quartile, welfare gains are similar, at 0.59 percent for the conditional transfers and 0.46 percent for the unconditional transfers. For the

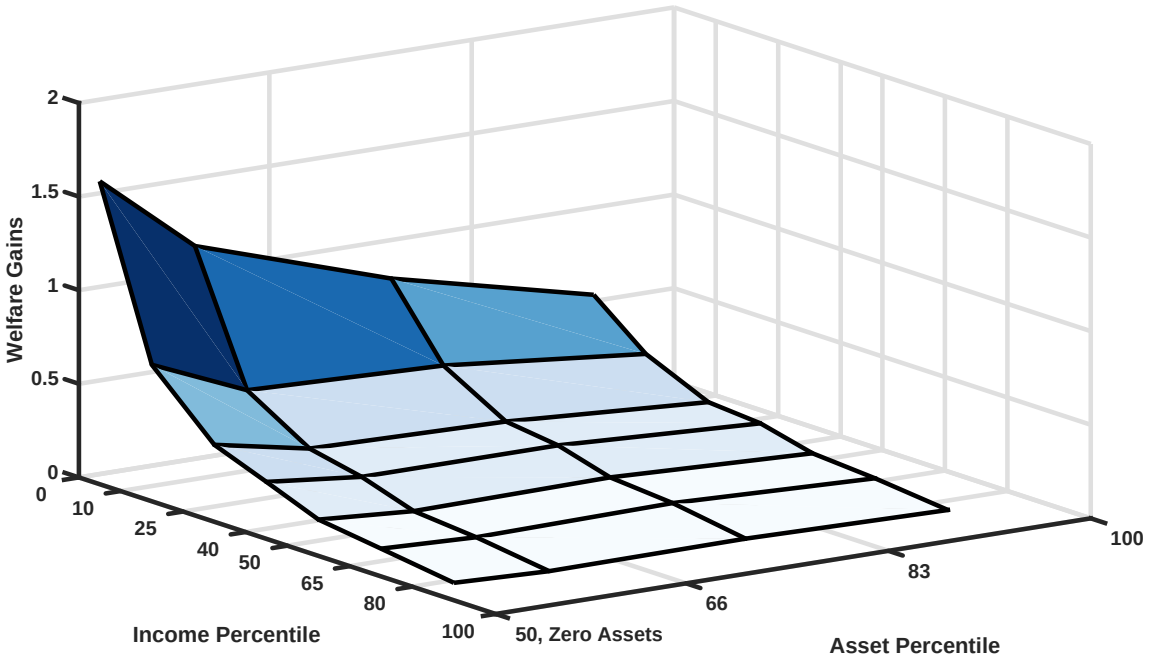
[11]There is a growing literature on the merits of conditions on transfers relative to unconditional transfers; see e.g., Baird, McIntosh, and Ozler (2016) and the references therein. In the setting of Baird, McIntosh, and Ozler (2016), conditions make the extreme poor worse off, since they are too poor even to satisfy the conditions of the transfer – i.e., sending their children to school. In contrast, in our environment, even the poorest can migrate given the transfer, and, moreover, they have a strong incentive to migrate.

third, fourth, and fifth quintile, the welfare gains from either program are smaller in magnitude, and higher for the unconditional transfer. In the fifth quintile (i.e. the richest quintile), the conditional migration transfer induces very little migration, and leads to a negligible 0.07 percent welfare equivalent, on average. The unconditional transfer affects many more households, though by a small amount, and leads to a 0.18 percent welfare increase.

