Risky Moves: Labor Market Risk and Migratory Destinations

Steven Brownstone

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1 Abstract

Labor mobility is essential to the process of economic growth. This research examines how the riskiness of migrants' destination earnings affects migrants' destination choices and how these choices affect economic growth. First, the paper provide evidence for the mechanism using two labor demand shocks: the introduction of genetically modified soy and China's entrance to the WTO. Migration flows increase when mean wages increase but decrease when the variance of wages increases. Including wage variance reduces the residuals in the standard gravity model of migration by 80%. The second part of the paper then develops a quantitative general equilibrium model with frictional labor markets. Increasing unemployment insurance has an important additional effect of encouraging migration to higher productivity locations and thus encourages growth when risk is considered in the migration decision.

2 Introduction

There are large rural-urban wage gaps, especially in developing countries. These persist even when accounting for amenities (Gollin et al., 2021) and individual characteristics (Lagakos et al., 2020). Growth in developing economies is associated with closing these wage gaps through migration from low to high-productivity locations. Some of the earliest models in development economics describe the process of surplus rural labor transitioning to a more productive industrialized sector (Lewis, 1954). Over the next eighty years, development success stories continue to be associated with rapid urban population shifts. Recent work attributes much of China's recent economic growth to declining inter-provincial migration costs (Hao et al., 2020). However, migrants face uncertainty over the job and wage they will get in urban areas (Porcher, 2021). Harris and Todaro (1970) argued that the risk of urban unemployment or underemployment explains wage gaps among the employed. The risk of poor employment outcomes directly deters migration through migrants' risk aversion. Thus, the riskiness of labor markets not only affects inequality, but it also has direct implications for countries' economic growth.

This paper departs from the modern spatial economics literature (Caliendo et al., 2019) (Allen and Donaldson, 2020) (Bryan and Morten, 2018) by considering workers who are risk averse. I develop a tractable partial equilibrium model to illustrate the impact of risk on migration flows and motivate an emperical test of the mechanism. Workers make a choice over all potential migration destinations, choosing the destination with the highest ex-ante utility after accounting for migration frictions. While risk-neutral migrants only consider the differences in mean earnings between locations, risk-averse migrants also consider the variance of earnings in different locations. In particular, risky destinations with greater variance of earnings have lower ex-ante utility than destinations with the same mean earnings, but lower variance. Using data from Brazil, I estimate that accounting for disutility from risk reduces the migration frictions needed to reconcile observed flows by eighty percent.

Using instruments for changes in the mean and variance of earnings, I estimate their impact on changes in migration flows between regions over time. Increasing mean earnings does increase flows, but increasing the variance of earnings decreases them. To illustrate the potential policy implication of this result, I build a quantitative general equilibrium model to show that government benefits for the unemployed have important effects on migration as well, which affects the economy's overall GDP. In the policy simulation, the migration channel reduces the GDP cost of increasing unemployment benefits from 2.8% of GDP to 1.8% of GDP.

I use two shocks to identify exogenous variation in labor demand between the 2000 and 2010 censuses which could lead to changes in wages. First, the introduction of genetically engineered soy dramatically improved agricultural productivity in Brazil's soy-growing regions (Bustos et al., 2016). This productivity shock generally increased mean wages. The second shock is the China trade shock (Costa et al., 2016). This shock provides two shift-share instruments for both imports and exports. The trade shock generated "Winners and Losers" (Costa et al., 2016); some Brazilian firms faced competition from cheap Chinese imports, while others benefited from new export markets, particularly for commodities. Thus, the trade instruments have strong effects on both the mean and the variance of earnings in localities. This is even true when earnings are restricted to only less educated workers, which more closely approximates the labor opportunities available to migrants.

The primary data source is the 2000 and 2010 Brazilian censuses. These provide information on where respondents lived five years prior. Brazil is one of the few countries that collects migration data on its census, which makes it particularly well suited for studying migration. The census also has data on earnings and employment in different industries. To construct the instruments, I use supplemental data on soy suitability and global trade flows. Brazil is a large economy with many distinct labor markets. Unlike some developing countries, migration is not simply characterized by movement from the rural hinterland to one or two metropolises. The average region is equally connected to six other regions through migration (Borusyak et al., 2022).

I develop a general equilibrium model to capture the trade-offs between policies that effect both the mean and variance of earnings. The Diamond-Mortensen-Pissarides (DMP) framework generates earnings risk through unemployment. Workers and firms bargain over wages with workers receiving unemployment benefits as an outside option. The benefits are financed through a proportional tax on both employed and unemployed workers' earnings. Thus, in the DMP framework, both unemployment rates and wages change endogenously with changes in unemployment benefits. In particular, wages increase as workers have more bargaining power, but unemployment may also increase since it is less costly. Migration introduces an additional potential effect of unemployment insurance, namely reduced earnings variance which lowers migration frictions. In developing countries with large productivity differences across space and high migration frictions, this migration effect could justify higher unemployment insurance.

While formal unemployment insurance is not available for most migrant workers in developing countries, governments do provide meaningful social safety nets that can help insure against underemployment. Historically, these benefits were not portable and had to be received in someone's location of permanent residence. However, advances in identification and financial systems have made portable benefits feasible. In India, the government is shifting to more direct benefit transfers, which are inherently portable as opposed to workfare schemes and discounted food rations, which are not (The Economist, 2022a). In China, the *Hukou* system famously excludes internal migrants from almost all public benefits, but calls for reform are growing (Chan and Wei, 2019). In Brazil, the government is similarly moving to more direct cash transfers (The Economist, 2022b) as opposed to the existing conditional cash transfer scheme where migrants may struggle to re-establish eligibility in a new location (Oliveira and Chagas, 2020). This paper argues that the ongoing policy debates about the portability and delivery of social safety nets in developing countries may have important implications for these countries' continued growth.

Literature A large body of evidence documents that migrants are risk averse, face substantial earnings risk, and respond to insurance. Migrants are risk averse, and the degree of risk aversion affects migration behavior. In China (Akgüç et al., 2016), Germany (Jaeger et al., 2010), and Ghana (Goldbach and Schlüter, 2018), more risk-averse people are less likely to move between labor markets. Looking within Chinese households, and thus controlling for economic characteristics that drive migration, it is the least risk-averse members who tend to be the ones that migrate (Dustmann et al., 2020). This selection effect means that the risk aversion I estimate and, thus, the magnitude of the quantitative effects of risk on migration are, if anything, underestimated since the remaining non-migrants have higher risk aversion than those that have already moved. The model conservatively assumes all potential migrants have the same risk aversion.

There is strong evidence that migrants face substantial earnings risk. An experiment that provided Bangladeshis with migration subsidies found average consumption increased by 30-35%, but if migrants had to pay back their subsidies the risk of falling below subsistence levels of consumption also increased by 36% (Bryan et al., 2014). Dispersion in earnings could be driven by differences in individual productivity in the urban area or labor search frictions which are substantial in developing country cities A crucial question is whether migrants know their urban productivity. Bryan and Morten (2018) show that if urban productivity is known then rural-urban wage gaps can largely be explained by skill sorting. Conversely, if urban productivity is unknown, then an interpretation of migration as a risky investment makes more sense, as suggested by the original authors of the Bangladesh migration experiment (Bryan et al., 2014). The presence of the urban unemployed strongly implies at least some of the uncertainty in urban earnings is unplanned. In the widely used panel data-set of Indian villages, 37% of migrants experience some involuntary unemployment at urban migration destinations (Morten, 2018). International migrants from Nepal have wide and incorrect priors about their potential net earnings from migrating to the Arabian Gulf, and inexperienced migrants update those priors based on basic information on the mean earnings of past migrants (Shrestha, 2019). In rural Kenya, people substantially underestimated the returns to migration and a randomized information intervention did increase migration substantially (Baseler, 2020).

