Moving to Opportunity: Successful Integration or Bright Lights?

by

Somik V. Lall, World Bank
Christopher Timmins, Duke University
Shouyue Yu, Duke University

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Introduction: *Motivation*

Economic models have traditionally explained internal migration as a result of differentials in economic opportunities.

Emphasis on rural-urban differentials in labor market returns (e.g., Harris-Todaro).

We argue that these approaches have ignored two important factors that could affect policy conclusions:

(1) Non-pecuniary factors (e.g., amenities, access to local public goods) may be important determinants of migration decisions. Care must be taken to properly separate-out the roles of these factors from those of unobserved local attributes.

(2) Migration is a non-random process. Individuals who choose to migrate to a particular place will likely have done so because they received a particularly good draw in the labor market there.

Introduction: *Motivation*

Failing to address (1) may lead us to overstate the value of particular public goods (e.g., public goods like healthcare may be spatially correlated with other desirable, but unobserved, urban amenities).

Failing to address (2) may lead us to overstate the labor market opportunities available to an average would-be migrant. This has important consequences for conclusions about policies to encourage rural-urban migration.

Introduction

In this paper, we develop a pair of models that we use to answer the following questions:

(1) What non-pecuniary factors most influence individual migration decisions? Do certain factors matter more to certain groups?

(2) Which groups face the largest migration costs?

(3) To what extent to observed wage distributions overstate the labor market opportunities available to would-be migrants?

(4) Which migrants are less able to "assimilate" into local labor markets (i.e., face a distribution of offer wages similar to that faced by non-migrant counterparts)?

Introduction: *Policy Conclusions*

(1) Non-pecuniary factors are important determinants of migration (particularly for those with less education), but failing to control for unobserved local attributes can bias our conclusions about which factors matter most.

(2) By improving public goods in rural areas, non-pecuniary factors will play a smaller role in individual migration decisions. Those individuals who do migrate to urban areas will do so more in response to high labor market returns.

- enhances aggregate productivity
- productivity spillovers and agglomeration benefits
- less stress on rivalrous local public goods and amenities

(3) Failing to control for non-pecuniary factors may lead us to overstate the role of labor market returns in driving migration to cities.

Introduction: *Policy Conclusions*

(4) Observed wage distributions significantly overstate the labor market opportunities for certain types of would-be migrants. Policies to encourage more rural-to-urban migration may be ill-advised.

(5) Those who choose to undertake rural-to-urban migration (particularly the less educated) are at a disadvantage in the destination labor market relative to non-migrant counterparts.

Model #1: *Recovering the Determinants of Migration*

(1) Utility:

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

$w_{i,j,k}$ = log wage earned by individual *i* from origin *j* in destination *k*

$D_{j,k}$ = migration distance (in km from origin *j* to destination *k*)

X_k = observable (by the econometrician) attributes of destination *k*

$\tilde{\xi}_k$ = unobservable (by the econometrician) attributes of destination *k*

$\tilde{\eta}_{i,j,k}$ = idiosyncratic unobservable (by the econometrician) determinants of individual *i*'s utility in location *k*

Model #1

(2) Normalized Utility: allows preference parameters to be interpreted as MWTP's as a percentage of wages

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

(3) Assumptions:

- migration cost is only a function of distance
- ignore labor market participation decision
- ignore involuntary unemployment
- $\eta_{i,j,k} \sim i.i.d.\, Type\ I\ Extreme\ Value$

Model #1

(4) Migration Choice Probability:

$$P(U_{i,j,k} \geq U_{i,j,l} \ \forall \ \ l \neq k) = \frac{\exp(\mu(w_{i,j,k} - \delta \log(D_{j,k} + 0.01) + \overbrace{X_k'\gamma + \xi_k}^{\theta_k}))}{\sum_{l=1}^{K} \exp(\mu(w_{i,j,l} - \delta \log(D_{j,l} + 0.01) + \underbrace{X_l'\gamma + \xi_l}_{\theta_l}))}$$

(5) Mean utility associated with destination *k*:

$$\theta_k = X_k'\gamma + \xi_k$$

Model #1

(6) ML Estimation: use to recover estimates of $\mu, \delta,$ and $\{\theta_k\}_{k=1}^{K}$

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

Use Berry (1994) contraction mapping to avoid non-linear search over $\{\theta_k\}_{k=1}^{K}$.