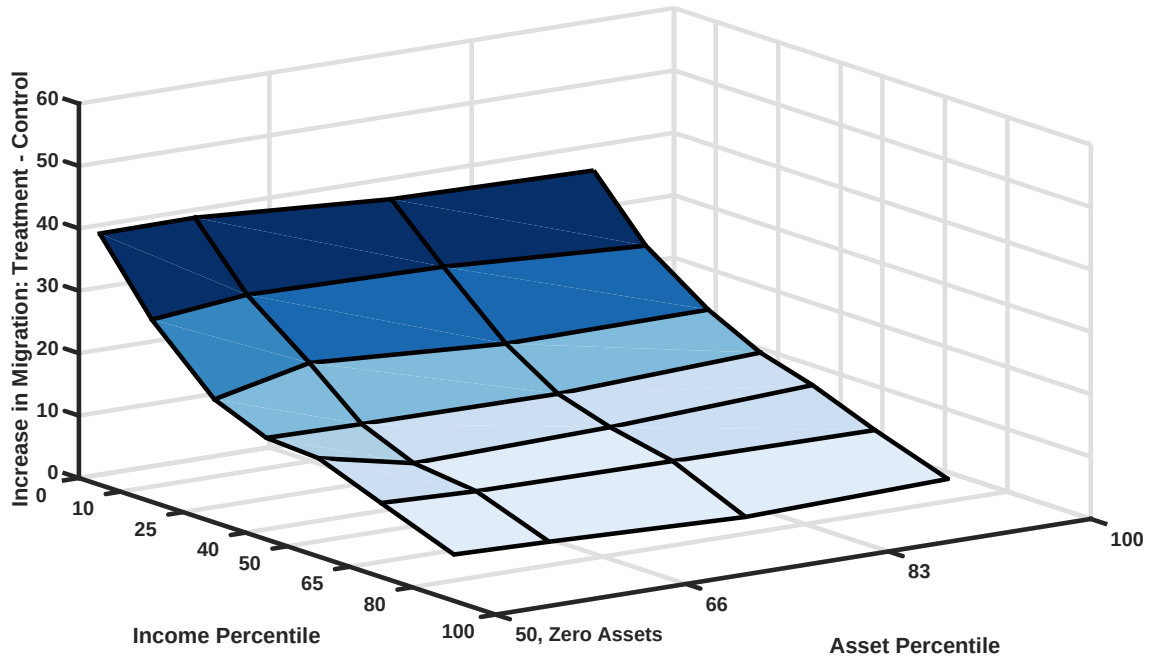
By plotting the consumption-equivalent welfare metric across all income and asset levels for the treated population, Figure 5 provides some more insight into how the welfare gains are determined. The top panel of the figure plots the welfare gains (the colored surface) for the conditional migration transfer, while the bottom panel plots the seasonal migration rates for these households. As the figure shows, the households with the lowest income and asset levels gain the most from the conditional migration transfers. The highest gains are around 1.5 percent in lifetime consumption equivalents, for the households with the lowest transitory productivity shock and no assets. The key reason is that, as shown in the bottom panel, households with low asset holdings and low transitory shocks are the most likely to migrate. When households are offered the conditional transfers to migrate, it is those with the lowest assets and worst shocks at present that have the highest take-up rates.

One can get some additional insight into how the welfare gains arise in the model by revisiting Figure 2. This figure shows the policy functions for a household with a moderate level of z and migration experience, in the control group. The policy functions for the treatment group are not depicted (for expositional purposes) but would expand the migration regions up and to the right. In the figure, household (i) is inframarginal and will make a temporary move whether or not it is offered a conditional migration transfer. Household (ii) is on the margin and is induced to migrate by a conditional transfer, but would otherwise stay in the rural area. Household (iii) will not migrate even when offered a transfer. Given the high level of assets and the high shock, this household prefers the rural area even with the transfer.

Who gains the most from the conditional migration transfers? Perhaps surprisingly, it is household (i), the inframarginal household. This household has low levels of assets and a bad shock, so has a low level of consumption. Marginal utility is relatively high for this household, so the transfer leads to a relatively large increase in its welfare. Household (ii) also gains, but by less, since this household has a higher level of consumption before the transfer. It is true that this household changed its behavior as a result of the experiment, but that is not the key driver of welfare gains. The consumption increase from the inframarginal households with low levels of assets and bad shocks is more important for welfare changes. Household (iii) doesn't take up the conditional transfer, and so its welfare does not change at all due to the intervention.



(a) **Welfare Gains**



(b) **Migration Rates**

Figure 5: **Welfare Gains and Migration Rates from Conditional Migration Transfers**

5.1. Welfare Under Alternative Scenarios

Why are the consumption-equivalent welfare gains from migration not higher if the workers induced to migrate gain 30 percent consumption on average? There are several other forces at work in the model that determine the model's welfare impacts – in particular, non-monetary disutility and selection. Below, we discuss each force and how it affects welfare.