Internet access helps drive better migration decisions in Brazil (Porcher, 2021). This paper's approach focuses on the idea that workers are correctly informed about destination labor markets but factor into their decisions that in both the risk of unemployment and mean wages if employed.

Reducing risk encourages migration. In the Bangladesh experiment, an alternative treatment arm offered index insurance correlated with destination earnings rather than a conditional cash transfer. The insurance was as effective as the conditional cash transfer at encouraging migration (Bryan et al., 2014). In China, a randomized micro-finance program led to a 36 percentage point increase in migration (Cai, 2020). A consistent empirical finding in the migration literature is that families of migrants are more likely to migrate themselves. This also holds when migration is induced in a randomized controlled trial, but the same social network effect is not present for friends (Bryan et al., 2014). One way to explain the difference between friends and families is that family members in an urban destination can offer specific job opportunities, reducing migration risks, while friends just provide general information without meaningfully reducing risk. Unfortunately, there is very limited evidence on the impact of portable social safety nets on migration since the portability reforms have generally been associated with the recent COVID-19 shock.

3 Motivating Regressions

3.1 Migration Data

The main data source is the Brazil census 10% sample from the Brazil census for the years 2000 and 2010. The migration data comes from a question about the municipality lived in 5 years ago. The census also has data on years living in current location and birth location. The municipality-level location data is very high resolution since there are 5,570 municipalities. Municipality boundaries change from year to year, so constructing regions with consistent boundaries is an important task for anyone using Brazilian data. The Brazilian census authority has its own system of minimum grouping called Area Mínima Comparável (AMC), there are 4,149 AMCs. These are too small to be useful as labor markets with an average population of only 39,858. Another grouping researchers often use are micro-regions. There are 588 microregions, which can be grouped into 411 areas comparable across years. Nonetheless, constructing migration flows as micro-region to micro-region leads to many zero flows. Only 18% of the 337,842 possible flows across 2000 and 2010 have non-zero migration flows for both years. Another potential solution is to use flows from the 26 provinces to microregions. While this definition of migration misses a lot of potential rural-urban migration within provinces as illustrated by figure 1, it results in far fewer zero flows with 60% non-zero in both years. Further, the results are stronger when the 4 smallest origin provinces, all in the remote Amazon, and the 2 smallest destination micro-regions are excluded. These exclusions increases the percentage of non-zero flows to 67%.

Areas with high migration are urban areas in southern Brazil and some of the municipalities in the Amazon. Thus the migration captured here is not just traditional rural-urban migration, but also migration to remote areas to engage in resource extraction. Figure 2 illustrates the average share of each origin province's population that migrates to each destination. This is the migration shared used in the model later in the paper.

Figure 1: Red dots are centers of Provinces and Yellow dots are centers of municipalities

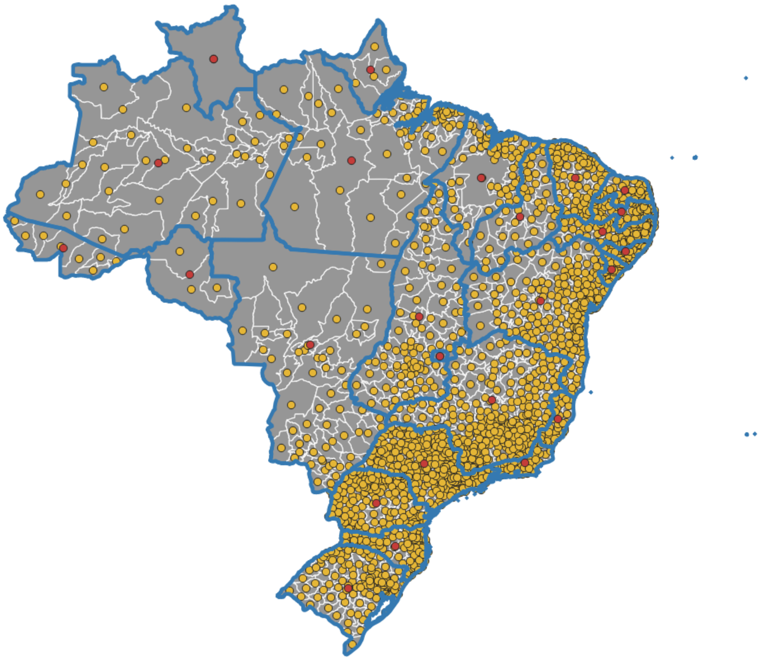
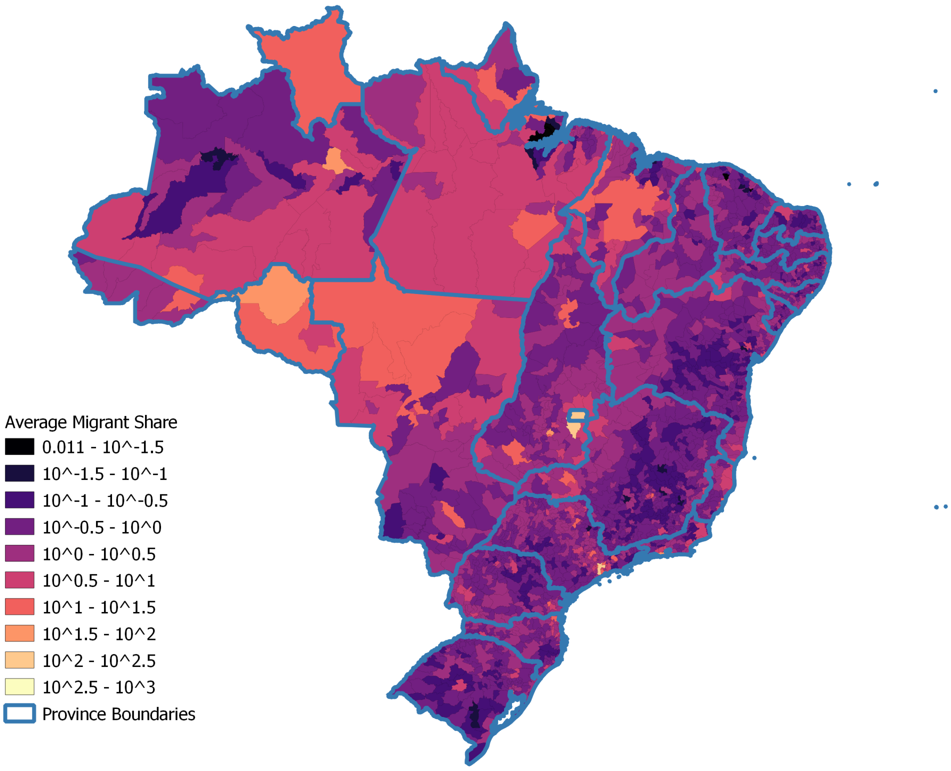


Figure 2: Migration Share per 100k Origin Population



3.2 Overview of Instruments

Two historical shocks created exogenous labor demand shocks. The first shock was the sudden legalization of genetically engineered soybeans in 2003. By 2011, 85% of the area planted with soy was genetically engineered. Importantly, this shock had substantial spatial heterogeneity driven by differences in an area's suitability for soy cultivation. The original paper about this shock also uses changes in labor markets as measured by the 2000 and 2010 census and does find significant effects on wages and the industrial composition of municipalities (Bustos et al., 2016). One challenge, is that the effects, while significant, are a little weak to be used as an instrument with the t-statistics on the soy shock coefficient around 2 or 3. Migration itself allowed labor markets to at least partially re-adjust in the 7 years between the beginning of the shock and 2010.