Model #1: *Valuing Non-Wage Determinants of Migration*

(1) Use OLS regression to decompose mean utility:

$$\hat{\theta}_k = X_k'\gamma + \xi_k$$

(2) Problem arises if $E[X_k \xi_k] \neq 0$ (IV strategies are not practical).

(3) Estimate model twice using data from two censuses (i.e., 1991 and 2000). Restrict $\{\mu, \delta\}$ to remain the fixed over time. Recover $\{\theta_{k,1991}\}_{k=1}^{K}$ and $\{\theta_{k,2000}\}_{k=1}^{K}$ using Berry (1994) contraction mapping.

Model #1: *Valuing Non-Wage Determinants of Migration*

(4) Identification: Assume $X_{k,t}$ is only correlated with time-invariant unobservable local attributes (ς_k). Estimate using panel data on locations.

$$\hat{\theta}_{k,t} = X'_{k,t}\gamma + \underbrace{\varsigma_k + \upsilon_{k,t}}_{\xi_{k,t}} \qquad E[\Delta X_k \Delta \upsilon_k] = 0$$

$$\Delta\hat{\theta}_k = \Delta X'_k \gamma + \Delta \upsilon_k$$

$$\Delta\hat{\theta}_k = \hat{\theta}_{k,2} - \hat{\theta}_{k,1}$$
$$\Delta X_k = X_{k,2} - X_{k,1}$$
$$\Delta \upsilon_k = \upsilon_{k,2} - \upsilon_{k,1}$$

Data

- 1991 and 2000 Brazilian Demographic Census
- Household heads aged 25-35
- Long-run migration decisions (i.e., relative to birth state)
- 3659 AMC (minimum comparable area) destinations
- Predict counterfactual wage outcomes for each AMC

Data: *Predicting Counterfactual Wage Outcomes*

Variable	2000			1991		
	Mean of Parameter Estimates	Mean of Std. Err.	Std. Dev. Parameter Estimates	Mean of Parameter Estimatess	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

Model #1

Recovering Determinants of Migration
[0, 6] Years Education

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
Scale Parameter	0.479		13.20		0.479	13.20	0.397	10.94
Moving Costs							-1.757	-10.87
Log Likelihood	28591.164				28591.164		21456.657	
Stage #2	1991		2000		Δ(1991-2000)		Δ(1991-2000)	
	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	

Model #1

Recovering Determinants of Migration
[7, 12] Years Education

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
Scale Parameter	0.138		19.95		0.138	19.95	0.253	7.75
Moving Costs							-2.598	-7.69
Log Likelihood	25098.315				25098.315		18231.261	
Stage #2	1991		2000		Δ(1991-2000)		Δ(1991-2000)	
	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	

Model #2: *Migration and Roy Sorting*

Build a model that both allows individuals to sort based on idiosyncratic labor market outcomes (i.e., Roy sorting) and non-pecuniary factors (i.e., local public goods and amenities).

Previous work on Roy sorting has not allowed for non-pecuniary factors to affect sorting behavior.

Two exceptions from the migration literature [Lee (1983) and Dahl (2001)] rely on strict single index sufficiency assumption.

Simple Example of Roy Sorting

(1) Utility of individual i from choosing to locate in destination k = 1, 2. Normalize $\theta_1 = \theta_2 = 0$.