The role of non-monetary disutility of migration. First, as we showed in Table 4, the model requires two features to match the consumption gains for induced migrants and the extent of persistence in repeat migration from the experiment. The first is a relatively high non-monetary disutility of migration for inexperienced migrants, coming through the $\overline{u}$ term. The second is a relatively high probability of losing migration experience. Putting these together, the model implies that the monetary gains from consumption are, in large part, offset by non-monetary disutility of migration that is not easy to overcome for those returning to the rural area each year.

Table 7: Consumption-Equivalent Welfare Gains, Surprise No Migration Disutility

		Welfare Gains: Surprise No $\bar{u}$ After Migration		
		Welfare	Welfare | Migr.	Welfare | Induced
Income Quintile	1	3.40	3.84	3.99
	2	1.69	2.61	3.05
	3	1.12	2.14	2.77
	4	0.89	1.83	2.52
	5	0.48	1.29	2.30
Average		1.51	2.60	3.21

To illustrate this point, we perform a counterfactual quantitative exercise. We start from the benchmark calibration, but surprise workers who choose to migrate with no migration disutility after they have already decided to migrate. In other words, workers in both the treatment and control groups expect to have disutility $\bar{u}$ of the benchmark model if they are inexperienced and migrate. But then we surprise those that choose to migrate with no disutility upon migration, just for one period, without any future expectation of a similar surprise later.

On average, the consumption-equivalent welfare gains of the experiment under this "no mi-

gration disutility" scenario are 1.51 percent – almost five times larger than the average gains in the baseline model. Across different income quintile, the gains are similarly systematically larger for poorer households. However, relative to the baseline, migration disutility affects the bottom second and third income quintiles. As in the discussion above, these are the more marginal households for whom the disutility is a larger deterrent.

The role of selection. The model also suggests that those induced to migrate are negatively selected. Thus, the model tells us that it is not predominantly high-productivity workers who are "misallocated" in the rural area and unable to migrate, due to, say, insufficient assets to pay for the moving cost. Instead, the model and experimental data imply that there are not many such high-z types stuck in the rural area. Therefore, the model requires that the induced migrants be the low-productivity households that pass up large consumption increases from migration (absent incentives to migrate) due to the non-monetary costs of moving.

To illustrate this point, we perform the following (counterfactual) quantitative exercise. Starting from the calibrated stationary equilibrium, we bring a representative set of urban households to the rural area and give each of them the asset holdings of the average rural household. These "forced return migrants" have relatively high z values, which is why they were in the urban area in the stationary equilibrium. We then redo the RCT experiment, and offer the conditional migration transfers to these new forced return migrants and to the same set of households as before.

We find that the welfare gains of the treatment group is now 3.3 percent in consumption equivalent terms, relative to the 0.4 percent average gain in the benchmark. The reason is that, in this scenario, the migration transfer helps the "misallocated" high-z workers leave the rural area earlier than they otherwise would have, which greatly increases their wages. Of course, there is a reason that these high-z workers—with a strong comparative advantage in urban work—were located in the urban area in the stationary equilibrium. The lesson in this second counterfactual is that, in principle, the welfare gains from the experiment could have been bigger if more rural individuals had been misallocated (in productivity terms) to begin with. But in equilibrium, there are not many permanently misallocated individuals in the rural area.

This counterfactual scenario also leads to the prediction that the OLS estimate of the effects of migration would be substantially higher than the LATE estimate (28 percent versus 12 percent), and this is not at all borne out in the experimental data (10 percent versus 30 percent). The lower OLS compared to the LATE coefficient of migration on consumption suggests that migrants are, on average, less productive. This is also on display in Figure 4: Induced

migrants tend to have relatively low, not relatively high, consumption levels.

5.2. Discussion: Relationship to Literature on Misallocation

The large and growing literature on misallocation and TFP has found evidence of large potential misallocation in developing countries, including in Indian and Chinese manufacturing (Hsieh and Klenow, 2009), and African and Chinese farming (Restuccia and Santaeulalia-Llopis, 2016; Adamopoulos, Brandt, Leight, and Restuccia, 2016). One major potential source of misallocation is worker sorting between agricultural and non-agricultural sectors (Gollin, Lagakos, and Waugh, 2014) or between rural and urban areas (Young, 2013). These papers hint at the possibility of large welfare gains from reallocation across firms or space, although none of them explicitly evaluate the welfare effects of reallocation policies.