Since there are two labor market variables of interest, estimation requires instruments. A second well-accepted instrument is the China trade shock, which took place after China joined the WTO in 2001. Recent work on Barthik-type instruments has shown that exogeneity can either come from exogenous shocks or projecting an endogenous shock over exogenous shares (Borusyak et al., 2022). While the industry shares of Brazilian municipalities are clearly endogenous, it is very clear that internal migration decisions between 1995 and 2000 were not driven by expectations about changes in Chinese trade. Previous research (Costa et al., 2016) has already shown that this trade shock had effects that varied substantially across space driven by the pre-existing industrial composition of different areas. Similarly, there is evidence of significant changes in earnings and in the industrial composition of municipalities between 2000 and 2010 as driven by this shock.

3.3 Details on Instrument Construction

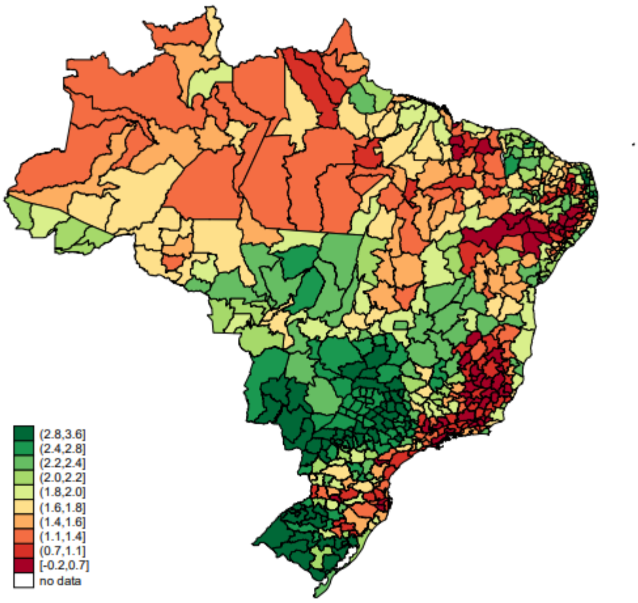
Since the genetic engineering shock is just for one crop, Bustos et al. (2016) directly uses a proxy for the potential yield impact of genetically engineered soy as their instrument. Specifically, Bustos et al. (2016) uses the FAO's Global Agro-Ecological Zones data product. In particular, they use the data-sets on the agro-climactic potential yield for soy under high and low inputs for approximately 9km by 9km grid-cells. The idea is that the gap between high and low input soy yields approximates the differential potential for GE soy across Brazil. The spatial distribution of these differences is illustrated in Figure 3 reproduced from (Bustos et al., 2016). Controlling for the proportion of the municipality that is rural since this directly affects how much the labor force could be directly affected by the shock and thus may threaten identification as a source of differential trends.

The construction of the China trade shock in Costa et al. (2016) that I follow is fairly complex. The basic Barthik instrument for the China trade shock would simply use changes in Brazilian imports and exports with China in each sector weighted by that sector's share of the labor market in each municipality. The issue is that changes in trade with China in a given sector could be correlated with Brazil-specific sectoral trends. The China shock literature deals with this problem by using Chinese trade with the rest of the world. Costa et al. (2016) goes even further by addressing the possibility of correlated world-level shocks to sectors. As long as the world-level shocks are exogenous to Brazilian migration flows, leaving those shocks might actually be advantageous in this setting, but without knowing exactly what those shocks are it is difficult to argue their exogeneity.

Costa et al. (2016) approach is to regress the growth between 2000 and 2010 in other countries imports/exports to all other countries aside from Brazil with sector and China-sector fixed effects. The sector fixed effect captures global trends in a sector while the China-sector fixed effect represents the growth in exports/imports attributable to China for a sector. The authors use the China-sector fixed effect multiplied by the trade in

Figure 3: Figure from (Bustos et al., 2019)

Figure 3: Δ in Potential Soy Yield 2000-2010



Notes: Authors' calculations from FAO-GAEZ data. Technical change in soy production for each microregion is computed by deducting the average potential yield under low inputs from the average potential yield under high inputs.

a given sector in 2000 as the export/import shock. In practice, these shocks are very strongly correlated with the "naive" Barthik China trade shocks

4 Results

The main estimates use province to micro-region labor flows. A challenge with all of these regressions is that there is a wide distribution of populations for both micro-regions and provinces. One option is to weight by the micro-region population times the share of the origin population e.g. for the flow from province i to micro-region j:

$$weight_{ij} = L_j * \frac{L_i}{\sum_i L_i}$$

This has the advantage that the weights will still sum up to the overall population, but the problem is that some states and microregions have very large populations, which means the weighted IV regressions have larger standard errors weakening the instruments. The preferred approach is to instead simply drop the smallest origins and destinations from the sample. Table [2] presents the first-stage for this preferred specification. The negative sign of the main regressor of interest is the same whichever approach I take. Table [3] presents the main results taking both the weighting and observation dropping approaches. I also show the specifications robustness to the controls used in Bustos et al. (2016) and Costa et al. (2016). Note that the soy instrumental variable appears to affect mean wages more than the variance of wages, while the trade instrumental variables affect both. Technically, all of the instruments can affect both endogenous variables. They just have to affect each variable differently enough that both shocks are identified.

Table 1: First Stage Results for Endogenous Variables

VARIABLES	(1) Δ Dest Wages	(2) Δ var Ln Wages
China Import Shock	-0.00157***	0.00135***
	(0.000600)	(0.000918)
China Export Shock	4.24e-05***	4.97e-05***
	(9.20e-06)	(7.32e-06)
Soy Productivity Shock	0.0171***	0.000260
	(0.00608)	(0.00652)
Constant	1.262***	0.0271
	(0.128)	(0.123)
Sanderson-Windmeijer F stat	19.85***	45.39***
Observations	6,281	6,281
R-squared	0.629	0.649

Table 2: *

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column (1) is the change in mean wages while column (2) is the change in the variance of log wages.

I report a variety of cluster-robust F stastics to test for weak instrument in the presence of multiple endogenous variable. The Sanderson-Windmeijer (S-W) F statistic (Sanderson and Windmeijer, 2016) is a conditional F-statistic measuring how well the instruments predict the residuals from an IV regression where only the other endogenous variable is instrumented. This test is useful for understanding whether there might be weak instrument issues for either endogenous variable. The KPW rk F stastistic is the Kleibergen-Paap rank Wald statistic (Kleibergen and Paap, 2006) which is the cluster robust analogue to the Cragg-Donaldson Wald Statistic. Both are testing the null statistic that the first stage matrix is not full rank.

Table 3: Main Instrumental Variable Results

	(1)	(2)	(3)	(4)
	Δ Log Share of Pop in origin Province Migrating to Micro-Region			
Δ Dest Wages	1.61**	1.21***	0.63	0.64**
se	[0.75]	[0.46]	[0.81]	[0.61]
Δ var Ln Wages	-2.10***	-2.77***	-3.53***	-2.43***
se	[0.65]	[0.82]	[0.65]	[0.27]
KPW rk F statistic	38.55	8.96	6.62	7.15
ν	**1.01**	0.34	0.06	0.10
η	**2.61**	4.58	11.28	7.56
Weights	N	N	Y	Y
Controls	Y	N	Y	N
S-W F stat avg	19.85***	11.27***	8.64***	6.50***
S-W F stat SD	45.39***	13.81***	13.85***	11.29***
N	6281	6281	6656	6656

Robust standard errors in brackets *** p<0.01 ** p<.05 * p<0.1

We can use the coefficients to calculate the residuals with and without the variance term.