$$U_{i,k} = \omega_{i,k} + \theta_k$$

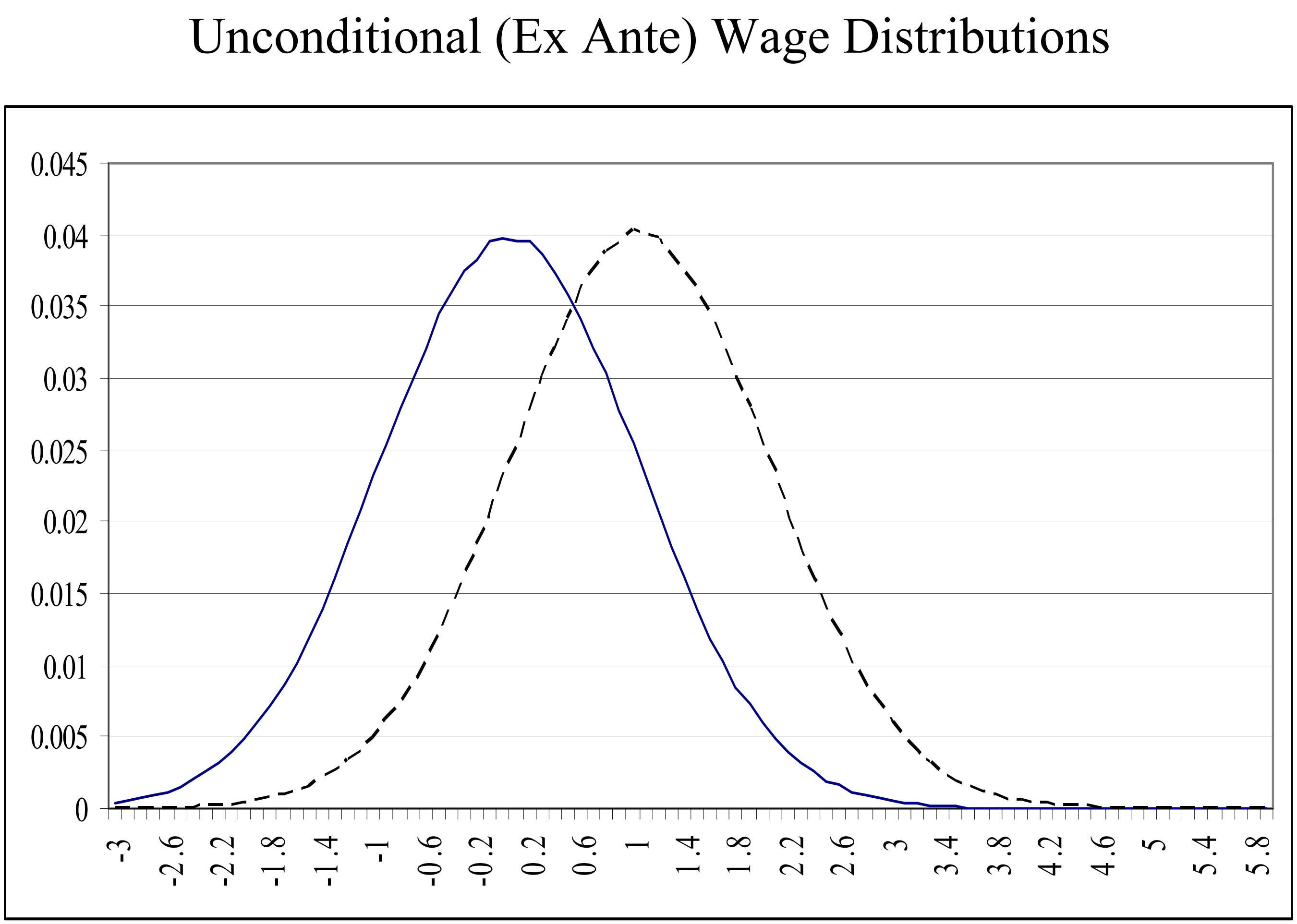
(2) Individual i will choose destination…

$$k = 1 \text{ if } \omega_{i,1} > \omega_{i,2}$$
$$k = 2 \text{ if } \omega_{i,1} \leq \omega_{i,2}$$

(3) Assume wages are drawn from the unconditional joint distribution:

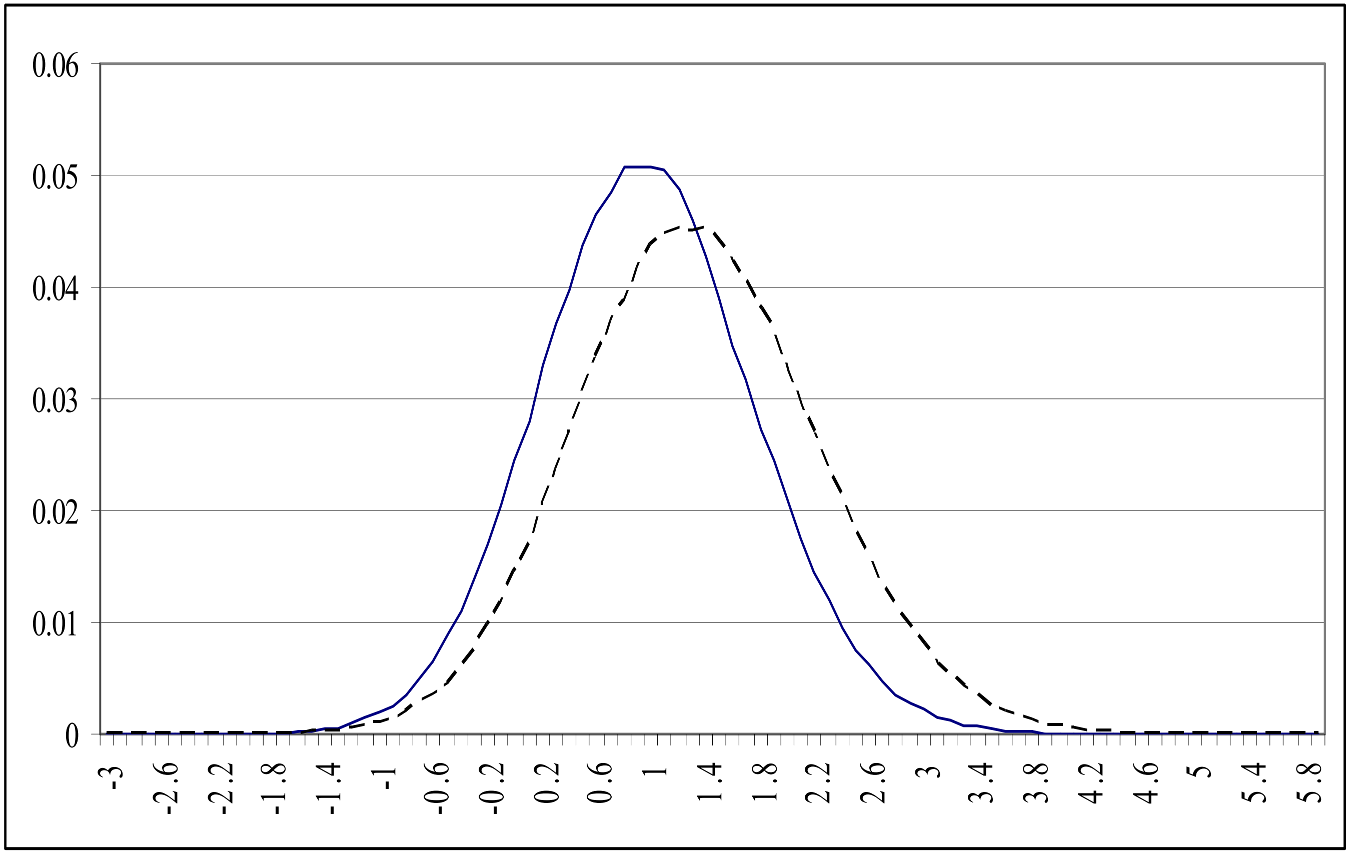
$$\begin{pmatrix} \omega_{i,1} \\ \omega_{i,2} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\right]$$

Simple Example of Roy Sorting



Simple Example of Roy Sorting

Conditional (Ex Post) Wage Distributions



Simple Example of Roy Sorting

Implications of Roy sorting for conditional wage distributions (relative to unconditional wage distributions):

(i) mean wage in both locations is higher

(ii) within-location variation in wages is smaller

(iii) variation of wages across locations is reduced

Roy sorting has the potential to make it appear as though migrants are doing quite well, both in absolute terms and relative to non-migrants (i.e., mistake selection for assimilation).

Model #2

(1) Utility ($U_{i,j,k}$) of individual *i* born in location *j* = 1

$$U_{i,1,1} = \omega_{i,1,1} + \theta_1$$
$$U_{i,1,2} = \omega_{i,1,2} - \delta + \theta_2$$

(2) Migration: individual *i* prefers to remain in location #1 if…

$$\omega_{i,1,1} + \theta_1 \geq \omega_{i,1,2} - \delta + \theta_2$$

(3) Migration Indicator: $d_i = 1$ if individual *i* chooses to stay in location #1

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

Model #2

(4) Observed Wage:

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

(5) Observed Joint Wage/Migration Probability Distributions:

$$\Psi_{1,1}(w) = P(d_i = 1, W_i < w) \qquad \varphi_{1,1}(w) = \frac{\partial}{\partial w} P(d_i = 1, W_i < w)$$

$$\Psi_{1,2}(w) = P(d_i = 0, W_i < w) \qquad \varphi_{1,2}(w) = \frac{\partial}{\partial w} P(d_i = 0, W_i < w)$$

Model #2

(6) Using definition of migration indicator and assuming independent wage draws:

$$\Psi_{1,1}(w) = P(d_i = 1, W_i \le w)$$

$$= P(\omega_{i,1,1} + \theta_1 \ \ge \ \omega_{i,1,2} - \delta + \theta_2, \ \ \omega_{i,1,1} \ \le \ w)$$

$$= P(\omega_{i,1,2} \ \le \ \omega_{i,1,1} + \theta_1 + \delta - \theta_2, \ \ \omega_{i,1,1} \ \le \ w)$$

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

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

Model #2

(7) Taking derivatives of $\Psi_{1,1}(w)$ and $\Psi_{1,2}(w)$**:**

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

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

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

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

Model #2

(8) Integration by parts:

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

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

(9) Change of variables: $u = s + \theta_1 + \delta - \theta_2$

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

Model #2

(10) Combining everything that we know:

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

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

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

$$\Downarrow$$

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

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

Model #2

(11) Repeating the exercise for each origin and destination:

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

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

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

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

Model #2

(12) General Case (J Origin Locations, K Destination Locations):

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

Model #2

(13) Identification: Assume wage distribution for migrants residing in location k is the same as for non-migrants, only shifted by ρ_k (ρ_k > 0 implies migrants face a lower wage distribution than non-migrants).

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

(14) Recover parameters with GMM estimation:

$2K+1$ parameters: $\{\theta_k\}_{k=1}^{K}$ $\{\rho_k\}_{k=1}^{K}$ δ

$K\ x\ (J-1)$ moment Conditions

Model #2: *Results*

(15) Recover unconditional wage distributions using simple extension of Kaplan-Meier estimator described in Bayer, Khan, and Timmins (2008).

