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Reshaping Economic Geography



BACKGROUND PAPER

**MOVING TO OPPORTUNITY:
SUCCESSFUL INTEGRATION OR BRIGHT
LIGHTS?**

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Moving to Opportunity: Successful Integration or Bright Lights?¹

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Abstract

Economists have long argued that migration decisions are motivated by the possibility of earning higher wages. But since many migrants don't find jobs after moving, is this attraction irrational? In this paper, using census data from Brazil, we empirically examine the causes and consequences of internal migration. We find that many poor/ uneducated people are pushed to migrate as they do not get access to basic services such as health care and clean water in their hometowns, and these migrants have lower chances of assimilating into destination labor markets. Policies that improve human capital and social services in lagging regions are likely to be useful for individual migrants.

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1. Background and Motivation

By moving to places that offer economic opportunities, people living in remote and lagging regions of countries can improve their employment opportunities. This is the fundamental idea of the Harris-Todaro model. Economically dynamic areas offer better prospects for jobs and higher wages. In many countries, migration from lagging to leading regions and from rural to urban areas has been an integral part of the development process. For example, migration from rural areas accounted for at least half of all urban growth in Africa during the 1960s and 1970s, and about 25% of urban growth in the 1980s and 1990s. (Brockerhoff, 1995) At the peak of Brazil's urbanization process between the 1950s and the 1970s, it is estimated that over 20 million people moved from rural to urban areas.

But in many countries, the pace of internal migration has outstripped the capacity of receiving regions to supply housing and public services. Further, many migrants find their skills are not suited for the jobs being offered in places where they now live. The result often has been large scale and visible slum formation and informal employment, suggesting that many migrants may have made irrational decisions when they decided to move. In light of this evidence, policymakers conclude that rather than adding to the economy in their new neighborhoods, migrants subtract from them by worsening problems of livability. This belief has often resulted in deterrent policies, ranging from migration disincentives to draconian regulations that limit the movement of people.

But are migration restriction policies justified? And are they efficient in terms of enhancing urban productivity? To answer these questions, there is need to identify why migrants decided to move in the first place. Was it to seek better economic opportunities or was it that living conditions in their hometowns or villages were so bad that they left in order to seek access to those public services elsewhere? In many developing countries, basic public services such as schools and primary health facilities are concentrated in places where economic activity is concentrated (World Bank, 2008). Thus, many people may move to seek better public services, not just employment opportunities. Distinguishing between these two motivations for migration is a primary goal of this paper.

The 2009b World Development Report “Reshaping Economic Geography” (World Bank 2008) uses household survey data to provide evidence that public service differentials do indeed induce migration. In Bolivia, 13.3 % of migrants reported to have moved to access better schools. In Romania, it was 10%. In Paraguay and Guatemala, over 15% of migrants moved due to poor living conditions. In Bulgaria, 15% of migrants sought better schools and 13% wanted better living conditions. So while market forces drive the concentration of economic activities, public services have not always been adequately provided in areas bypassed by the market. This disparity induces migration in order to obtain public services, not necessarily in search of economic opportunity. The result is that migration may actually reduce productivity in the urban areas (i.e., many migrants drawn by urban amenities will not have good employment matches). In these cases, policies focused on improving rural public services (rather than restricting newcomers) would result in more of the people who choose to migrate doing so for

reasons of economic opportunity (i.e., high paying jobs). This could have beneficial spillover effects (i.e., adding to agglomeration economies in leading areas), while simultaneously easing pressure on local governments to accommodate large numbers of migrants.

To base these debates and policy choices on empirical evidence, we first examine the determinants of migration and then assess whether there are particular groups of migrants who are less successful in assimilating into urban labor markets? Specifically, we examine the following two questions:

1. *What factors influence individuals' migration decisions?* We examine the factors that most influence individuals' migration decisions and the role that particular amenities (e.g., access to health and education services, urban infrastructure) play in each group's migration decisions.
2. *Are specific groups of migrants (defined according to socio-demographic attributes or origin location) less able to successfully assimilate into their destination labor market?* In particular, we assess the labor market consequences of migration by examining the extent to which good observed labor market outcomes of migrants are simply a result of selection bias (as opposed to reflecting true economic opportunities for an average individual)?

In measuring assimilation, we look at the *ex ante* distributions of wages from which migrants draw, compared to the *ex ante* distributions from which the native population of the urban area draw. Importantly, these distributions may be very different from the *ex post* observed distributions of wages that individuals actually receive. The latter are conditional upon individuals having made optimal migration decisions with respect to those wage draws. This sorting process has the potential to seriously distort our impressions of labor market opportunities.

In addressing these questions, we make progress on two methodological fronts. First, we show how to use repeated cross-sectional data to control for time-invariant unobserved local attributes in a utility-based model of individual migration decisions. Even the best data set will necessarily lack information about important amenities, local public goods, and geo-economic features that might motivate migration behavior. If these unobserved factors are correlated with migration determinants about which we do have information (e.g., access to piped water, sewage, electricity, or healthcare), they can bias our conclusions about the role those observed determinants play in the migration decision. Following Bayer, Keohane and Timmins (2007), we incorporate repeat cross-sectional data on migration behavior into a two-stage discrete choice model that allows us to easily overcome many of these biases, with important implications for our conclusions regarding many of these factors.

Second, we demonstrate a new empirical approach for recovering the *ex ante* wage distributions from which individuals received draws when making their migration decisions. This builds upon early work in the modeling of occupational choice. (Roy,

1951; Heckman and Honore, 1991). Our contribution to that literature is to add explicit controls for the influence of non-pecuniary factors (i.e., amenities and local public goods) which are likely to be important to migration decisions. Migration behavior is not random – individuals move in response to both economic opportunities and amenities/local public goods. This means that observed migration outcomes (including *ex post* wage distributions) are the result of a complicated non-random selection process. Given the high dimensionality of the choice set available to migrants, this presents a formidable econometric problem.

Bayer, Khan, and Timmins (2008) illustrate how this problem can be corrected, and we apply their techniques here. Using those techniques, we are able to recover the *ex ante* distributions from which potential migrants draw wages, along with a non-parametric measure of the utility garnered from non-pecuniary factors. We first show that the *ex ante* wage distributions look significantly different from the *ex post* distributions that we observe. This is important, as these are the wage distributions from which a new migrant would draw if he were induced to migrate by some government policy.

We show in particular that one will overstate that migrant's labor market opportunities if the non-random sorting process is ignored. We then use these *ex ante* distributions to demonstrate that migrants are typically at a labor market disadvantage relative to conditionally similar non-migrants – evidence of a failure to assimilate. This problem is particularly acute for the least educated in the most attractive urban destinations. This suggests policies that improve human capital at origin are likely to be

useful, as they would give migrants not only a greater endowment but a wider set of opportunities at their destination.

Our empirical application is based on an analysis of census data from Brazil. For this country, we have been able to access representative samples of households down to the second level of sub-national administration (e.g., counties in the United States). These data record migration history over a short-term horizon (e.g., 5 years) and relative to birth location.² Our analysis of Brazilian census data confirms our hypothesis on the importance of public service differentials in influencing long-run migration decisions. In particular, we find that working-age men migrated from the lagging Northeast region not only to look for better jobs, but also to get better access to basic public services such as piped water, electricity and health care. For the poorest migrants, differences in access to basic public services mattered in ‘making the move’, and poor migrants are in fact willing to accept lower wages to get access to better services. A full-time minimum wage worker earning Rs\$7 per hour (about US\$2.3 in February 2008) was willing to pay Rs\$390 per year in compensating wage differentials to have access to better health services, Rs\$84 for better access to sewage services, and Rs\$42 for better access to electricity.

The paper proceeds as follows. In Section 2, we use a simple model of location choice that depends upon both earning opportunities and local public goods to illustrate that the latter matter in individual migration decisions. In Section 3, we develop an

² We focus on the latter, where missing observations are less of a concern. Our methodology is, however, applicable to migration behavior defined relative to any time horizon.

econometric framework, based on the model described in Bayer, Khan, and Timmins (2008), which shows how to recover the *ex ante* distributions from which migrants actually received wage draws when deciding to move while controlling for the distortions resulting from Roy sorting (i.e., sorting based on idiosyncratic labor market returns). Given the realities of the migration decision, this sort of bias is likely to be important. Section 4 describes the results of that model, while Section 5 concludes.