The average value of the residual with the risk term is 251, and without the risk term, it is 1220. This suggests earnings risk explains 80% of the residual migration frictions in the benchmark framework.

These results also have a structural interpretation if we assume that earnings in a potential destination have a log-normal distribution. This structural interpretation is discussed in more detail in appendix A.1.

Using this structure, the coefficients of my instrumental variables regression can be interpreted as the elasticity of a destination's utility to migration and the average risk aversion of potential migrants. The estimated CRRA risk aversion parameter of 2.61 is well within the range of values found elsewhere in the macro-development literature. These parameters can be used to show moving from the 20th to 80th percentile in earnings variance would increase migration between locations with a 30% productivity gap by five percentage points, increasing economy-wide earnings by 1%.

5 Model

To quantify the role job market frictions play in deterring migration, we model an economy in which migration flows respond to both wages and employment probabilities in each destination. While higher wages attract workers to high-productivity locations, the risk of being underemployed in a high-cost location deters migration.

The economy has N locations. Each location is characterized by its productivity for firms that operate there A_i and Q_i its utility value for workers that live there.

Each location's population L_i is an endogenous measure of workers. The workers incur some costs τ_{ij} moving from i to j measured in utils. These reflect both the financial costs of moving as well as the psychological costs of being far away from one's culture or friends. Each individual worker ω decides where to move and then draws a location specific idiosyncratic taste shock ε_i^{ω}. If a worker decides to move to a city, they draw the taste shock and enter the labor market where they either receive a wage or face underemployment.

Firms in each location produce a single location specific intermediate good using only labor. This good is aggregated into a single final good using a CES production function. The final good is treated as the numeraire ($p = 1$)

5.1 Workers

Workers are risk averse. They spend all their income on consumption which they value with a CRRA utility function with the risk aversion parameter η.

$$U(C_i) = (1-\eta)^{-1} C_i^{1-\eta}$$

The ex-ante utility of a migrant from location i to destination j is:

$$u_{ij} = \frac{\mathbb{E}[U(C_j)]Q_j}{\tau_{ij}\varepsilon_{j\omega}}$$

We model the heterogeneity in utility from living in different location following Eaton and Kortum (2002). The idiosyncratic component of the utility ε_j^ω is drawn from an independent Frechet distribution: $G(\varepsilon_{j\omega}) = \exp(-\varepsilon_{j\omega}^{-\nu})$

Since the utility of each potential migration destination for someone living in i going to destination j is a montonic function of a Frechet random variable ε_j it is itself Frechet distributed. The migration decision is made by maximizing the expected utility u_{ij}^ω of all potential destinations.

$$u_{ij} = \frac{\mathbb{E}[U(C_j)]Q_j}{\tau_{ij}\varepsilon_j^\omega}$$

$$\max_j u_{ij} = \max_j \left[\frac{\mathbb{E}[U(C_j)]Q_j}{\tau_{ij}\varepsilon_{j\omega}}\right]$$

The maximum of a Frechet distributed random variable is Frechet distributed itself. Using properties of the Frechet CDF detailed in appendix A.1 we can derive the probability a worker chooses to move from i to j.

$$\pi_{ij} = \frac{-u_{ij}^{-\nu}}{\sum_j -u_{ij}^{-\nu}} \tag{1}$$

5.1.1 Labor Market

The basic labor market is the Diamond-Mortesen-Pissarides model of undirected costly search. However, these models generally make a continuous time assumption that there are infinite periods to search and match. In the context of my overall model, the idea is that job search happens at a far higher frequency, daily or monthly, than migration decisions which are made annually or in the calibration data over the course of a decade.

Workers engage in undirected search in the model. $\theta = \frac{v}{u}$ or the ratio of vacancies to unemployment ratio commonly known as labor market tightness. $q(\theta^t)$ is the probability a vacancy matches with a worker and $\theta q(\theta^t)$ is the probability a worker and vacancy both match. Workers match using the Cobb-Douglas matching function $M(u, v) = \Psi u^\alpha v^{1-\alpha}$

We can solve for a system of equations defining the steady state labor market tightness (θ) and wage (w). I omit the i subscript in this section since each labor market steady state is solved independently. First, we need to define the value of a job and vacancy for the firm and employment and unemployment for the worker. Firms derive surplus from a job which is equal to the marginal product of labor ($y = p_i A_i$) minus wage w. Firms need to use c of the final good to search for a new worker if they face a vacancy. Unemployment benefits are b. These benefits are financed through a lump-sum tax τ on all workers' earnings. See Appendix A.2 for an alternative formulation where workers who do not match to firms are simply less productively self-employed.

This leads to the first equation defining the steady state which requires that the surplus from filling a job $y - w$ equals the expected cost of a vacancy.

$$y - w = (r + \chi)\frac{\theta^\alpha}{\Psi}c \tag{2}$$

The second equation defining the steady state is derived from the workers and firms engaging in nash bargaining over the surplus from the match.

$$\max_{E(w)-U,J-V}(E(w)-U)^{\phi}(J(w)-V)^{1-\phi} \tag{3}$$

subject to $P=E-U+J-V$

The Nash bargaining solution reduces after some algebra in appendix $A.3$

$$(1-\phi)[(w-\tau)^{1-\eta}-(b-\tau)^{1-\eta}](1-\eta)^{-1}=\phi(w-\tau)^{-\eta}[(y-w)+\theta c] \tag{4}$$

The third equation defining the steady state is simply the government's budget constraint.

$$ub=(\tau)$$

$$\frac{b\chi}{\Psi\theta^{1-\alpha}+\chi}=\tau \tag{5}$$

Together the equations (2), (4),and (5) define the steady state labor market equilibrium in each location.

The expected utility of consumption in destination j, $EU(C_j)$, is now just derived from the probability of employment and the unemployment benefit.

$$EU(C_j)=(1-\eta)^{-1}(1-u_j)(W_j-\tau)^{1-\eta}+(1-\eta)^{-1}u_j(b_j-\tau)^{1-\eta}$$

We can plug in the values we derived for the expected utility of each labor market into the equation (1) to get an equation governing migration flows in terms of the economy's fundamentals.

$$\pi_{ij}=\frac{\left(-\left\{(1-\eta)^{-1}(1-u_j)(W_j-\tau)^{1-\eta}+(1-\eta)^{-1}u_j(b_j-\tau)^{1-\eta}\right\}Q_j^{-1}\tau_{ij}\right)^{-\nu}}{\sum_j\left(-\left\{(1-\eta)^{-1}(1-u_j)(W_j-\tau)^{1-\eta}+(1-\eta)^{-1}u_j(b_j-\tau)^{1-\eta}\right\}Q_j\tau_{ij}^{-1}\right)^{-\nu}}$$

To find the steady state, we simply find the vector of population L_i such that net inflows equal net outflows in each location so that each location's population is stable. This means $\sum_j \pi_{ij}L_i=\sum k\neq i\pi_{ki}L_i$.

The steady state is unique because because the model does not have exogenous agglomeration and congestion.

5.2 Goods Market

The basic approach to the general equilibrium model is a simple Armington goods market with Diamond-Mortesen-Pissarides frictional labor market. This structure isolates the role of labor market frictions. There is no concept of a downward sloping labor supply curve in each location, but the prices reflect changes in population. As population in a location increases the price it can charge for its good decreases thus reducing wages in that location.