Our paper shows that even when there is evidence of apparent misallocation in cross-sectional data, or hints of it in people's large migration responses in controlled experiments, the welfare gains from encouraging migration are actually *not* driven by better allocation of workers who were misallocated according to their permanent comparative advantage. Instead, welfare gains from encouraging migration arise from channeling funds to rural households with poor current income prospects and recent adverse shocks that depleted their asset stocks. Urban areas offer higher wages, but many of the workers who can command those wages are probably already there, while others (who are not) experience large non-monetary disutility from moving. Therefore, regarding productivity misallocation, our interpretation is closer to that of Lagakos and Waugh (2013), Young (2013) and Herrendorf and Schoellman (2016), who posit that existing allocations are close to efficient.[12]

The more notable insight from our model and the experimental data is that there is a very different form of misallocation present, which the existing macroeconomics literature has not considered. Specifically, extremely poor households can gain a lot by relocating temporarily to urban areas during the periods after they have faced bad shocks and depleted their assets. Policy (such as subsidies for migration) can play a role in improving welfare precisely under such conditions, when moving costs pose a big hurdle for poor households. While such migration encouragement may be good development policy, it is not necessarily good growth policy. This is because the extent of productivity misallocation is low even if the welfare gains are large.

[12]One difference is that these studies focus exclusively on selection, whereas our model, combined with the experiment, highlight that *both* selection and migration disutility play a role in explaining the patterns in the data.

5.3. Alternative Rural-Based Policies

Our analysis suggests that the migration encouragement program should be judged on its contribution to the welfare of the extreme poor, who need insurance, instead of on its contribution to productivity growth. It is therefore useful to compare the welfare generated from migration subsidies to other methods that policy makers often use to address rural poverty. Unconditional cash transfers (UCTs) are one such policy tool, and we have already shown that migration transfers are better at targeting the poor and needy compared to UCTs. Another common place-based policy utilized in developing countries are rural "workfare" programs that provide employment guarantees in rural areas. For example, India's enormous NREGA program provides funding for rural workers to work in public projects in rural areas. These policies are explicitly tied to rural areas, and, thus, discourage rural-urban migration (Imbert and Papp, 2016).

The only fully experimental RCT-based evaluation of a rural workfare program finds no significant benefits and even negative spillovers on non-beneficiaries (see Beegle, Galasso, and Goldberg (2017) for Malawi). In contrast, Imbert and Papp (2015) report some positive benefits from India's program. Thus, we simulate the effects of a rural workfare program in our model as transfers to rural households conditional on those workers remaining in the rural area for that period. The goal is to capture the general spirit of rural workfare programs without tying our exercise to particular policy details in specific countries. To conduct a budget-neutral comparison with the migration subsidy, we set the total expenditure on workfare transfers to be equal to the conditional migration subsidies.

Table 8 compares the welfare gains from rural workfare and migration subsidies. Overall, the rural workfare programs result in lower welfare gains relative to the conditional migration transfers, because they distort household decisions away from accessing the more productive urban labor markets. This is evident in migration rates: 56 percent of households send a migrant with the transport subsidy, while only 25.5 percent migrate under rural workfare. The welfare gap is particularly stark for the poorest quintile of the income distribution, who gain 1.01 percent of lifetime consumption from the migration transfers and 0.59 percent from the rural workfare programs.

6. Model Validation: Empirical Evidence on the Source of Migration Disutility

Our model infers that many rural residents experience significant non-monetary disutility from migration, and this plays an important role in our interpretations. This is also crucial for our welfare calculations, in that some of the large consumption gains from migration are

Table 8: **Migration Transfers vs Rural Workfare Policy**

		Migration Transfers		Rural Workfare	
		Welfare	Migr. Rate	Welfare	Migr. Rate
Income Quintile	1	1.01	85.8	0.59	29.2
	2	0.35	59.1	0.35	24.3
	3	0.21	48.8	0.26	24.3
	4	0.13	40.9	0.20	26.2
	5	0.07	35.8	0.15	23.2
Average		0.35	56.0	0.31	25.5

Note: The table reports the (lifetime) consumption-equivalent welfare gains from the conditional migration transfers relative to an unconditional transfer program costing the same total amount. The numbers in the table are the average percent increase in consumption each period that would make the households indifferent between the consumption increase and the transfers.

offset by this disutility. Therefore, we explore whether the large disutility is plausible, and what the source of that disutility might be. To do so, we collect new survey data from Bryan, Chowdhury, and Mobarak's (2014) experimental sample of migrants on their preferences for specific migration attributes. This allows us to characterize exactly what this disutility may represent, for the exact same sample of households that we used to calibrate our model.