2. Modeling the Determinants of Migration

We first present a simple model that is geared towards the recovery of the value placed on specific local public goods and amenities by potential migrants. This approach ignores the issue of non-random selection, which we take-up in Section 3. The model presented there explicitly controls for local public goods and amenities, but does so non-parametrically, making it difficult to learn about the value of one in particular (such as access to electricity).

2.1 Model

We begin by defining the individual indirect utility function of a potential migrant. As in traditional migration models, we assume that individuals receive utility from wage compensation while trying to avoid higher migration costs. (Falaris, 1987) In addition, we assume that individuals enjoy local public goods/amenities such as access to piped water and electricity. Consider an individual i from origin location j . We can write his utility, should he choose to reside in location k , as:

$$(1) \quad \tilde{U}_{i,j,k} = \tilde{\beta} w_{i,j,k} - \tilde{\delta} \ln(D_{j,k} + 0.01) + X'_k \tilde{\gamma} + \tilde{\xi}_k + \tilde{\eta}_{i,j,k}$$

where

- $w_{i,j,k}$ = log wage earned by individual i in location k
- $D_{j,k}$ = migration distance (in km from origin j to location k)
- X_k = observable (by the econometrician) attributes of location k
- $\tilde{\xi}_k$ = unobservable (by the econometrician) attributes of location k
- $\tilde{\eta}_{i,j,k}$ = idiosyncratic unobservable (by the econometrician) determinants of individual i 's utility in location k

For the purpose of easy interpretation, we re-scale equation (2) so that the marginal utility of the natural log of wage is normalized to be one. We remove the “~” from each parameter to reflect this re-scaling.

$$(2) \quad U_{i,j,k} = w_{i,j,k} - \delta \ln(D_{j,k} + 0.01) + X'_k \gamma + \xi_k + \eta_{i,j,k}$$

We can now interpret estimates of γ as the marginal willingness-to-pay (as a percentage of wage) for a one-unit increase in any of the attributes in X_k .

This model makes a few simplifying assumptions. First, the migration cost is simply related to the migration distance. This is typical of previous analyses, but the model could be extended to treat migration cost as a function of the difference between origin and destination attributes. Second, we do not model the individual's labor market participation decision (i.e., the individual's choice of working hours). Moreover, we also ignore the possibility of involuntary unemployment, but plan to account for this

possibility in future work by including unemployment rates in X_k .³ This is in line with the Harris-Todaro model's emphasis on expected labor market returns.

Suppose there are K locations and individual i can choose one of them as his destination. He will then choose the utility maximizing location. If we assume that $\eta_{i,j,k} \sim i.i.d. \text{ Type I Extreme Value}$, the probability that individual i chooses a particular location k as his destination can be written as:

$$(3) \quad P(U_{i,j,k} \geq U_{i,j,l} \quad \forall \quad l \neq k) = \frac{\exp(\mu(w_{i,j,k} - \delta \log(D_{j,k} + 0.01) + X'_k \gamma + \xi_k))}{\sum_{l=1}^K \exp(\mu(w_{i,j,l} - \delta \log(D_{j,l} + 0.01) + X'_l \gamma + \xi_l))}$$

Since the marginal utility of log wage has been rescaled to be one, the model dictates that we explicitly estimate the logit scale parameter, μ . Let N denote the total population. We would like to maximize the probability associated with the chosen destination of each individual (k_i^*). This implies the following log-likelihood function, where $I(k = k_i^*)$ is an indicator function that takes the value 1 if individual i chooses location k_i^* :

$$(4) \quad \ell = \sum_{i=1}^N \sum_{k=1}^K \ln[P(U_{i,j,k} \geq U_{i,j,l} \quad \forall \quad l \neq k)] * I(k = k_i^*)$$

Using equation (3), the model predicts that the population of location k would be:

³ One could also make the distinction between formal and informal employment

$$(5) \quad p\hat{op}_k = \sum_{i=1}^N P(U_{i,j,k} \geq U_{i,j,l} \quad \forall l \neq k)$$

which, in equilibrium, should be equal to the observed population of location k (pop_k).

This applies to all K locations. That is, in equilibrium:

$$(6) \quad p\hat{op}_k = pop_k, \quad \forall k = 1, \dots, K$$

We use this information in order to employ the two-stage estimation procedure in Bayer and Timmins (2007). In the first stage, we define the “mean utility” (i.e., separate from idiosyncratic components) enjoyed by all migrants who choose location k :

$$(7) \quad \theta_k = X_k' \gamma + \xi_k$$

and obtain estimates of μ , δ and $\{\theta_k\}_{k=1}^K$. Bayer and Timmins (2007) show how, based on equation (6), the contraction mapping formulated in Berry, Levinson, and Pakes (1995) and Berry (1994) can be used to simply calculate the vector $\{\hat{\theta}_k\}_{k=1}^K$ for any guess at remaining utility parameters $[\mu, \delta]$ and an arbitrary normalization (e.g., the average value of $\hat{\theta}_k$ is set equal to zero). We can then estimate our parameters $[\mu, \delta, \{\theta_k\}_{k=1}^K]$ with a maximum likelihood procedure using the log likelihood function (4).

In the second stage, we decompose the estimates $\{\hat{\theta}_k\}_{k=1}^K$ from the first stage according to equation (7). This would yield a vector containing the individual’s marginal willingness-to-pay (as a percentage of the wage) for each element of the vector X_k .

Since ξ_k and X_k are likely correlated with each other (e.g., cities with desirable public goods may be “high quality” in other unobserved dimensions), the simple OLS estimator of γ will be biased. Ideally, one might use an instrument for each endogenous component of X_k . Given the number of potentially endogenous local attributes that might be important to the individual’s migration decision, however, this solution is not practical. Instead, we deal with this problem by assuming that any correlation between X_k and ξ_k is only with components of X that do not vary over time (i.e., ς_k).

$$(8) \quad \theta_{k,t} = X'_{k,t} \gamma + \underbrace{\varsigma_k + \nu_{k,t}}_{\xi_{k,t}}$$

Assuming $E[\Delta X_k \Delta \nu_k] = 0$, differencing this expression over time will remove any source of bias. While it is unlikely that this assumption holds perfectly, in practice it is a far better option than simply ignoring the role of correlated unobserved local attributes, and it will likely eliminate of much of any potential endogeneity bias.

Practically, we expand the first-stage of the model to include data from two census years, restricting the parameters $[\mu, \delta]$ to remain fixed over that time-period. We then solve for two vectors, $\{\hat{\theta}_{k,1}\}_{k=1}^K$ and $\{\hat{\theta}_{k,2}\}_{k=1}^K$ using an extension of the Berry, Levinson, and Pakes (1995) contraction procedure. Finally, the unbiased estimates of γ can be obtained by estimating:

$$(9) \quad \Delta \hat{\theta}_k = \Delta X'_k \gamma + \Delta \nu_k$$

where

$$(10) \quad \begin{aligned} \Delta \hat{\theta}_k &= \hat{\theta}_{k,2} - \hat{\theta}_{k,1} \\ \Delta X_k &= X_{k,2} - X_{k,1} \\ \Delta \nu_k &= \nu_{k,2} - \nu_{k,1} \end{aligned}$$

2.2 Data

The 1991 and 2000 Brazil censuses provide information on current residence and birth state for most individuals. Therefore, we define migration by an individual's current location relative to his birth state. That is, we use a long-run measure of migration. One could also employ a short-run definition of migration – i.e., relative to where the individual was living 1, 2, or 5 years before, if necessary data are available. We use 3659 AMC's (i.e. minimally comparable areas) as destination locations and 27 states as origin locations. AMCs are similar to counties but are aggregated in some cases to make them comparable over time.

For each census year, we focus our attention on household heads who were between the ages of 25 and 35 years. In this way, we are assured that no household heads can show up in both the 1991 and 2000 samples. Moreover, by using individuals from this cohort, we focus our attention on first migration decisions – i.e., those made after an individual initially finishes school and/or leaves his parent's home. This move may be accompanied by marriage, the birth of a child, etc. Our goal is to avoid mixing these individuals with older individuals who may be making location decisions based on retirement considerations, or who may have made location decisions many years in the

past. Finally, we also control for individual attributes, since amenities and employment opportunities are likely to have different effects on migration behavior for different types of individuals. Given that age has already been restricted to be between 25 and 35 years, we further divide those household heads according to their education level. Household heads with post-secondary education are excluded from the analysis.