Firm Level Production $y_i=f(L^{\omega})=A_i$ where A_i is location i's productivity. Each firm employs 1 worker so a location's output is simply $y_i=A_iL_i$

Aggregate Production Each location produces a specific good which is aggregated into a homogeneous composite good with CES paremeter ζ.

$$Y = \left(\sum_{i \in N} y_i^{\frac{1-\zeta}{\zeta}} \right)^{\frac{\zeta}{1-\zeta}}$$

The individual prices are determined by assuming the representative firm producing the composite good maximizes the total economy output Y subject to the cost of production $\sum_{i \in N} p_i y_i$

This implies $p_i = (Y/y_i)^{\frac{1}{\zeta}}$

5.3 Full Stationary Equilibrium

The full stationary equilibrium is defined by the exogenous parameters of the worker's utility functions (η, ζ, ν), the migration frictions (τ_{ij}), and location amenity values (Q_j) as well as the parameters of the labor market (α, Ψ, χ, ϕ, β, c_j, and b_j).

Conditional on these parameters solve for the vector of taxes τ_i, prices p_i, wages w_i, and market tightness $\theta = \frac{u}{v}$ such that individuals are maximizing their utility and firms are making 0 profits. For individual ω born in i their destination j satisfies: $j = \arg\max_{i \in N} \frac{\mathbb{E}[U(C_j)]Q_j}{\tau_{ij}\varepsilon_j^{\omega}}$ when they maximize utility. Firms make 0 profits when $y - w = (r + \chi)\frac{\theta^{\alpha}}{\Psi}c$.

The wages also satisfy the Nash bargaining solution: $(1-\phi)[(w-\tau)^{1-\eta} - (b-\tau)^{1-\eta}](1-\eta)^{-1} = \phi(w-\tau)^{-\eta}[(y-w)+\theta c]$. The taxes ensure the local government budget constraint is satisfied: $u_i b_i = \tau_i$.

Finally, the labor, local goods, and aggregate goods markets must all clear. The **Labor** market clears when $\sum_i \hat{L}_i = 1$. The **Local Goods** market clears when $y_i = (1-u_i)L_i A_i - u_i L_i c_i / p_i$. The **Aggregate Goods** market clears when $Y = \left(\sum_{i \in N} y_i^{\frac{1-\zeta}{\zeta}} \right)^{\frac{\zeta}{1-\zeta}}$

6 Policy Counterfactual

I simulate the impact of increasing unemployment insurance in the urban area in a world with and without migration. In particular, I simulate going from a status quo with limited benefits portability where the urban unemployment benefits are a far smaller fraction of wages than in rural areas to a world where they are more equalized. Since I do not have all of the relevant labor market friction variables for the Brazilian economy and the point of the exercise is to illustrate the existence of my mechanism I simply chose standard parameter values for the DMP model. The additional parameters where I used standard values for the simulation can be found in Appendix A.4.

To solve the economy I guess a population vector and then calculate the associated prices and marginal products of labor in each location. I plug these variables into the system of equations that represent the labor market steady state in each location to get wages and unemployment in each location. I then calculate the migration probabilities associated with mean and variance of wages in each location. I then update the population guess based on the migration probabilities. I repeat the procedure until the net migration between locations is zero and thus the whole economy is in a steady state.

Table 4: Policy Simulation Results

	Low Insure	High Insure	Low Insure Mig	High Insure Mig
Parameters				
Risk Aversion η	2.6	2.6	2.6	2.6
Bargaining Weight ϕ	0.50 0.50	0.50 0.50	0.50 0.50	0.50 0.50
% Unemp benefit b	6.00 6.00	6.00 12.00	6.00 6.00	6.00 12.00
Posting Cost	15.00 15.00	15.00 15.00	15.00 15.00	15.00 15.00
Productivity	12.00 24.00	12.00 24.00	12.00 24.00	12.00 24.00
Endogenous Objects				
Price	1.18 1.06	1.17 1.06	1.20 1.05	1.20 1.05
Post Tax Wages	8.41 15.15	8.37 17.19	8.59 15.04	8.61 16.94
Post Tax Benefits	4.26 5.11	4.25 9.26	4.30 5.10	4.30 9.24
taxes	1.74 0.89	1.75 2.74	1.70 0.90	1.70 2.76
theta	0.43 2.34	0.42 0.81	0.45 2.29	0.46 0.80
Emp. Prob.	71% 85%	71% 77%	72% 85%	72% 77%
Var Earn High Prod	12.75	11.10	12.58	10.52
Var Earn Low Prod	3.55	3.51	3.75	3.77
Mean Earn High Prod	13.66	15.38	13.55	15.17
Mean Earn Low Prod	7.21	7.17	7.37	7.40
High/Low Prod Pop	50.03%	50.04%	55.55%	57.64%
High Prod Mig	0%	0%	18%	21%
Low Prod Mig	0%	0%	7%	5%
High Prod Util	-0.85	-0.70	-0.86	-0.70
Low Prod Util	-1.52	-1.53	-1.49	-1.49
GDP	34.30	32.98	35.73	34.75

The key result is that with the migration channel shut down increasing benefits in the high productivity area decreases GDP by 3.8%. Allowing for migration means equalizing benefits, leading to a GDP decrease of only 2.7%. This is not driven by differences in migration employment across the two worlds. This result is driven by the increase in urban population which goes from 55.55% to 57.64%. This is driven by the benefits of both pushing up wages and reducing earnings variance in the high-productivity location.

7 Discussion

The empirical part of the paper is wholly focused on what aspects of a destination's labor markets are attractive. When estimating the model, I eliminate any origin effects with origin-by-year fixed effects. However, in the model itself, what matters for migration is the ratio of the riskiness of a potential destination to all other potential destinations, including no migration. Thus, if the origin labor market becomes very risky, my model would also predict increased migration. This channel of migration as a response to shocks at origin has a rich literature. Most notably, the Bangladesh migration experiment, which was originally framed as demonstrating migration was a risky investment, has been re-analyzed to show that migration was driven by households responding to bad shocks at their origin, with wealthier households, able to self-insure through assets, not migrating at all (Lagakos et al., 2018).

The paper and model do not differentiate seasonal from permanent migration since the focus is aggregate flows. Seasonal migrants may face lower risk than more permanent migrants since they are not bringing their household with them. However, even for seasonal migrants, going to a city and not finding work is a substantial risk since the round-trip transportation costs and opportunity costs of not working in the origin can be high. Furthermore, these migrants may face particularly strong utility costs since they are away from their families and may choose to stay in the lowest possible cost accommodations, which can be incredibly uncomfortable.

7.1 Future Directions

While providing strong evidence that risk does deter migration, there is substantial room to improve the empirical part of the paper to make the parameter estimates more credible. First, shifting to estimating meso-region to meso-region flows would avoid throwing out migrants who move within provinces but across labor markets. Second, I am observing the impact of the labor demand shocks more than five years after they occurred. I may be underestimating the response of wages since the local economies are already in a new equilibrium at the time of the next census. Also, since I count anyone who moved since 2005 as a migrant, it is important to capture the wages the migrants actually faced. One option would be to use data from PNAD, Brazil's version of the current population survey, to explore alternate results with annual wages. This survey could also provide helpful data on rents and costs of living in each destination, which I currently abstract away from in my model. The potential soy yield instrument can be strengthened. In particular, the instrument could be reconstructed as a shift-share instrument where the national increase in soy yields is the shock and the potential yield-gap times the area under cultivation is the share. Revisiting this paper in light of (Borusyak et al., 2022), it appears the authors were unnecessarily concerned about the exogeneity of the shares when what is really exogenous is the national soy productivity shock that came with the introduction of GE soy in 2003.