6.1. Discrete-Choice Experiments using Hypothetical Migration Choices

Conducting field experiments that vary a number of non-monetary attributes of the migration experience (such as quality of living conditions, wages, risk, family separation) would be practically challenging and prohibitively expensive, so our approach in this section is to conduct discrete-choice experiments (DCE) on the migrant sample. The DCE presented respondents with a series of hypothetical scenarios in which we randomly varied a few key attributes associated with one of two migration options. The surveys presented respondents with (hypothetical) options for the fall 2015 lean season and asked them to indicate which migration choice they would make. The attributes we presented under each option randomly varied the probability of finding employment in the city, the wage if employed, how

frequently the migrant could return to visit family (to minimize separation), and access to a hygienic latrine in their residence at the migration destination, which is a useful proxy for the quality of housing amenities that the migrant would experience in the city.

It would have been impossible to vary all of these attributes in a controlled manner in a field experiment. DCEs are frequently used in marketing to estimate the effect of specific attributes on the attractiveness of a product to consumers; in environmental economics (and in environmental policy making) to infer the value of environmental goods and services for which market transaction data do not exist (Hanemann, 1994); in health economics to understand service provider and patient preferences; and, most relevant to our setting, in migration research to understand the determinants of mobility (Batista and McKenzie, 2017). There is a reasonable concern that, in DCEs, people's responses to hypothetical questions may not accurately reflect their real-world behavior. They may, for example, express an interest in migrating in response to a hypothetical question, even though they may be more hesitant if the actual choice ever presented itself. We are therefore careful not to make any inferences about people's overall migration propensity using this exercise. Instead, in analyzing people's responses to the hypothetical scenarios, we infer the *relative weights* people place on quality of living conditions relative to wages or concerns about family separation.

In the Appendix, Figure A.1 presents one example of the choices we presented to the respondents. Each respondent was asked to choose one of two migration options or a third, "opt-out" no-migration option.[13] The experimental setup for the hypothetical options was created to mimic the circumstances under which the equivalent decision would be made in the real world (Ryan and Skatun, 2004). In the example shown in Figure A.1, both options feature a 33 percent chance of employment. Choice #1 offers a lower wage if employed but better amenities (more regular family contact and a hygienic latrine in the residence) compared to Choice #2.

We conducted these DCEs on a sample of 2,714 respondents, presenting each respondent with seven different choice sets for which the values of attributes are varied. We used the Choice Experiment tools in JMP12 (built on SAS) to generate algorithms that pick values for the attributes under each migration option in each choice problem in such a way that the power of the experiment is maximized. We observed a total of 18,998 choices, but to eliminate any bias stemming from recent induced migration experience, we used only choices made by respondents who resided in the control villages in the Bryan, Chowdhury, and Mobarak (2014) migration subsidy experiment. We estimated a multinomial logit model of migration choice as a function of the offered attributes of each location, using the remaining

[13]The methodological literature on DCEs strongly recommends that an opt-out option consistent with the decision at hand is always provided (Lancsar and Louviere, 2008).