The Brazil censuses also contain information on employment and income. Recall that our current model ignores the possibility that the individual would be unable to find work. We therefore keep only those household heads who were employed. Thus, for each household head in our sample, we can observe his wage in the destination location where he actually resides. However, in order to model his destination location decision, we need to know what he would earn in every other location. Properly recovering these counterfactual wages can be quite difficult. In this part of the paper, we adopt the relatively simple approach of using the average wage earned by conditionally similar individuals in those other locations.⁴ Practically, this means that we run a separate log wage regression for each AMC:

$$(11) \quad w_{i,j,k} = \mathbf{Z}'_i \alpha_k + v_{i,j,k}$$

where \mathbf{Z}_i is a vector of variables describing individual i , including age, sex, education level and occupation dummy variables and α_k is a set of wage parameters for location k .

⁴ Section 3 relaxes this assumption, paying particular attention to the biases introduced by individuals sorting based on idiosyncratic labor market returns.

We model moving costs as a function of migration distance, which is calculated from the longitude and latitude of the center of the individual's birth state and destination AMC. Except for a log-linear function of migration distance, we may also specify moving costs using a set of distance dummies.

Our primary interest is in the role played by local public goods in the migration decision. We focus on variables describing (1) local infrastructure (i.e., % households with access to piped water, sewerage, and electric lights), (2) access to healthcare (i.e., number of hospitals), and (3) network infrastructure (i.e., transportation costs to the state capital and Sao Paulo). Any list of local attributes would, however, necessarily be incomplete. As described above, we use census data from two years to control non-parametrically for all local attributes that do not vary over time.

2.3 Results

We find strong evidence that individuals' migration decisions depend upon more than just returns in the labor market. Ignoring these non-pecuniary determinants may cause us to overstate the role of wages in driving migration decisions. This can be seen in Tables 2 and 3, which describe the results of the procedure described in Section 2.2 for those with less (i.e., 0-6 years) and more (i.e., 7-12 years) education. Columns 2-5 of each table describe the results of cross-sectional procedures applied to each census year individually and ignoring moving costs. The likely effects of omitted variable bias are evident in the estimates of the utility parameters on access to piped water and number of hospitals. It is likely that each of these variables (particularly the number of hospitals in

an AMC) are correlated with other desirable urban amenities. This has the effect of biasing upward the coefficient on each of these variables for both education groups. Access to electricity has a counterintuitive sign or is insignificant. While access to sewage shows the expected sign for those in the lower education group, it exhibits the counterintuitive sign (although it is insignificant) for the higher education group in 1991. In all, these results appear to be unstable over time and likely reflect omitted variable biases caused by unobserved urban amenities.

Columns 6-7 report the results of a differencing procedure that ignores the costs of migration. While controlling non-parametrically for time-invariant unobservable local attributes, this specification ignores the fact that it may be difficult, for example, for someone born in the Northeast to migrate to locations in the Southeast or South of Brazil. The signs of most of the coefficients correspond to expectations; very few of the parameter estimates are, however, statistically significant (only access to electricity and the number of hospitals for those in the lower education group, and the number of hospitals for those in the higher education group are significant). For both groups, an increasing cost of transporting commodities to Sao Paulo (a measure of national market connectedness) enters negatively into utility, while the cost of transporting commodities to the nearest state capital (a measure of local market connectedness) enters positively. This latter result is counterintuitive.

Columns 8-9 report the results of our most complete model. Here, we difference over time and control for migration costs. Doing so, we find that % Sewage, # hospitals, and transportation cost to the nearest state capital all enter significantly and with the

expected sign into the utility of those with less education, while % Electric Light and % Piped Water are only marginally insignificant. This reflects the fact that local public goods are indeed important in this group's migration decision process. For the more educated group, # hospitals and % Electric Light both enter significantly with the expected sign. For this group, however, transportation cost to the nearest state capital and % Sewage do not seem to matter. It is likely that this group is not on the margin in terms of its access to sewage services (or piped water, for that matter), so a marginal improvement in access to either of these public goods is not likely to provide much inducement for choosing a particular destination. Increasing access to electricity and hospitals are more likely to be important for this group on the margin.

For both groups, increased transportation cost to Sao Paulo enters into utility positively and significantly in this specification. This result may initially seem counterintuitive. However, after controlling for access to healthcare and other forms of infrastructure (such as proximity to a state capital), this variable may simply proxy for a low cost of living (a desirable amenity).

We can interpret the coefficients on each variable as the percentage of the individual's wage that he is willing to pay for a one unit increase in each variable. For example, an individual from the [7, 12] year education group would be willing to pay 4.17% of his wage in exchange for an additional hospital in his AMC, while he would be willing to pay 1.15% of his wage in exchange for an additional percentage point of the population being covered by electric lights. An individual from the lower education group would be willing to pay only 0.3% of his wage in exchange for another percentage point increase in the population covered by electric lights, but would be willing to pay

0.6% in exchange for an additional percentage point increase in the population with access to sewage services.

3. The Roy Model and Sorting Based on Idiosyncratic Returns

3.1 Sorting Based on Idiosyncratic Returns

In addition to recovering the determinants of migration decisions, a primary focus of our analysis is the extent to which migrants have assimilated in their destinations' labor markets. We look for evidence of assimilation by comparing the *ex ante* wage distributions faced by migrants and a conditionally similar group of non-migrants in the same location. Determining the wage distributions faced by migrants and non-migrants is, however, complicated by the fact that *observed distributions are the outcome of a selection process* – individuals choose where to live based on both pecuniary and non-pecuniary returns.⁵

Thus, individuals found to be living in a particular location are there because the combination of wage and non-pecuniary returns they receive from that choice exceed that which they receive from being in alternative locations. As a result, the observed distribution of wages in that location will not reflect the distribution of wages faced by an *average* individual were he to be placed there. If some migrants face very high migration costs (i.e., negative values of non-pecuniary attributes for choices outside their origin location), the only individuals who we will see choosing to migrate will have very high

⁵ Borjas (1987) asks a similar question. He examines the way in which the earnings of an international immigrant population differ from those of non-migrants, using economic and political conditions in the home-country at the time of migration to achieve identification. Borjas' model considers only pecuniary determinants of migration.

wage draws in their destination location. This is evidence of selection, but could easily be mistaken as evidence of assimilation.

Previous papers that have modeled selection bias in migration have tended to focus on migration as a binary decision (i.e., to migrate or not). In that case, the selection problem could be dealt with using a traditional Heckman correction, or its non-parametric variant, described by Ahn and Powell (1993). However, there is a problem with binary models of migration – they do not allow one to explore the non-pecuniary determinants of migration behavior. This can only be done in a multinomial choice framework that incorporates both pecuniary and non-pecuniary attributes. This is a difficult econometric problem. Lee (1983) and Dahl (2001) solve it by exploiting a “single-index sufficiency” assumption that is not testable, and not likely to hold in situations with many choices. Here, we adopt a new approach based on recent work by Bayer, Khan, and Timmins (2008).

In order to answer these questions, we must first recover the true wage distribution faced by an individual when he migrates to a new location. To make this idea clear, consider the following stylized example of two locations (we generalize the model to any number of locations for empirical work). Individuals originate in location #1 and can choose between remaining in that location or migrating to location #2. Let $\omega_{i,k}$ represent individual i 's wage draw in location k and let θ_k represent an individual's “taste” for the non-pecuniary features of that location. Denote utility by:

$$(12) \quad U_{i,k} = \omega_{i,k} + \theta_k$$

Without loss of generality, we can normalize one of the θ 's to zero (i.e., $\theta_1 = 0$)

Individual i would prefer to remain in location #1 if:

$$(13) \quad \omega_{i,1} > \omega_{i,2} + \theta_2$$

but he would choose to migrate to location #2 if:

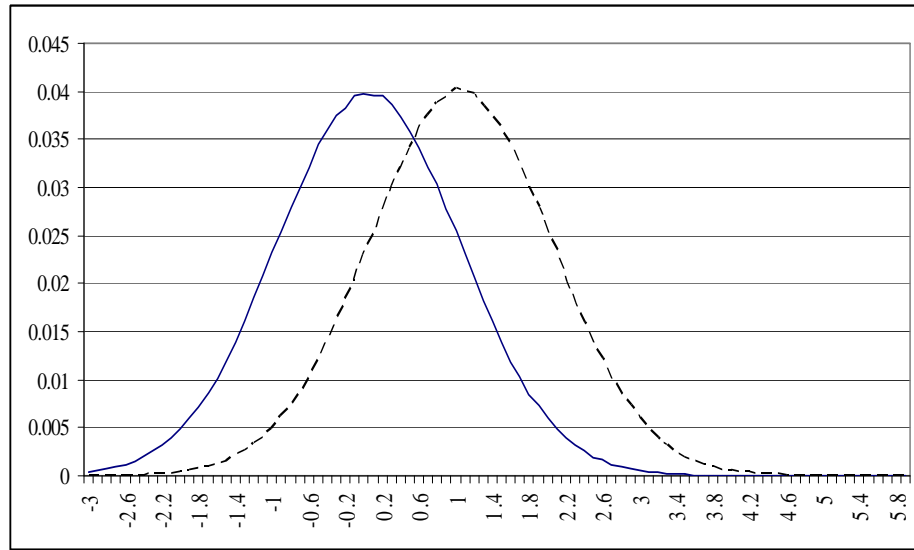
$$(14) \quad \omega_{i,1} \leq \omega_{i,2} + \theta_2$$

Therefore, individuals found to be living in location k are there because the combination of wage and non-pecuniary returns they receive from that choice exceed that which they receive from being in an alternative location. As a result, the observed distribution of wages in location k will not reflect the distribution of wages faced by an *average* individual were he to be placed there.

Without any non-pecuniary determinants of utility (i.e., $\theta_1 = \theta_2 = 0$) the location selection process is known as the Roy (1951) model. To illustrate its effects, suppose wages are drawn from the following multivariate normal distribution:

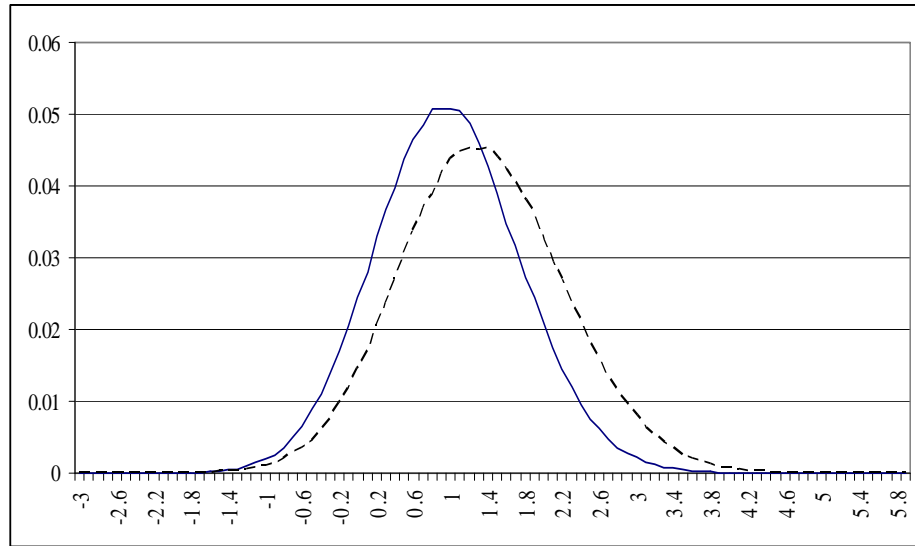
$$(15) \quad \begin{pmatrix} \omega_{i,1} \\ \omega_{i,2} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right]$$

The following figure illustrates the *unconditional* (i.e., not dependent upon sorting) wage distribution in each location:



Unconditional Wage Distribution (Dashed line: Natives; Solid Line: Migrants)

The distribution with the dashed line (- - -) shows the native population and the distribution with the solid line (___) shows the migrant population. We now determine the migration decisions and wages of one-million simulated individuals according to the wage distribution in (15). The following figure describes the resulting *conditional* wage distributions in each location:



Conditional Wage Distribution

The implications of Roy sorting for the conditional wage distributions are (i) the mean wage in both locations is higher, (ii) the within-location variation in wages is smaller, and (iii) the variation of wages across locations is reduced, compared with the unconditional wage distributions. Correcting for the biases introduced by (i) and (ii) is particularly important for determining whether migrants are able to assimilate into the local labor market.

We now describe an estimation strategy for recovering unconditional wage distributions in the presence of Roy sorting based on pecuniary and non-pecuniary determinants of migration. Recall that in the model described above, in to recover the wage of individual i in a location that is not his observed destination, we simply used the average wage earned by conditionally similar individuals in that location. While simple and straightforward, this approach to modeling wages ignores a potentially important

complication. Individuals sort geographically based on the returns to both observable attributes (like experience) as well as idiosyncratic skills (i.e., unobserved ability).⁶ This means that the average wage we see in a particular destination for individuals with certain observable characteristics is likely higher than what a randomly chosen individual would earn if moved there involuntarily – i.e., a form of selection bias. Dealing with this problem requires the solution to a high-dimensional sorting model, where individuals care about both pecuniary and non-pecuniary (i.e., amenities) returns. Following Bayer, Khan, and Timmins (2008), we deal with this problem semi-parametrically.

We continue with our stylized example of two locations. All results generalize to a model with an arbitrary number of locations. Consider an individual i from origin location 1. If that individual stays in location 1, he takes a random wage draw from the local labor market, which is denoted as $\omega_{i,1,1}$. He also enjoys local amenities θ_1 .⁷ His utility is composed of these two parts:

$$(16) \quad U_{i,1,1} = \omega_{i,1,1} + \theta_1$$

If the individual chooses to move and reside in location 2, he has to pay a migration cost, and his utility is:

⁶ While the typical interpretation in the labor literature is that individuals sort into occupations based on observable and idiosyncratic skills, a more relevant interpretation for the migration model may be that individuals have idiosyncratic “connections” – e.g., a family friend in the city who is able to set-up a migrant with a high-paying job prior to moving. The abnormally high wage earned by that migrant is not something we should expect to see the average individual making the same migration decision receiving.

⁷ We non-parametrically summarize all non-pecuniary components of utility in this single parameter. The only assumption we make is that there are no idiosyncratic determinants of utility related to amenities. Note that we do, however, allow preferences for amenities to vary with observable individual attributes.

$$(17) \quad U_{i,1,2} = \omega_{i,1,2} - \delta + \theta_2$$

Here, we simplify the migration costs to be a constant that applies to all migrants.

Individual i would therefore prefer to remain in location 1 if:

$$(18) \quad U_{i,1,1} \geq U_{i,1,2} \quad \text{or} \quad \omega_{i,1,1} + \theta_1 \geq \omega_{i,1,2} - \delta + \theta_2$$

Otherwise, he would move to location 2. We define a variable d_i which functions as an indicator that individual i chooses to stay in location 1:

$$(19) \quad d_i = I(U_{i,1,1} \geq U_{i,1,2})$$

We can therefore define individual i 's observed log wage as:

$$(20) \quad W_i = d_i \omega_{i,1,1} + (1 - d_i) \omega_{i,1,2}$$

Next, define the following joint probability distributions, which are observable by the econometrician:

$$(21) \quad \begin{aligned} \Psi_{1,1}(w) &= P(d_i = 1, W_i < w) \\ \Psi_{1,2}(w) &= P(d_i = 0, W_i < w) \end{aligned}$$

We will also work with the derivatives of these expressions:

$$(22) \quad \begin{aligned} \varphi_{1,1}(w) &= \frac{\partial}{\partial w} P(d_i = 1, W_i < w) \\ \varphi_{1,2}(w) &= \frac{\partial}{\partial w} P(d_i = 0, W_i < w) \end{aligned}$$

These conditional probabilities (i.e., conditional upon optimal migration decisions) are easily observed in available data, and functions describing them can be estimated non-parametrically. We will now use them to recover the unconditional distributions from which individuals took random wage draws in each location.