Model #2: *Results*

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	

θ_k

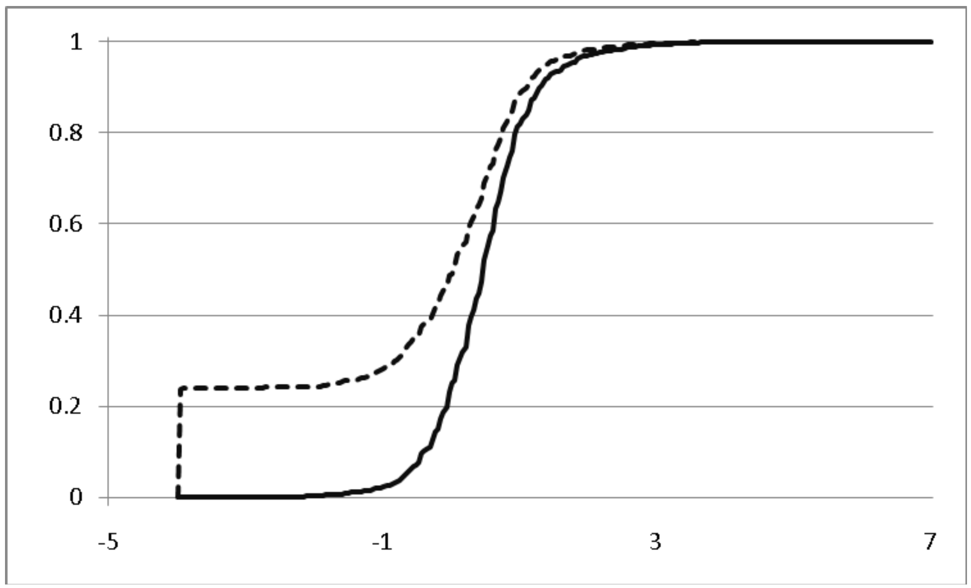
Model #2: *Results*

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

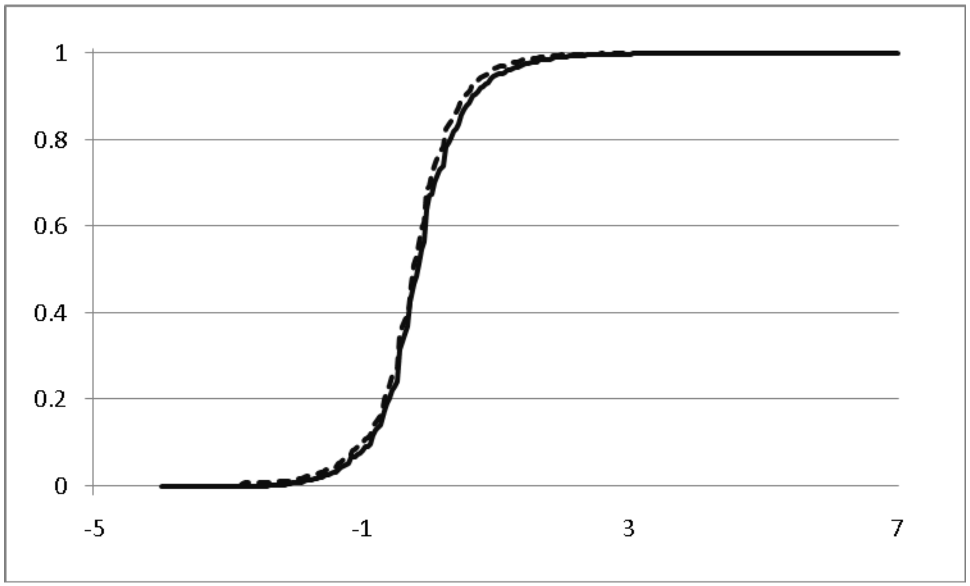
Model #2: *Results*

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



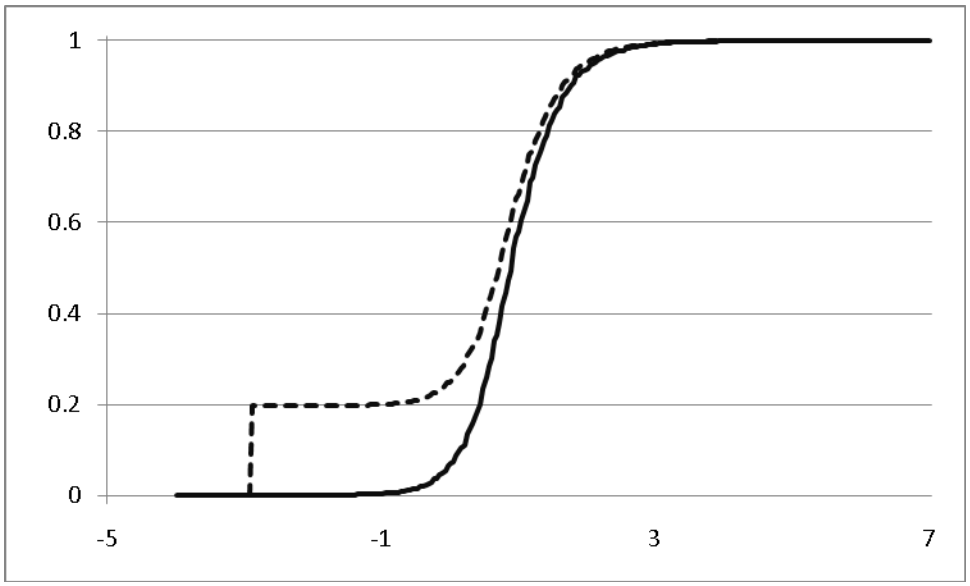
Model #2: *Results*