There are also other approaches for measuring labor market shocks I could explore. A recent job market paper compiled a list of ten major positive labor demand shocks that led to substantial in-migration as a way to test whether the migration dynamics in response to these shocks matched his model (Porcher, 2021). Theoretically, more of these shocks could be manually compiled as a way to calibrate the model. Helpman et al. (2016) use mass layoff events as a labor supply shock for the surviving firms. While it is difficult to argue that these plant closures are fully exogenous, these events can be used to measure the size of the frictions in a municipality's labor market since there is far less selection for sudden layoffs than migration.

A major concern is that the variance of wages is not a particularly good measure of the actual risk faced by individual migrants. Increases in wage variance could be due to changes in labor force composition rather than known risk. There are two paths forward to address this issue. First, I can use mincerian regressions to isolate the "unexplained" variance in wages within a location following Helpman et al. (2016). I can also segment migration flows at least by education level under the theory that adults rarely change their educational attainment. Another approach would be to try to conduct an information experiment partnering with job placement platforms targeting blue-collar workers experimentally removing frictions by providing job matches.

Another approach is to look at other measures of labor market frictions, such as unemployment rates. However, in the Brazilian context, there is evidence that the informal sector and self-employment act as employment buffers, making unemployment difficult to interpret (Dix-Carneiro and Kovak, 2019). Changes in self-employment and informal sector employment relevant to formal employment might be another promising approach for trying to quantify the earnings risk faced by individual migrants. Other researchers in Brazil have had success calibrating macroeconomic models of migration using informal sector employment as a stand-in for unemployment (Busso et al., 2021). The challenge with this approach is that if unemployment benefits are calibrated to match informal sector wages it is hard to think about social safety net policy experiments.

8 Conclusion

The main take-away of this paper is that risk aversion is an important component of the barriers that prevent workers from moving to higher productivity areas. Allowing workers to move to high-productivity areas is important for a country's growth. Migration is a channel that allows social safety net policies to have important impacts not just within the current labor markets where their beneficiaries work, but across entire countries. In particular, social safety nets that ignore internal migrants may have serious impacts on growth. On the other hand, policies that make internal migration less risky can encourage growth for less cost than direct migration subsidies. In particular, making it easier for migrants to match with jobs before committing to move could both reduce urban poverty and increase overall GDP. While risk may deter migrants from seeking new opportunities, understanding the role risk plays in migration presents policymakers with many new opportunities for encouraging economic growth.

A Appendix

A.1 Structural Partial Equilibrium Model

A.1.1 Environment

Geography There are N locations separated by τ_{ij} moving costs which reflect the costs of moving from i to j measured in utils. These reflect both the financial costs of moving as well as the psychological costs of being far away from ones culture or friends.

Individual Characteristics and Preferences Individuals ω are characterized by their current location i and a vector of location taste shocks ε_i^ω which characterizes an individual's preferences for a given location. We assume these shocks are drawn from an i.i.d Frechet distribution with shape parameter ν. A location can also provides non-individual specific amenity value to individuals Q_i. They spend all their income on consumption which they value with a CRRA utility function with the risk aversion parameter η.

$$U(C_i) = (1-\eta)^{-1} C_i^{1-\eta}$$

The ex-ante utility of a migrant from location i to destination j is:

$$u_{ij} = \frac{\mathbb{E}[U(C_j)]Q_j}{\tau_{ij}\varepsilon_j^{\omega}}$$

Earnings Worker ω's earnings in destination j, R_j^{ω} are drawn from a log-normal distribution. The underlying normal distribution has mean μ_j and standard deviation σ_j e.g. $\log R_j^{\omega} \sim Normal(\mu_j, \sigma_j)$

We assume people eat their earnings so $C_j^{\omega} = R_j^{\omega}$

Timeline Individuals make one migration decision. Let the initial distribution of the population across the vector of locations is $\{L_{i0}\}$. I normalize the vector of populations so that $\sum_i L_i = 1$. Individuals draw there taste shock ε_i^{ω} and then chose a destination j. After the migrants move, their destination productivity a_j is drawn from their selected destination j's productivity distribution.

A.1.2 Solving the Migration Problem

First, we will derive the expected utility of moving from location i to j. Then we will use properties of the frechet distribution to derive the share of migrants initially at i that move to j.

Expected Utility The CRRA utility function is $U(C_j) = (1-\eta)^{-1}C_j^{1-\eta}$
Note that $C^{1-\eta} = e^{(1-\eta)\ln C} = e^{(1-\eta)\tilde{C}}$ where $\tilde{C}$ is normally distributed. Since $\mathbb{E}[e^{(1-\eta)\tilde{C}}]$ is just the normal moment generating function with parameter $(1-\eta)$. However, we want an expression in terms of the wage distribution and the price. Since our agents only consume, we have $C_j = R_j$ for any location.

Thus we can calculate the expected utility, $\mathbb{E}\left[U(R_j^{\omega})\right]$ where R_j^{ω} is distributed log-normally with underlying normal have a mean of μ and variance of σ^2.

$$\mathbb{E}\left[(1-\eta)^{-1}(R_j^{\omega})^{\eta-1}\right] \tag{6}$$

$$\mathbb{E}\left[(1-\eta)^{-1}e^{(1-\eta)\ln R_j^{\omega}}\right] \tag{7}$$

$$\left[(1-\eta)^{-1}\exp\left((1-\eta)\mu + \frac{\sigma_j^2}{2}(1-\eta)^2\right)\right] \tag{8}$$

note that $\mathbb{E}\left[R_j^{\omega}\right]^{1-\eta} = \exp\left(\mu + \frac{\sigma_j^2}{2}\right)^{1-\eta} = \exp\left((1-\eta)\mu + \frac{\sigma_j^2}{2}(1-\eta)\right)$ which we get from the normal moment generating function embedded in 7

Now we can re-arrange to get in terms of the mean, $\mathbb{E}\left[R_j\right] = \bar{R}_j$:

$$\left[(1-\eta)^{-1}\exp\left((1-\eta)\mu + \frac{\sigma_j^2}{2}(1-\eta)^2 + (1-\eta)\frac{\sigma_j^2}{2} - (1-\eta)\frac{\sigma_j^2}{2}\right)\right]$$

$$\left[(1-\eta)^{-1}\exp\left(\underbrace{(1-\eta)\mu+(1-\eta)\frac{\sigma_j^2}{2}}_{\ln \bar{R}_j^{1-\eta}}+(1-\eta)^2\frac{\sigma_j^2}{2}-(1-\eta)\frac{\sigma_j^2}{2}\right)\right]$$

$$\left[(1-\eta)^{-1}\bar{R}_j^{1-\eta}\exp\left(((1-\eta)^2-(1-\eta))\frac{\sigma_j^2}{2}\right)\right]$$

Simplifying:

$$\mathbb{E}[U(\bar{R}_j)] = \left[(1-\eta)^{-1}\bar{R}_j^{1-\eta}\exp\left(-\eta(1-\eta)\frac{\sigma_j^2}{2}\right)\right]$$

This is the expected utility we can plug into our standard migration model.

Note that we can do mean preserving spreads by holding $\bar{R}_j$ fixed an increasing σ_j, noting that the mean of the underlying normal must adjust down accordingly. See A.1.4 for details.