Table 9: Estimated Marginal Effects on Migration

	Migration Opp. #1		Migration Opp. #2		No Migration	
	PP	ME	PP	ME	PP	ME
33% Prob. Employment	0.116***	0.000	0.597***	0.000	0.286***	0.000
	(0.018)	(.)	(0.053)	(.)	(0.055)	(.)
66% Prob. Employment	0.067***	-0.049***	0.732***	0.135***	0.200***	-0.086***
	(0.012)	(0.010)	(0.046)	(0.030)	(0.045)	(0.029)
100% Prob. Employment	0.048***	-0.068***	0.791***	0.193***	0.161***	-0.125***
	(0.009)	(0.012)	(0.040)	(0.033)	(0.038)	(0.033)
Family visit once in 60 days	0.071***	0.000	0.760***	0.000	0.169***	0.000
	(0.014)	(.)	(0.041)	(.)	(0.040)	(.)
Family visit twice in 60 days	0.067***	-0.004	0.732***	-0.027	0.200***	0.032
	(0.012)	(0.008)	(0.046)	(0.024)	(0.045)	(0.023)
Family visit 4 times in 60 days	0.058***	-0.013*	0.763***	0.003	0.179***	0.010
	(0.012)	(0.007)	(0.049)	(0.028)	(0.046)	(0.028)
No Latrine in residence	0.067***	0.000	0.732***	0.000	0.200***	0.000
	(0.012)	(.)	(0.046)	(.)	(0.045)	(.)
Pucca Latrine in residence	0.029***	-0.038***	0.906***	0.174***	0.065***	-0.136***
	(0.006)	(0.008)	(0.021)	(0.032)	(0.019)	(0.032)
Daily Wage (Taka), Opp #2		-0.001***		0.004***		-0.002***
		(0.000)		(0.000)		(0.000)
Observations	3449	3449	3449	3449	3449	3449

Note: Standard errors are adjusted for 2,566 clusters in hhid. PP columns represent predicted probabilities of migrating at given condition, and ME columns represent marginal effects of changing migration conditions in each category. PP and ME are measured while fixing 1st migration conditions (wage, employment chance, family visit, latrine) at the worst, and fixing 2nd migration condition at the median. Analysis sample includes only those households in the control group.

3,349 observations.

Table 9 presents the predicted probabilities and estimated marginal effects from this multinomial logit regression. We report the marginal effects of improving each attribute associated with option #2.[14] The middle two data columns of Table 9 show the predicted probabilities (PP) and marginal effects (ME) on the propensity to migrate to destination #2. The first and last two data columns show the PP and ME on destination #1 and "No Migration" when the characteristics of destination #2 are varied.

The four attributes for each destination that we specified in our surveys are as follows:

1. The probability of employment, with three possible values that were randomly varied across the choice scenarios: 33%, 66% and 100%.

2. The daily wage, which could take one of five possible values: 200, 235, 270, 305 and 340 taka per day.

3. Living conditions in the city, which had two categories: either a *pucca* (hygienic) latrine in the residence, or no latrine. This is a context-relevant proxy for the overall quality of housing.

4. The extent of family separation, which had three possible categories: the ability to go back and visit family once, twice or four times during the seasonal migration period.

The daily wage is modeled as a continuous variable in the multinomial logit, while the other attributes are modeled as categorical variables.

Table 9 shows that an increase in employment probability at destination 2 from 33 percent to 66 percent or 100 percent (holding destination #1 characteristics fixed) increases the propensity to migrate to destination #2 by by 13.5 and 19.3 percentage points. Unemployment risk is, therefore, a quantitatively important deterrent to migration. The next three rows show that the frequency of family visits has a negligible (and statistically insignificant) effect on migration choices.

In stark contrast, having a latrine in one's residence increases the probability of choosing destination #2 by 17.4 percentage points. Housing conditions at the destination therefore appear to be an important determinant of migration choices. Finally, the probability of migrating to destination #2 increases by 0.4 percentage points for every additional Taka in daily wage

[14] We set all attributes associated with option #1 at their least attractive values, and those associated with option #2 at median values. The rationale for this is to effectively create only two relevant choices for the potential migrant: either migrate to destination 2, or stay at home. This binary choice most closely resembles the decisions made by agents in our model. Recall that we model a binary migration choice.

that is offered. In other words, the migration probability jumps by 20 percentage points if the destination offers an extra 50 Taka in daily income. Thus, having a better housing option is similar to an additional 44 Taka per day in wages. Fourty-four Taka represents a 22 percent increase over the base value of 200 Taka per day that we used in our hypothetical DCE scenarios, and it corresponds to roughly the average wages earned by migrants in the city. In other words, migrants appear to care a lot about the quality of housing conditions in the city, when they decide whether to travel. To the extent that rural-urban migrants generally face poor urban housing options (proxied by a lack of access to convenient latrines, which is a realistic worry in the slums of South Asian cities), this represents a large non-monetary cost of migration and a substantial offsetting force to the higher wages earned by migrants. The large migration disutility that our model infers from people's actual migration and re-migration behavior does appear to be validated in the DCEs when these (potential) migrants are asked to explicitly consider the non-monetary dimensions of the migration experience.