Focusing on the expression for $\Psi_{i,1}(w)$, we can rewrite it using equations (18) and (20)

as follows:

$$(23) \quad \begin{aligned} \Psi_{1,1}(w) &= P(d_i = 1, W_i \leq w) \\ &= P(\omega_{i,1,1} + \theta_1 \geq \omega_{i,1,2} - \delta + \theta_2, \omega_{i,1,1} \leq w) \\ &= P(\omega_{i,1,2} \leq \omega_{i,1,1} + \theta_1 + \delta - \theta_2, \omega_{i,1,1} \leq w) \\ &= \int_{-\infty}^w f_{1,1}(\omega_{1,1}) d\omega_{1,1} \int_{-\infty}^{\omega_{1,1} + \theta_1 + \delta - \theta_2} f_{1,2}(\omega_{1,2}) d\omega_{1,2} \\ &= \int_{-\infty}^w f_{1,1}(\omega_{1,1}) F_{1,2}(\omega_{1,1} + \theta_1 + \delta - \theta_2) d\omega_{1,1} \end{aligned}$$

where F and f stand for the CDF and PDF of the unconditional distribution of the random wage draw, respectively. Note that here we assume that individual i takes independent

random wage draws in different locations.⁸ From equation (23), $\varphi_{i,1,1}(w)$ can be easily derived as:

$$(24) \quad \varphi_{1,1}(w) = \frac{\partial}{\partial w} \int_{-\infty}^w f_{1,1}(\omega_{1,1}) F_{1,2}(\omega_{1,1} + \theta_1 + \delta - \theta_2) d\omega_{1,1}$$

$$= f_{1,1}(w) F_{1,2}(w + \theta_1 + \delta - \theta_2)$$

By an analogous argument,

$$(25) \quad \varphi_{1,2}(w) = \frac{\partial}{\partial w} \int_{-\infty}^w f_{1,2}(\omega_{1,2}) F_{1,1}(\omega_{1,2} + \theta_2 - \delta - \theta_1) d\omega_{1,2}$$

$$= f_{1,2}(w) F_{1,1}(w + \theta_2 - \delta - \theta_1)$$

Going back to the final integral in equation (23) and carrying out integration-by-parts yields:

$$(26) \quad \Psi_{1,1}(w) = \int_{-\infty}^w f_{1,1}(\omega_{1,1}) F_{1,2}(\omega_{1,1} + \theta_1 + \delta - \theta_2) d\omega_{1,1}$$

$$= F_{1,1}(w) F_{1,2}(w + \theta_1 + \delta - \theta_2) - \int_{-\infty}^w F_{1,1}(s) f_{1,2}(s + \theta_1 + \delta - \theta_2) ds$$

Performing a change of variables $u = s + \theta_1 + \delta - \theta_2$, equation (26) becomes:

$$(27) \quad \Psi_{1,1}(w) = F_{1,1}(w) F_{1,2}(w + \theta_1 + \delta - \theta_2) - \int_{-\infty}^{w + \theta_1 + \delta - \theta_2} F_{1,1}(u - \theta_1 - \delta + \theta_2) f_{1,2}(u) du$$

⁸ This assumption implies that an individual receiving an idiosyncratically high wage draw in one location is no more likely to receive a similarly high draw in other locations. While undesirable, this assumption is required for identification using cross-sectional data (i.e., observing each individual only once). We are currently working on extensions of this model that allow the assumption to be relaxed by using panel data. In the current application, where a high idiosyncratic wage draw may be as much a function of family connections as unobservable skill, independence may not be a bad assumption.

Make use of equation (24) and (25):

$$(28) \quad \Psi_{1,1}(w) = \frac{F_{1,1}(w) \varphi_{1,1}(w)}{f_{1,1}(w)} - \int_{-\infty}^{w+\theta_1+\delta-\theta_2} \varphi_{1,2}(u) du$$

Noting that the integral term in equation (28) is simply $\Psi_{1,2}(w+\theta_1+\delta-\theta_2)$, we can define $\lambda_{1,1}(w)$:

$$(29) \quad \lambda_{1,1}(w) = \frac{f_{1,1}(w)}{F_{1,1}(w)} = \frac{\varphi_{1,1}(w)}{\Psi_{1,1}(w) + \Psi_{1,2}(w+\theta_1+\delta-\theta_2)}$$

Analogously, we have:

$$(30) \quad \lambda_{1,2}(w) = \frac{f_{1,2}(w)}{F_{1,2}(w)} = \frac{\varphi_{1,2}(w)}{\Psi_{1,2}(w) + \Psi_{1,1}(w-\theta_1-\delta+\theta_2)}$$

Repeating the whole process for individuals from origin location 2, we can derive:

$$(31) \quad \lambda_{2,2}(w) = \frac{f_{2,2}(w)}{F_{2,2}(w)} = \frac{\varphi_{2,2}(w)}{\Psi_{2,2}(w) + \Psi_{2,1}(w-\theta_1+\delta+\theta_2)}$$

$$(32) \quad \lambda_{2,1}(w) = \frac{f_{2,1}(w)}{F_{2,1}(w)} = \frac{\varphi_{2,1}(w)}{\Psi_{2,1}(w) + \Psi_{2,2}(w+\theta_1-\delta-\theta_2)}$$

It is straightforward to extend the simple two-location case to the general K-location case and derive $\lambda_{j,k}(w)$ as follows:

$$(33) \quad \lambda_{j,k}(w) = \frac{f_{j,k}(w)}{F_{j,k}(w)} = \frac{\varphi_{j,k}(w)}{\sum_{m=1}^K \Psi_{j,m}(w-\theta_m + \delta * I(j=m) + \theta_k - \delta * I(j=k))}$$

The commonly believed story about labor market discrimination against migrants motivates the following moment conditions:

$$(34) \quad \lambda_{k,k}(w) = \frac{f_{k,k}(w)}{F_{k,k}(w)} = \frac{f_{j,k}(w + \rho_k)}{F_{j,k}(w + \rho_k)} = \lambda_{j,k}(w + \rho_k)$$

This implies that the wage distribution of migrants in location k is different from that of the natives only by a shifter, ρ_k . The value of ρ_k measures how well migrants assimilate into the local labor market. A smaller ρ_k means better assimilation of migrants in location k (in particular, a negative value of ρ_k would imply that migrants are drawing from a better distribution than non-migrants).

Our goal is to recover GMM estimates for $\{\rho_k\}_{k=1}^K$, $\{\theta_k\}_{k=1}^K$, and δ , i.e. $2K + 1$ parameters. Suppose there are J origin locations and K destination locations. Equation (34) represents $K \times (J - 1)$ moment conditions. As long as $K \times (J - 1) \geq 2K + 1$, the model is identified. Once we have obtained the estimates for those parameters, we can non-parametrically recover the unconditional wage distributions, $F_{j,k}(w)$, using a simple extension of the Kaplan-Meier algorithm, which is described in detail in Bayer, Khan, and Timmins (2008).⁹

4. Results

Once again, we find strong evidence that non-pecuniary factors play an important role in individual migration decisions. Table 4 reports estimates of the local amenity parameters (θ_k) for each destination region (here, a destination is defined to be one of Brazil's five

⁹ The intuition for this approach is that, once one knows the value of the non-pecuniary utility parameter, θ_k , utility (defined according to equations (16) and (17)) is observable. We simply apply the Kaplan-Meier algorithm to these utility data, as one would to any other variety of competing risks model.

regions – North, Northeast, Southeast, South, and Center-West, differentiated by urban/rural status). Many of the results correspond to our intuition – for example, the strong amenity value placed by all education groups on the urban Center-West, which saw a tremendous rise over the period being studied. We similarly see a clear preference for urban areas on the Southeast, which grows with increasing education. There is also a generally stronger preference for urban areas over rural areas amongst those who have completed primary or secondary education. Moreover, we see a strong preference across education groups for the non-pecuniary returns to living in the North. This is a result of the model’s attempts to explain peoples’ decisions to live there in spite of low wage draws. The opposite is true for all individuals with respect to the South. These results likely reflect spatial variation in costs of living.

Turning attention to migration costs, we find clear evidence that they are an important determinant of location decisions. Moreover, they decline steadily with increasing education.

We next use our estimates to gain some understanding of the bias introduced by ignoring Roy sorting in predicting the labor market outcomes for would-be migrants. I.e., if we were to undertake a policy to induce an individual to undertake rural-urban migration, what would we expect his wage draw to be? Figures 1 – 6 describe the *ex post* conditional and *ex ante* unconditional wage distributions for non-migrants with varying levels of education living in either the urban part of Bahia or Sao Paulo. For those with less than primary education, we see clear evidence of an upward bias in the conditional wage distribution for those living in Sao Paulo. That bias does not show up, however, for

non-migrants in Bahia. There is a significant bias for non-migrants in both locations who had completed primary education, although it is bigger for those in Bahia. The bias from Roy sorting is greatly reduced for those who have completed secondary education in both locations.