Deriving Migration Flows

The ex-ante utility for agent ω moving from i to j where τ_{ij} is moving cost Q_j is amenity value is:

$$u_{ij}^{\omega} = \frac{\mathbb{E}[U(C_j)]Q_j}{\tau_{ij}\varepsilon_j^{\omega}}$$
$$\max_j u_{ij}^{\omega} = \max_j \left[\frac{\mathbb{E}[U(C_j)]Q_j}{\tau_{ij}\varepsilon_j^{\omega}}\right]$$

Note that the probability of migration is The probability of migrating from i to j is $Pr(u_j^{\omega} > \max_j u_{ij}^{\omega}) = \pi_{ij}$

In deriving the migration probabilities we use the CDF of the Frechet distribution $G(u) = \exp(-u^{-\nu})$. However this is defined only for $x > 0$. For values of $\eta > 1$ the utilities $U(C_j) = (1-\eta)^{-1}C_j^{1-\eta} < 0$. Utility is still increasing in consumption, but $U(C_j)$ just becomes less negative as consumption goes up. To ensure the values of u_j^{ω} are positive we can multiple by -1 and flip the sign of the probability.

$$Pr(-u_j^{\omega} < \min_j -u_{ij}^{\omega}) = \pi_{ij}$$

We also need to change how we define τ_{ij} and Q_j so that utility is increasing in Q_j and decreasing in τ_{ij}

$$u_{ij}^{\omega} = \frac{\mathbb{E}[U(C_j)]\tau_{ij}}{Q_j\varepsilon_j^{\omega}}$$

Using Freceht random variables to aggregate minimums is a standard problem in the trade literature where consumers look for minimum prices and the solution yields the form:

$$\pi_{ij} = \frac{-u_{ij}^{-\nu}}{\sum_j -u_{ij}^{-\nu}}$$

Now we can plug in for u_{ij} to get the expression in terms of our variables. For simplicity, let $\Lambda_i = \left(\sum_k -u_{ik}^{-\nu}\right)^{-1}$.

$$\pi_{ij} = \frac{\left(-(1-\eta)^{-1}\bar{R}_j^{1-\eta}\exp\left(-\eta(1-\eta)\frac{\sigma_j^2}{2}\right)Q_j^{-1}\tau_{ij}\right)^{-\nu}}{\sum_j\left(-(1-\eta)^{-1}\bar{R}_j^{1-\eta}\exp\left(-\eta(1-\eta)\frac{\sigma_j^2}{2}\right)Q_j^{-1}\tau_{ij}\right)^{-\nu}}$$

Note that the $-(1-\eta)^{\nu}$ factors out from the numerator and denominator. We can then the define the denominator as a scale constant $\Lambda_i = \sum_j \left(\bar{R}_j^{1-\eta}\exp\left(-\eta(1-\eta)\frac{\sigma_j^2}{2}\right)Q_j^{-1}\tau_{ij}\right)^{-\nu}$

$$\pi_{ij} = \left(\bar{R}_j^{1-\eta}\exp\left(-\eta(1-\eta)\frac{\sigma_j^2}{2}\right)Q_j^{-1}\tau_{ij}\right)^{-\nu}\Lambda_i \tag{9}$$

If we set $\eta = 0$ and $p_{ij} = 1$ then the model collapses to our traditional model. However, we need to note that the expected utility values, $a_{ij} = \frac{\bar{R}_j Q_j}{\tau_{ij}} \geq 0$, are now positive so we have to use a different formula for π_{ij} based on $Pr(a_j^{\omega} > \max_j a_{ij}^{\omega}) = \pi_{ij}$.

$$\pi_{ij} = \frac{u_{ij}^{\nu}}{\sum_j u_{ij}^{\nu}}$$

$$\pi_{ij} = \left(\frac{\bar{R}_j Q_j}{\tau_{ij}}\right)^{\nu}\Lambda_i$$

Now we can see that this model collapses nicely back to the "standard" model used by Allen and Donaldson (2020).

A.1.3 Identification

First we take the log of the equation giving the probability of migrating from i to j [9]

$$\log \pi_{ij} = -\nu(1-\eta)\log \bar{R}_j + \nu\eta(1-\eta)\frac{\sigma_j^2}{2} + \nu \log Q_j - \nu \log \tau_{ij} + \log \Lambda_i$$

Since we have migration and labor market data for multiple years we can write the same equation down with year subscripts and take the first difference.

$$\Delta \log \pi_{ij,y} = -\nu(1-\eta)\Delta \log \bar{R}_{j,y} + \frac{\nu\eta(1-\eta)}{2}\Delta(\sigma_{j,y}^2) + \nu \log \Delta Q_{j,y} - \nu\Delta \log \tau_{ij,y} + \Delta \log \Lambda_{i,y}$$

The easiest way to turn this into an equation we can estimate is to simply assume amenities and moving costs are time invariant e.g. $Q_{j,y+1} = Q_{j,y}$ and $\tau_{ij,y+1} = \tau_{ij,y}$. These are strong assumptions, but it is worth noting that moving costs are often assumed to be proportional to distances which is obviously a time invariant characteristic. Technically we only need to assume any changes in amenities or migration costs are uncorrelated with changes in real wages and the standard deviation of real wages so that we can subsume $\nu\Delta \log Q_{j,y}$ and $-\nu\Delta \log \tau_{ij,y}$ into the error term of the regression.

The $\Delta \log \Lambda_{i,y}$ term can be controlled for in a regression by adding origin and year fixed effects.

This motivates two possible regression:

$$\Delta \log \pi_{ij,y} = \beta_1 \Delta \log \bar{R}_{j,y} + \beta_2 \Delta \sigma_{j,y}^2 + \alpha_i + \varepsilon_j \tag{10}$$

$$\log \pi_{ij,y} = \beta_1 \log \bar{R}_{j,y} + \beta_2 \sigma_{j,y}^2 + \alpha_{ij} + \alpha_{i,2000} + \alpha_{i,2010} + \varepsilon_j \tag{11}$$

Where α_{ij} are route fixed effects, $\alpha_{i,y}$ are origin year fixed effects, and ε_j are destination clustered standard errors. We can then use the coefficients to identify ν and η. $\beta_1 = -\nu(1-\eta)$ and $\beta_2 = \frac{\nu\eta(1-\eta)}{2}$.

We can use equation (9) to back out the the value of of the residual migration fictions $\frac{\tau_{ij}}{Q_j}$ implied by the estimation results.

$$\log \pi_{ij} = -\nu(1-\eta) \log \bar{R}_j + \nu\eta(1-\eta)\frac{\sigma_j^2}{2} + \nu \log Q_j - \nu \log \tau_{ij} + \log \Lambda_i$$

$$\log \pi_{ij} - \log \sum_j \pi_{ij} = -\nu(1-\eta) \log \bar{R}_j + \nu\eta(1-\eta)\frac{\sigma_j^2}{2} + \nu \log Q_j - \nu \log \tau_{ij}$$

$$\log \pi_{ij} - \log \sum_j \pi_{ij} + \nu(1-\eta) \log \bar{R}_j - \nu\eta(1-\eta)\frac{\sigma_j^2}{2} = \nu \log Q_j - \nu \log \tau_{ij}$$

We can re-arrange and plug in the estimation results.

$$\frac{\tau_{ij}}{Q_j} = \exp([(1-2.61)(1.01) \log \bar{R}_j + 1.01(2.61)(1-2.61)/2\sigma_j^2 - \log \pi_{ij} + \log \sum_j \pi_{ij}]/1.01)$$

A.1.4 Why sigma is a mean preserving spread

If you restrict the mean of the log-normal distribution to 1 by defining μ as a function of σ_j then a change in σ_j actually is a mean preserving spread. The mean of the log-normal is $\bar{C} = e^{\mu}\sqrt{e^{\sigma_j^2}} = \exp\left(\mu + \frac{\sigma_j^2}{2}\right)$

let $\theta = e^{\sigma_j^2}$ then if we fix $\mu = -\ln\sqrt{\theta}$ we fix $\bar{C} = 1$ so we can plug these values into the expression for the expected utility [8] in terms of μ and σ to re-write in terms of θ which is a mean preserving spread.