The contrast between the weight that potential migrants place on urban housing conditions versus their relative inattention to the length of family separation is notable. For short-run seasonal migration, frequency of family visits appears less important than housing quality. What makes this contrast interesting from a policy perspective is that concerns about housing conditions can be more easily addressed through policy compared to concerns about family separation. The large welfare gains for the poor and the disutility parameter that we estimate from our model, coupled with these DCE results suggest that governments may want to improve urban slum housing conditions, as a way to raise the welfare gains from migration to cities.[15] In contrast, if family separation were the main source of welfare loss, that would be a more "intrinsic" characteristic of the migration experience that is not easy to affect through policy, and it would suggest that the welfare gains from encouraging migration would always remain small.

7. Conclusions and Future Work

This paper studies the welfare implications of subsidizing rural-urban migration in low-income countries. Cross-sectional data show that wages are much higher in urban areas than in rural areas in many low-income countries. It is tempting to conclude that these wage gaps signal some sort of worker misallocation across space (due to, say, credit constraints), and that there would be substantial productivity gains from reallocation. However, our welfare analysis, using a combination of cross-sectional data, randomized-controlled-trial based experimental data, and a dynamic model of migration, suggests that this is not the correct

[15]This is further underlined in our counterfactual simulation in which we surprise migrants with a removal of $\bar{u}$ in the city, and the welfare gains look much larger.

interpretation.

Instead, our model indicates - and our data confirm - that people who are induced to migrate by such subsidies tend to be negatively selected on income and productivity, because those who would be highly productive are likely already living in cities. Our model also suggests that people face large non-monetary disutility costs of moving, and thus, migration subsidies benefit mostly the extreme poor who have experienced recent bad shocks and become desperate to travel because their marginal utility of consumption is very high. The travel cost acts as a constraint under such conditions, and migration subsidies help alleviate that. We are able to validate these model inferences by studying the heterogeneity of who is induced to migrate in the experiment (moments that the model were *not* targeted to), and by analyzing migrant preferences over non-monetary attributes of the travel experience by conducting a new set of discrete choice experiments over hypothetical migration options.

We find that for the poorest households, the welfare gains from migration subsidies are higher than unconditional cash transfers or a rural workfare program costing the same total amount. This suggests that conditional migration transfers may be a useful way to raise the welfare of poor rural households in the developing world. Our study does not, however, point to a low-cost path to large productivity gains from better allocating workers across rural and urban areas, at least in Bangladesh. Specifics from the discrete choice experiment data teach us that investments in urban housing infrastructure may be an important input to generating large welfare gains from migration. Future research should explore the consequences of encouraging migration over space in other countries and settings, as well as the interactions between urban infrastructure and the welfare gains from migration.

Our paper departs from the previous macroeconomics literature in how we discipline our model quantitatively, and in particular, how we replicate a randomized controlled trial within the model. Our method of combining a dynamic incomplete-markets macro model with experimental data can be used more broadly to study other macroeconomic phenomena, such as savings behavior, labor market search activity or investment in new technologies, which have been the focus of recent randomized experiments.

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Table A.1: Calibration Results under Alternative Parameter Restrictions

	Specification:		(i)	(ii)	(iii)	(iv)
Moments	Data	Baseline	$\theta = \infty$	$\bar{u} = 1$	$\lambda = 0$	$\gamma = 1$
Migration, Control	36	36	48	29	37	
Migration, Treatment - Control	22	22	31	10	16	
Migration, Treatment - Control, year two	9	6	0	0	0	
Consumption, OLS	10	10	51	2	10	
Consumption, LATE	30	30	20	6	30	
Urban-Rural wage gap	1.80	1.80	1.80	1.80	1.80	
Percent in rural	63	63	57	89	92	

Note: The table reports the results of the calibration in the benchmark case and in several alternative parameter restrictions. The first two data columns report the values in the data and in the benchmark model. The third, $\theta = \infty$, shuts off heterogeneity in permanent worker ability, z. The fourth, $\bar{u} = 1$, shuts of disutility of migration. The fifth, $\lambda = 1$, eliminates the possibility of gaining experience through migrating. The sixth, $\gamma = 1$, shuts off differential risk in the urban and rural areas.