Finally, in assessing assimilation of rural-urban migrants, we look at the *ex ante* distribution of wages from which these migrants draw compared to the *ex ante* distribution from which the observationally similar native population of the urban area draw. This is most easily summarized by the labor market assimilation parameter, ρ_k , which is described in Table 5. In every location (with the exception of the lowest education group in the urban south, where the result is likely insignificant), migrants face a worse labor market than their non-migrant counterparts. For example, an individual with a primary education migrating to the urban Northeast will receive a draw from a log wage distribution that has a mean 1.020 lower than that of a non-migrant.

Of all the urban locations, those with the least education face the worst labor market conditions in the Southeast. This, in conjunction with the results in Figure 1, call into question any plan to encourage more migration from Brazil's Northeast to the city of Sao Paulo. Figures 7 – 9 describe unconditional wage distributions for migrants (from Bahia) and non-migrants living in Sao Paulo. For the two lower education groups, it is clear that migrants draw from a significantly lower wage distribution than their non-migrant counterparts. That disadvantage appears to be greatly reduced for those who have completed secondary education. This suggests that policies should try to improve human

capital development in rural or lagging areas, so that potential migrants can improve their outcomes at their destinations.

5. Conclusions

In this paper, we examine the determinants of internal migration, and the extent to which migrants assimilate into labor markets of destination regions. In identifying determinants, we pay particular attention to the role of amenities such as access to health and education services and urban infrastructure in migration decisions of individuals/ households. In terms of examining assimilation, we examine the extent to which good observed labor market outcomes of migrants in terms of wages reflect true economic opportunities for an average individual or are simply a result of selection bias?

We empirically answer these questions using census data for Brazil. One of our main findings is that the poor from the country's lagging regions are often deprived of access to basic public services such as health care, water supply and electricity in their hometowns. Lack of public services pushed many poor people to migrate, and these migrants are willing to accept lower wages to get access to better services. In terms of policy response, it would be useful to improve public services in lagging areas so that it directly enhances well being of local residents and encourages people to migrate for reasons that add more to agglomeration economies in leading areas.

In measuring assimilation, we find that non-random sorting overstates the average migrant's labor market opportunities. Using *ex ante* wage distributions, we demonstrate that migrants are typically at a labor market disadvantage relative to conditionally similar non-migrants – evidence of a failure to assimilate. And this problem is severe for the

least educated in the most attractive urban destinations. This would suggest that improving human capital at origin is likely to be useful – by providing potential migrants with a wider set of opportunities at their destination. However, by reducing migration costs we are likely to see increase in benefits to individuals, but may be accompanied by worsening labor market outcomes and congestion costs for residents in destination regions. Further research is needed to examine the consequences of policies that influence migration flows.

* * * * *

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Table 1
Summary of Regression Procedures to Predict Counterfactual AMC Wages

Variable	2000			1991		
	Mean of Parameter Estimates	Mean of Std. Err.	Std. Dev. Parameter Estimates	Mean of Parameter Estimates	Mean of Std. Err.	Std. Dev. Parameter Estimates
age	0.0155	0.0014	0.0356	0.0109	0.0009	0.0299
primary education dummy	0.2131	0.1302	0.3643	0.1336	0.0679	0.2680
secondary education dummy	0.6636	0.2198	0.5217	0.6039	0.1783	0.5507
female dummy	-0.4100	0.1533	0.4272	-0.4374	0.1875	0.4923
occupation dummies						
1	0.1784	0.2679	0.6140	0.4611	0.2874	0.6873
2	0.3918	0.4337	0.9072	0.2959	0.3367	0.6998
3	0.1860	0.3247	0.7365	-0.3494	0.2332	0.5950
4	0.1851	0.4341	0.8089	0.0191	0.1440	0.4605
5	0.0156	0.4112	0.7394	0.1038	0.2568	0.5923
6	-0.1675	0.4092	0.7996	0.2645	0.2987	0.6850
7	-0.4817	0.3900	0.7959	0.2328	0.2886	0.6349
8	-0.0893	0.4021	0.7887	-0.1614	0.3107	0.6246
9	-0.1742	0.4039	0.7467	0.1776	0.2549	0.5270
10	-0.0608	0.3799	0.7384			
constant	-0.1780	1.8395	1.3723	5.1162	1.1139	1.1206

Table 2
Migration Estimation Results
Education = [0,6] Years

Stage #1	No Moving Costs Second-Stage Without Differencing				Second-Stage Differencing (No Moving Costs)		Moving Costs and Second-Stage Differencing	
	Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat
Scale Parameter	0.479	13.20	0.479	13.20	0.397	10.94	0.397	10.94
Moving Costs ¹⁰							-1.757	-10.87
Log Likelihood	28591.164				28591.164		21456.657	
	1991		2000		$\Delta(1991-2000)$		$\Delta(1991-2000)$	
Stage #2	Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat
% Electric Light	-1.35E-03	-0.72	-1.47E-02	-5.46	1.12E-02	8.61	2.89E-03	1.52
% Piped Water	2.15E-02	11.69	1.01E-02	4.86	1.99E-03	1.21	2.48E-03	1.04
% Sewage	1.64E-03	1.14	6.07E-03	4.97	1.38E-03	1.22	6.35E-03	3.86
# Hospitals	1.75E-01	31.35	1.81E-01	33.93	4.73E-02	5.4	2.79E-02	2.19
Transportation Cost (SP)	1.87E-04	4.1	1.17E-04	2.25	-7.10E-04	-7.63	1.15E-03	8.44
Transportation Cost (SC)	-3.70E-04	-3.93	-6.00E-04	-6.35	6.83E-04	2.15	-9.60E-04	-2.06
Constant	-1.25E+00	-6.27	5.11E-01	1.87	-2.93E-01	-8.3	-4.53E-02	-0.88
R2	0.3522		0.3215		0.0886		0.0418	

¹⁰ Moving costs are measured as the natural log of the number of kilometers (in 1,000's) from the AMC of residence to the center of the individual's birth state.

Table 3
 Migration Estimation Results
 Education = [7,12] Years

Stage #1	No Moving Costs Second-Stage Without Differencing				Second-Stage Differencing (No Moving Costs)		Moving Costs and Second-Stage Differencing	
	Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat
Scale Parameter	0.138		19.95		0.138	19.95	0.253	7.75
Moving Costs ¹¹							-2.598	-7.69
Log Likelihood	25098.315				25098.315		18231.261	
	1991		2000		$\Delta(1991-2000)$		$\Delta(1991-2000)$	
Stage #2	Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat
% Electric Light	2.60E-03	0.34	-4.68E-02	-4.07	3.85E-04	0.08	1.15E-02	3.68
% Piped Water	2.02E-01	26.74	1.68E-01	18.92	8.73E-03	1.48	4.52E-03	1.15
% Sewage	-6.27E-03	-1.06	2.22E-02	4.25	1.63E-03	0.4	-3.00E-04	-0.11
# Hospitals	7.17E-01	31.17	7.41E-01	32.55	8.29E-02	2.64	4.17E-02	1.99
Transportation Cost (SP)	1.80E-03	9.59	1.05E-03	4.73	-1.57E-03	-4.69	4.12E-04	1.84
Transportation Cost (SC)	-2.16E-03	-5.59	-1.79E-03	-4.46	1.53E-03	1.35	-9.20E-05	-0.12
Constant	-1.35E+01	-16.47	-9.16E+00	-7.85	-3.66E-01	-2.89	-3.03E-01	-3.59
R2	0.4209		0.4917		0.0153		0.0088	

¹¹ Moving costs are measured as the natural log of the number of kilometers (in 1,000's) from the AMC of residence to the center of the individual's birth state.