$$\frac{1}{1-\eta}\exp\left((1-\eta)\mu + \frac{\sigma_j^2}{2}(1-\eta)^2\right) = \frac{1}{1-\eta}\exp\left((1-\eta)(-\ln\sqrt{\theta}) + \frac{\ln\theta}{2}(1-\eta)^2\right)$$

$$= \frac{1}{1-\eta}\exp\left(-(1-\eta)\ln\sqrt{\theta} + \ln\sqrt{\theta}(1-\eta)^2\right)$$

$$= \frac{1}{1-\eta} \exp\left(-\eta(1-\eta)\ln\sqrt{\theta}\right)$$

Note that this is the same result as if we had plugged directly into the expected utility formula:

$$\mathbb{E}\left[\theta_j\right]^{1-\eta} = \exp\left(\mu + \frac{\sigma_j^2}{2}\right)^{1-\eta} = \exp\left((1-\eta)\mu + \frac{\sigma_j^2}{2}(1-\eta)\right)$$

A.2 Self-Employment as an Alternative to Unemployment

Rather than treating unemployment benefits as the outside option b we can instead consider b as the wages from self-employment. We assume workers just have a lower productivity b_i when self-employed. Since they are self-employed they get their full marginal product of labor. In this world, there are no taxes, but we can still think of interventions that improve productivity for self-employed workers. The computation becomes simpler because we don't have to worry about a government budget constraint and it more closely matches the actual set-up in developing countries.

The rest of the model is the same except for the aggregate production in the goods market. The overall output becomes an employment weighted average of the two productivies. Thus overall output becomes $y_i = (E_i A_i + (1-E_i)b_i)L_i$ where E_i is the fraction employed in a location.

A.3 Bargaining Solution

In this appendix I will solve for the nash bargaining solution (4) in terms of the endogenous variables (θ,w) and the parameters.

The labor market can be summarized into value function: for the firm, filling a job J and having a vacancy V; for the worker, being employed E and being unemployed U.

$$J = y - w + \beta[\chi V + (1-\chi)J] \tag{12}$$
$$V = -c + \beta[q(\theta)J + (1-q(\theta)V] \tag{13}$$
$$E = u(w-\tau) + \beta[(1-\chi)E + (\chi)U] \tag{14}$$
$$U = u(b-\tau) + \beta[\theta q(\theta)E + (1-\theta q(\theta)U] \tag{15}$$

By free entry $V = 0$ so we can simplify the $J(w)$, written as a function of w since I will take derivatives later, value function:

$$(1-\beta(1-\chi))J(w) = y - w \tag{16}$$

$$(1-\beta+\beta\chi)J(w) = y - w$$
$$\beta(r+\chi)J(w) = y - w$$

We can re-arrange the equation for E (14) and get:

$$E = \frac{u(w-\tau) + \beta\chi U}{1-\beta(1-\chi)}$$

First we simplify the FOC from the nash bargaining maximization problem (3):

$$\frac{\partial E(w) - U}{\partial w} = \frac{\partial}{\partial w} \frac{u(w-\tau) + \beta\chi U - U}{1-\beta(1-\chi)} = \frac{(w-\tau)^{-\eta}}{1-\beta(1-\chi)}$$
$$\frac{\partial J(w) - V}{\partial w} = \frac{\partial}{\partial w} \frac{y-w-V}{1-\beta(1-\chi)} = \frac{-1}{1-\beta(1-\chi)}$$

$$(\phi)\frac{(w-\tau)^{-\eta}}{E(w)-U} + (1-\phi)\frac{-1}{J(w)-V} = 0$$
$$(\phi)(J(w)-V)(w-\tau)^{-\eta} = (1-\phi)(E(w)-U) \tag{17}$$

We can use the fact that $V = 0$ and the re-arranged equation for E to get:

$$(\phi)J(w)(w-\tau)^{-\eta} = (1-\phi)\frac{u(w)}{1-\beta(1-\chi)} + \frac{\beta\chi U}{1-\beta(1-\chi)} - U \tag{18}$$

now using $J(w) = \frac{y-w}{1-\beta(1-\chi)}$ from (16) we get

$$\frac{u(w)}{1-\beta(1-\chi)} + \frac{\beta\chi U}{1-\beta(1-\chi)} - U = \frac{\phi}{1-\phi}\frac{(y-w)(w-\tau)^{-\eta}}{1-\beta(1-\chi)}$$

$$\frac{w^{1-\eta}}{(1-\eta)(1-\beta(1-\chi))} + \frac{\beta\chi U}{1-\beta(1-\chi)} - U = \frac{\phi}{1-\phi}\frac{(y-w)(w-\tau)^{-\eta}}{1-\beta(1-\chi)}$$

$$w^{1-\eta}(1-\eta)^{-1} + \beta\chi U - U(1-\beta(1-\chi)) = \frac{\phi}{1-\phi}(y-w)(w-\tau)^{-\eta}$$
$$w^{1-\eta}(1-\eta)^{-1} - U + \beta U = \frac{\phi}{1-\phi}(y-w)(w-\tau)^{-\eta}$$
$$w^{1-\eta}(1-\eta)^{-1} = \frac{\phi}{1-\phi}(y-w)(w-\tau)^{-\eta} + (1-\beta)U$$
$$(1-\phi)w^{1-\eta}(1-\eta)^{-1} = \phi(y-w)(w-\tau)^{-\eta} + (1-\phi)(1-\beta)U \tag{19}$$

We can also solve for U in terms of $E(w) - U$ from (15)

$$(1-\beta)U = u(b) + \beta\theta q(\theta)(E(w)-U)$$

use the fact $E(w) - U = \frac{\phi}{1-\phi}J(w)(w-\tau)^{-\eta}$ from (17), $J(w) = \frac{c}{\beta q(\theta)}$ we have:

$$E(w) - U = \frac{\phi}{1-\phi}\frac{pc(w-\tau)^{-\eta}}{\beta q(\theta)}$$

Thus

$$(1-\beta)U = u(b) + \beta\theta q(\theta)\frac{\phi}{1-\phi}\frac{pc(w-\tau)^{-\eta}}{\beta q(\theta)}$$
$$(1-\beta)U = (b)^{1-\eta}(1-\eta)^{-1} + \frac{\phi}{1-\phi}\theta pc(w-\tau)^{-\eta}$$

Plugging back into (19) we get:

$$(1-\phi)w^{1-\eta}(1-\eta)^{-1} = \phi(y-w)(w-\tau)^{-\eta} + (1-\phi)(b)^{1-\eta}(1-\eta)^{-1} + \phi\theta pc(w-\tau)^{-\eta}$$

$$(1-\phi)[w^{1-\eta} - (b)^{1-\eta}](1-\eta)^{-1} = \phi[(y-w)(w-\tau)^{-\eta} + \theta pc(w-\tau)^{-\eta}]$$

$$(1-\phi)(1-b^{1-\eta})w^{1-\eta}(1-\eta)^{-1} = \phi(1-\tau)(((1-\tau)w)^{-\eta} - b((1-\tau)bw)^{-\eta})[(y-w)+\theta pc]$$

$$(1-\phi)(1-b^{1-\eta})w^{1-\eta}(1-\eta)^{-1} = \phi(1-\tau)(1-b^{1-\eta})((1-\tau)w)^{-\eta}[(y-w)+\theta pc] \quad (20)$$

A.4 Additional Parameters for Simulation

Parameter	Value	Source
Amenity values: Q_j	1	Standard
Elasticity for Intermediates: ζ	8	Bryan and Morten (2018), p.2258
Discount for DMP: β	.96	Standard
Exogenous Separation: χ	0.08	Standard
Cobb-douglas parameter in M(u,v): α	.5	Standard
productivity of labor matching function: Ψ	.3	Standard

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