Appendix (for Online Publication)

A. Alternative Sensitivity Analysis

In this section, we consider an alternative sensitivity analysis to illustrate how the parameters are identified using the moments we target. In particular, we re-calibrate the model repeatedly each time restricting one parameter so as to shut off one particular channel, such as disutility of migration or differential risk between the two regions. Table A.1 presents the target moments in the data and in the benchmark calibration, as well as the best fit of the targeted moments under four alternative calibrations. These are (from column 4 to column 7) (i) when taking a limit as $\theta = \infty$, so that worker heterogeneity is shut down, (ii) when setting $\overline{u} = 1$, so that there is no disutility of migration, (iii) when setting $\lambda = 1$ so that workers never become experienced, and (iv) when $\gamma = 1$, so that there is no differential risk between the urban and rural areas. We discuss each calibration in turn.

When worker heterogeneity is shut down, the model does much worse on the baseline seasonal migration rate (48 percent versus 36 percent in the data) and experimental migration

rate. The OLS coefficient of migration on consumption is way off (51 percent versus 10 percent in the data). Intuitively, this means that the "marginal households" are hard to get right without worker heterogeneity. The parameter θ helps the model get the right number of households near the margin. The migration rate in the control group, and the experimental migration rate, therefore are informative about the model's value of θ.

When migration disutility is shut down, the consumption gain for induced migrants is far too low (6 percent in the model versus 30 percent in the data). Similarly, the OLS coefficient of migration on consumption is too low (2 percent versus 10 percent in the data). This highlights how it is hard to match such large increases in consumption for induced migrants without disutility of migration in the model. Put differently, if there is no disutility of migration, it is hard to reconcile why workers require incentives to migrate and raise their consumption by 30 percent. In terms of identification, this means that the LATE of migration on consumption is informative about the model's value of $\overline{u}$.

When the effect of experience on migration disutility is shut down, the model's repeat migration rate is off (0 percent versus 9 percent in the data). Households in the model simply will not repeat migrate after being incentivized in the previous period, since the cost of migration is the same in the second period, but the incentives have been removed. The parameter λ is therefore necessary to get this repeat migration rate correct, and the repeat migration is the main moment in the data that informs the calibrated model's value of λ.

Finally, when differential risk is shut down, i.e. $\gamma = 1$, the OLS coefficient of migration on consumption is too high (20 percent versus 10 percent in the data). In the data, the experimental effect of migration on consumption is much higher than the OLS coefficient on migration from a regression of consumption on migration. This is consistent with the set of workers who migrate without incentives being negatively selected on income. When $\gamma = 1$, there is not enough negative selection in the model relative to the data. Thus, the model requires a lower γ coefficient to match the data. Put differently, the γ term is informative about the extent to which rural-urban migrants are positively or negatively selected on income relative to all workers in the rural area.

S.1.C.2			
Given the attributes below, which option do you choose? Please evaluate each new pair of migration options independent of the ones you saw earlier.			
	Choice #1: Migration	**Choice #2: Migration**	**Choice #3: No Migration**
Chance of Employment	33%	33%	N/A
Daily Wage (Taka)	270	340	Wage at Home in November
Latrine Facility during Migration	Pucca Latrine in Residence	Walk to Open Defecate or Public Pay Toilet	N/A
Family Contact	See Family Every Month	See Family Every 2 Month	N/A
s16bq2_1 Your Choice *(Tick Single Box)*	☐	☐	☐

Figure A.1: Sample Migration Opportunity

Table A.2: Urban-Rural Wage Gaps in Bangladesh

	Mean	Median
All urban / All rural	1.80	1.72
All urban / Rangpur rural	2.12	1.87
Dhaka / Rangpur rural	2.20	2.01

Note: The table reports the ratio of average wages in urban to rural areas in Bangladesh in 2010 with alternate subsets of rural and urban areas. In all rows, wages are calculated as monthly labor earnings divided by hours worked. The sample is restricted to workers with positive wage earnings that are at least 15 years old and who worked at least six months in the last year. The wages are computed using the 2010 HIES of Bangladesh.