Table 4
Roy Model Utility Parameters

	Individuals with Less than Primary Education		Individuals with Primary Education Completed		Individuals with Secondary Education Completed	
	Urban Area	Rural Area	Urban Area	Rural Area	Urban Area	Rural Area
	Local Amenities (θ_k)					
North Region	3.197	1.470	4.082	2.197	3.728	1.649
Northeast Region	-1.218	2.913	0.061	-1.295	1.226	-1.084
Southeast Region	0.206	-0.194	0.462	-2.371	2.227	-4.747
South Region	-6.178	-2.878	-0.675	-2.803	-1.457	-2.442
Midwest Region	2.071	0.611	1.282	-0.941	2.431	-1.533
	Migration Costs (δ)					
	1.438		1.251		0.391	

Table 5
Labor Market Assimilation (ρ_k)

	Individuals with Less than Primary Education		Individuals with Primary Education Completed		Individuals with Secondary Education Completed	
	Urban Area	Rural Area	Urban Area	Rural Area	Urban Area	Rural Area
North Region	0.885	0.181	1.159	1.106	0.219	0.274
Northeast Region	0.279	0.048	1.020	1.056	0.289	0.264
Southeast Region	0.991	0.191	1.200	1.247	0.268	0.273
South Region	-0.016	0.271	0.957	1.185	0.274	0.780
Midwest Region	0.279	0.492	1.029	1.096	0.382	0.449

Figure 1
Conditional (Solid) and Unconditional (Dashed) Wage Distributions
Sao Paulo Non-Migrant, Less Than Primary Education

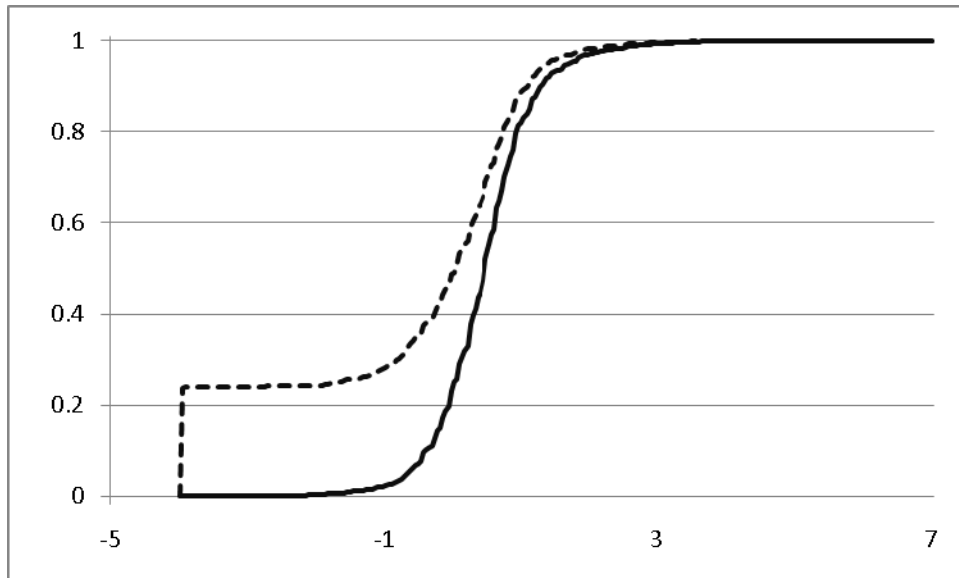


Figure 2
Conditional (Solid) and Unconditional (Dashed) Wage Distributions
Bahia Non-Migrant, Less Than Primary Education

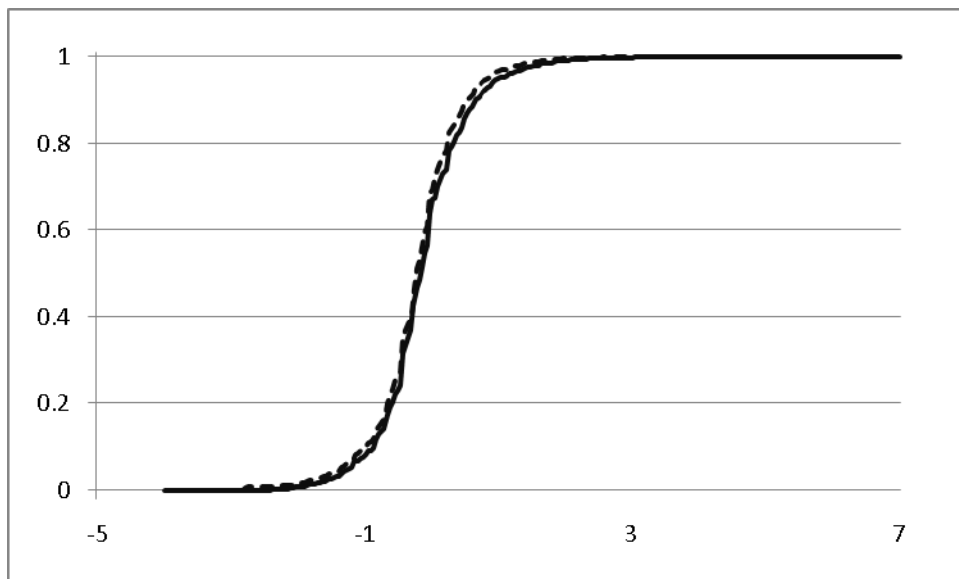


Figure 3
Conditional (Solid) and Unconditional (Dashed) Wage Distributions
Sao Paulo Non-Migrant, Completed Primary Education

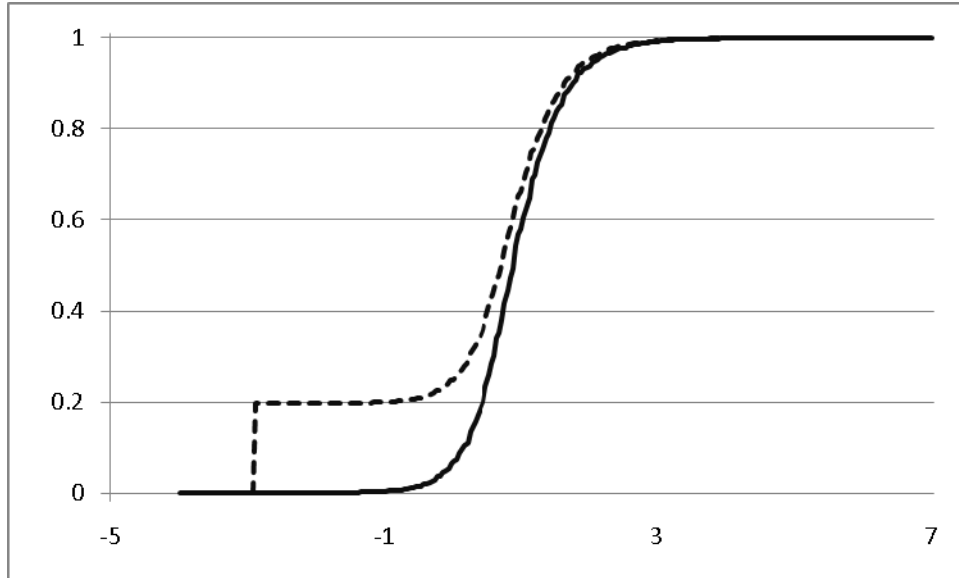


Figure 4
Conditional (Solid) and Unconditional (Dashed) Wage Distributions
Bahia Non-Migrant, Completed Primary Education

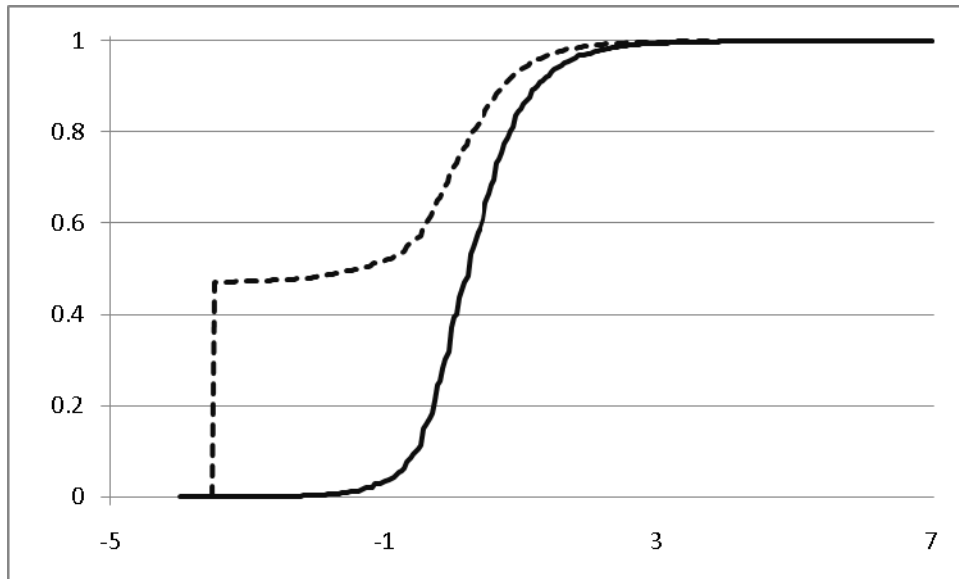


Figure 5
Conditional (Solid) and Unconditional (Dashed) Wage Distributions
Sao Paulo Non-Migrant, Completed Secondary Education