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



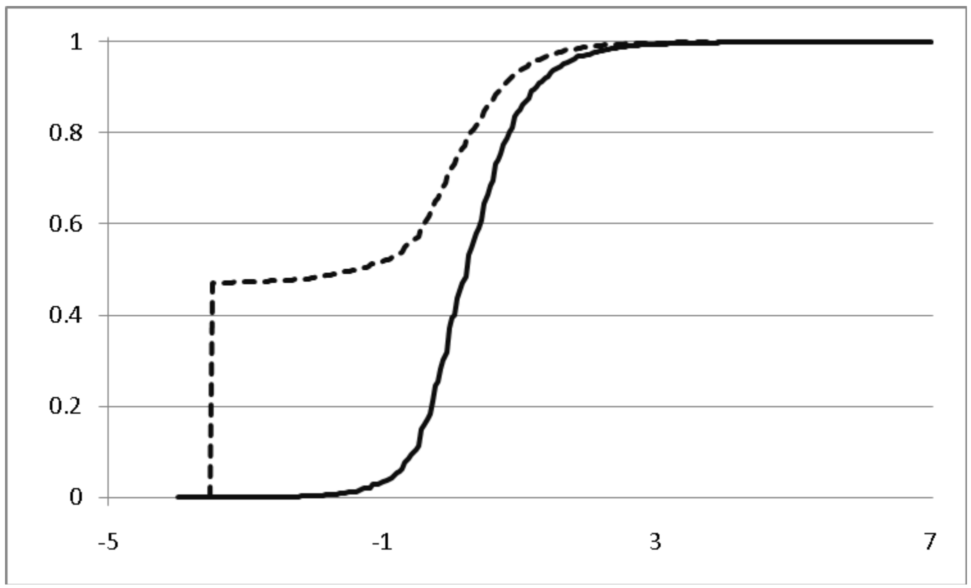
Model #2: *Results*

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



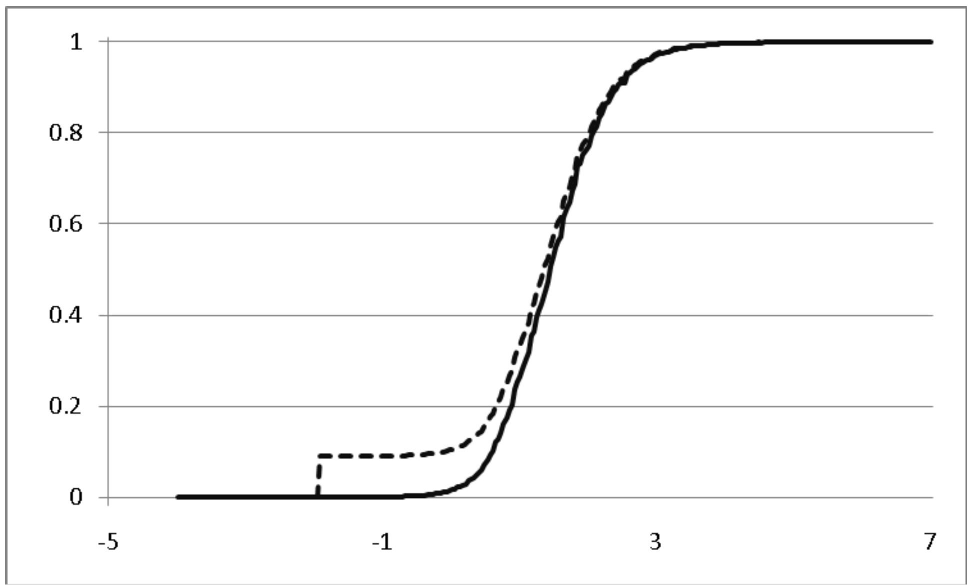
Model #2: *Results*

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



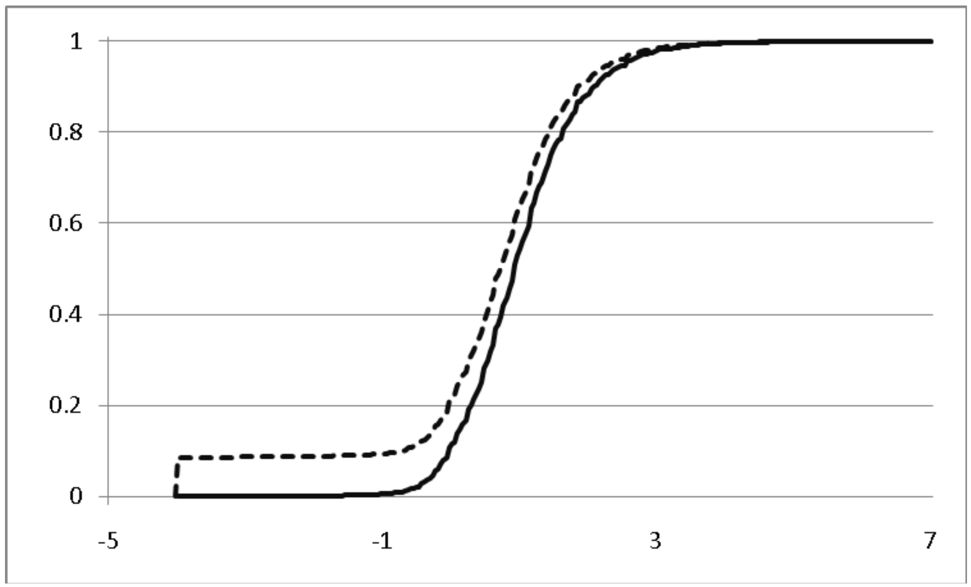
Model #2: *Results*

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