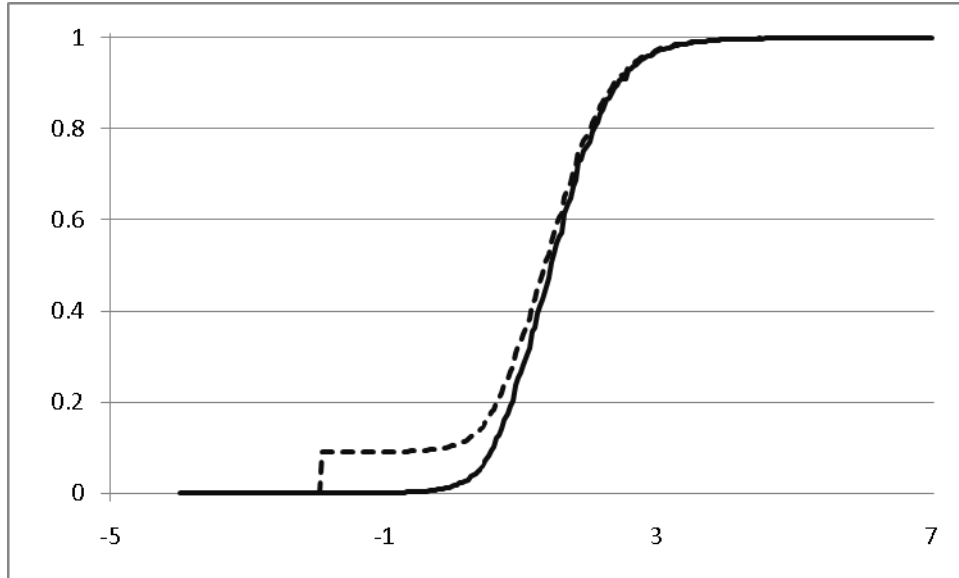


Figure 6
Conditional (Solid) and Unconditional (Dashed) Wage Distributions
Bahia Non-Migrant, Completed Secondary Education

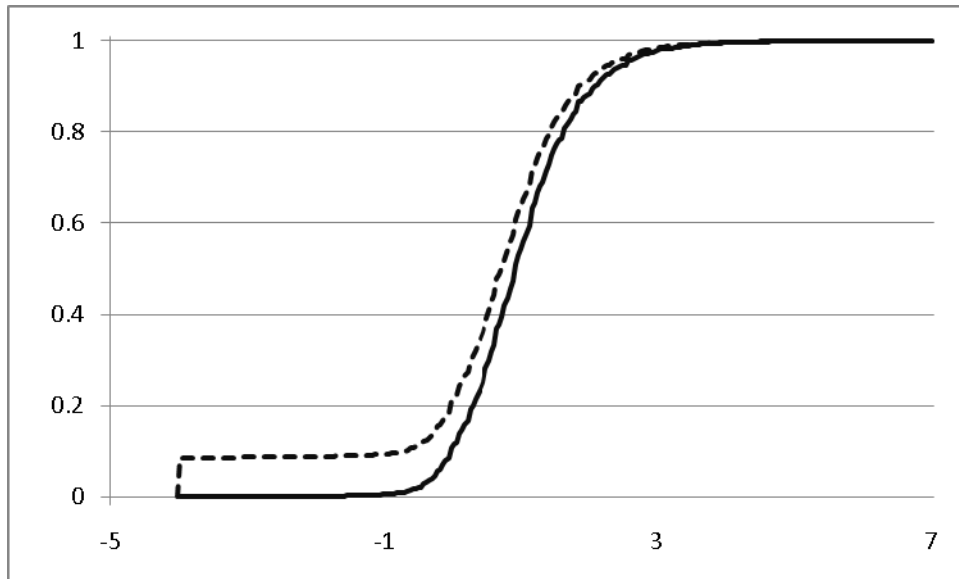


Figure 7
Unconditional Log Wage Distributions
Less Than Primary Education, Living in Sao Paulo
Non-Migrants (Solid), Migrants from Bahia (Dashed)

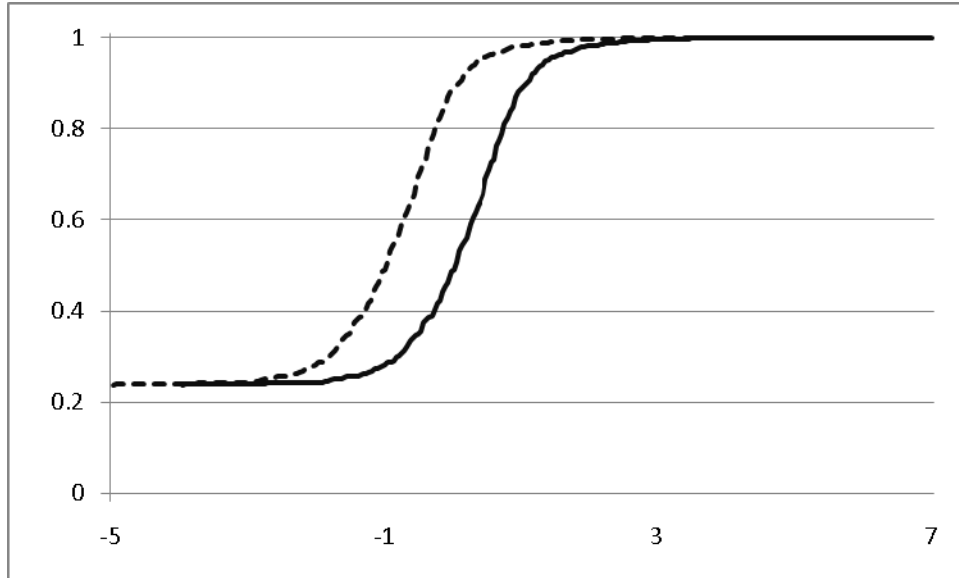


Figure 8
Unconditional Log Wage Distributions
Completed Primary Education, Living in Sao Paulo
Non-Migrants (Solid), Migrants from Bahia (Dashed)

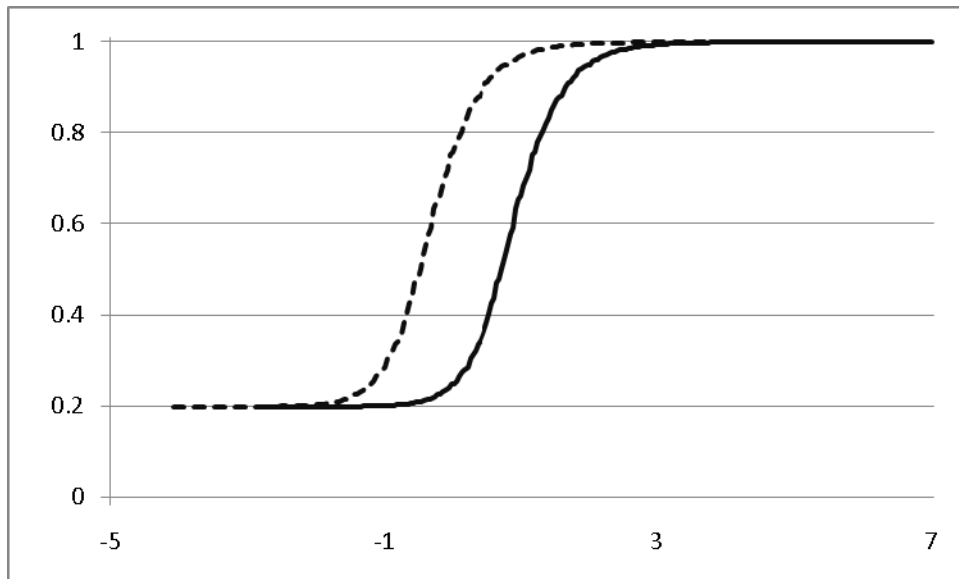


Figure 9
Unconditional Log Wage Distributions
Completed Secondary Education, Living in Sao Paulo
Non-Migrants (Solid), Migrants from Bahia (Dashed)