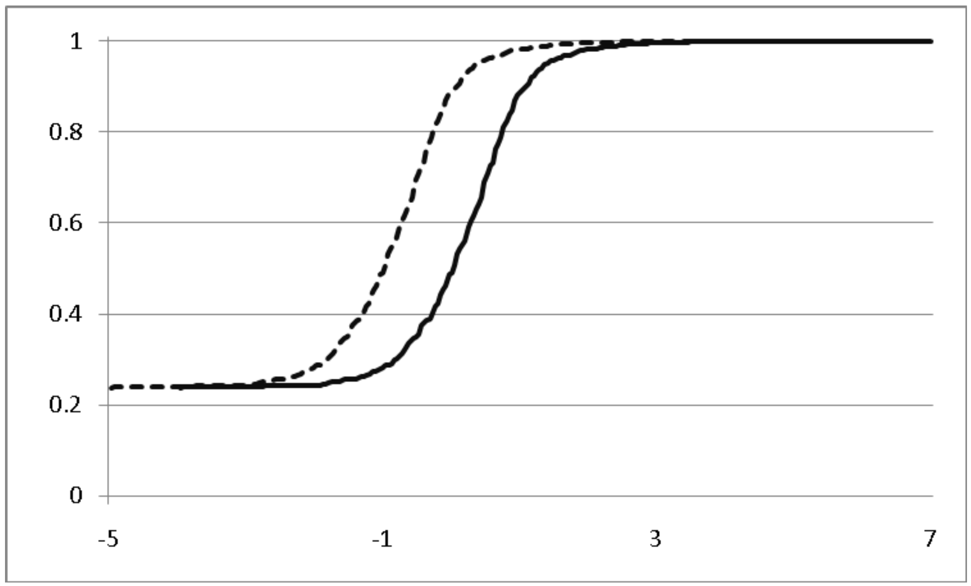
Model #2: *Results*

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



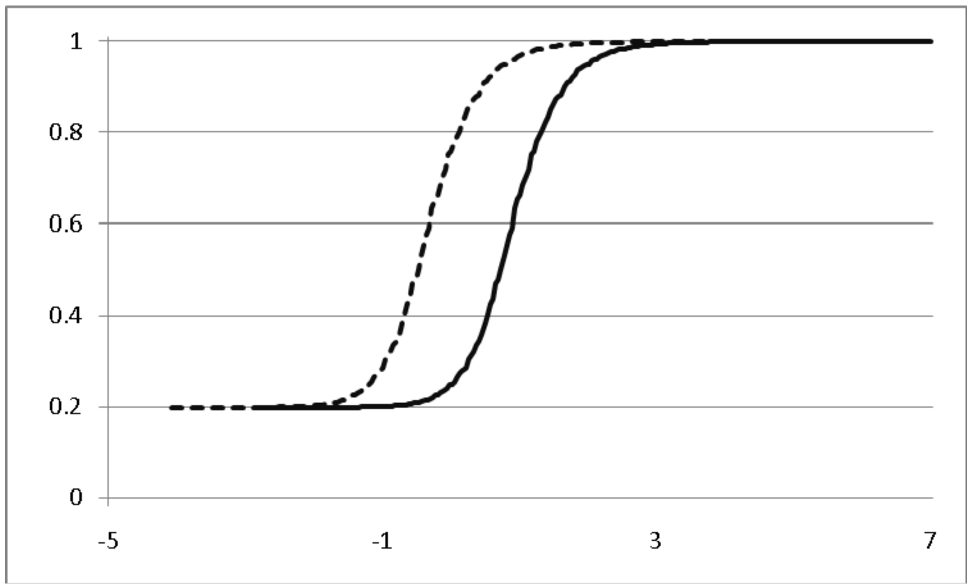
Model #2: *Results*

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



Model #2: *Results*

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



Model #2: *Results*

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