**Timothy N. Bond[2] / Laura Salisbury[1]**

# Local Information, Income Segregation, and Geographic Mobility

[1] Department of Economics, York University, Toronto, Canada, E-mail: lsalisbu@yorku.ca
[2] Department of Economics, Krannert School of Management, Purdue University, 403 W. State St., Lafayette, IN, USA, 47907, E-mail: tnbond@purdue.edu

**Abstract:**
We develop a model of migration in the face of geographic information asymmetries. Firms from a given city observe whether or not a local worker is a member of a disadvantaged local community, a negative indicator of productivity, but do not have this information for migrants to this city. With this knowledge, workers must decide whether to migrate and obscure information about their community of origin. Our model generates results consistent with recent trends in intergenerational mobility and internal migration as well as new predictions about the relationship between migrant outcomes and income segregation. We confirm these predictions using data from the U.S. census.

**Keywords:** migration, asymmetric information, income segregation

**JEL classification:** J61, J31

**DOI:** 10.1515/bejeap-2017-0314

## 1 Introduction

It is widely recognized that employers use observable characteristics to formulate beliefs about potential workers. Some characteristics, such as race, gender, and quantity of education, are both readily observable and potentially correlated with important economic characteristics. However, certain salient characteristics may be difficult to observe or interpret. Workers who possess a negative but difficult-to-observe characteristic have an incentive to seek out an employer who cannot perceive it, which in turn influences employers' beliefs about the types of workers who seek them out.

We develop a model of migration based on the above intuition. Workers are born into either an advantaged or a disadvantaged group. Because of their knowledge of local culture, employers in a worker's birth city observe the worker's group membership and offer wages based on this characteristic. However, employers in other cities cannot perceive group membership. Instead, they simply observe that the worker is a migrant from his city of birth. Workers must decide whether to exploit this information asymmetry and migrate (at cost) to escape the stigma they face at home. In equilibrium, employer beliefs adjust to account for the endogenous selection of migrants from each city.

We posit that the quality of one's home neighborhood is an important characteristic which is plausibly difficult to observe by non-locals. We use our model to generate empirical predictions about the relationship between migration out of a city and the degree of variation in neighborhood quality in that city, which we measure using income segregation. Specifically, our model predicts that as income segregation in a worker's home city increases (i.e. neighborhoods become more unequal), emigrants become more negatively selected. As a consequence, migrants from highly segregated cities will receive lower wages compared to migrants from less segregated cities. However, because of the information asymmetry, disadvantaged migrants earn higher wages than disadvantaged non-migrants (relative to advantaged migrants and non-migrants), and this gap *increases* in origin city segregation. We find empirical support for these predictions using data on income segregation and migration from the 2000 United States Federal Census. A one standard deviation increase in a city's income segregation is associated with a 1.1 percent decrease in the wages of migrants from that city, and a 3.9 percentage point closing of the migration wage gap between migrants from poorer areas and wealthier areas.

Several recent papers, such as Chetty and Hendren (2017) and Chetty, Hendren, and Katz (2016), have established that, even conditional on readily observable characteristics like race and education, early childhood exposure to high quality neighborhoods has a positive causal effect on long-run outcomes. However, it can be very difficult for this information to be obtained for a migrant. First, migration itself obscures origin; address

**Laura Salisbury** is the corresponding author.

information from a resume will clearly no longer reflect the address from one's childhood. Second, even if a nonlocal employer could observe one's neighborhood, they may not be fully aware of the neighborhood's quality. Until the advent of the Internet, obtaining demographic information about neighborhoods was very costly. Even the types of demographic information that are now publicly available may miss specific nuances that local employers are aware of. For example, Kirschenman and Neckerman (1991) report local employer preferences for black workers from the West Side of Chicago rather than the South Side, two demographically similar areas, due to beliefs that black workers from the West Side had better work ethics.

Geographic information asymmetries have thus far received limited attention in the migration literature. Katz and Stark (1984, 1986, 1987a, 1987b, and 1989) , and Kwok and Leland (1982) were the first to explore this topic. These early papers focused on characterizing how asymmetric information can influence the skill composition of international migrants relative to the case of symmetric information, and how allowing workers to signal their ability can reduce these differences. More recently, Dequiedt and Zenou (2013) generalize their framework by allowing destination employers to receive a signal of workers' ability before entering an employment relationship. This leads to a coordination problem and thus multiple equilibria, which they characterize. They also develop several empirical predictions which they do not test.

Our work differs from these papers in several important ways. First, we explicitly model differences in employers' ability to evaluate workers from different places: home city employers categorize workers based on group membership, while destination city employers categorize workers based on birth city. Second, we use a simpler modeling framework than Dequiedt and Zenou (2013), in that workers have no mechanism to signal additional information about their productivity to a prospective employer. While this is a gross simplification–-and abstracts from the problem of multiple equilibria–-it allows us to isolate the effect of information asymmetries on the characteristics of migrants in a clear and tractable way. Third, and most importantly, our paper is empirically focused. The purpose of our model is to provide intuition and to generate testable empirical predictions about patterns of internal migration in the United States. Our empirical section is the first to specifically test a migration model of asymmetric information against a model of symmetric information.

The paper is outlined as follows. In Section 2, we develop our theory of migration under local information and derive our testable predictions. In Section 3, we describe our data. In Section 4, we test our model's predictions. Section 5 concludes.

## 2 A Theory of Local Information and Migration

In this section, we develop a simple model to illustrate the impact of local statistical discrimination on mobility patterns. Local employers use home neighborhood (an indicator of group membership) to form beliefs about a worker's productivity, which determine the wage this worker is offered. As such, increasing neighborhood inequality decreases local opportunities for disadvantaged workers and increases them for advantaged workers. As non-local markets cannot observe whether one is disadvantaged, this encourages (discourages) disadvantaged (advantaged) workers to migrate, which in turn generates the negative relationship between neighborhood inequality and migrant skill that drives our empirical predictions.

### 2.1 Primitives

A continuum of workers is born in a city into one of two distinct groups, $k \in \{A, D\}$. The groups could represent several different locally observable characteristics, but in our empirical work they will be best viewed as neighborhoods. Workers are either productive or unproductive, and group membership is correlated with productivity. The advantaged ($A$) group has fraction $(q + \alpha)$ workers who are productive, while the disadvantaged ($D$) group has fraction $(q - \alpha)$ workers who are productive. The set of workers in each group is of Lebesgue measure 1, so that $q \in (0, \frac{1}{2})$ represents the fraction of productive workers in the economy and $\alpha \in (0, q)$ is a parameter of inequality across groups which we will later measure as income segregation.[1] The distribution of types across groups is common knowledge.

There are two cities: the birth city ($b$) and the migration city ($m$). While the precision of information about workers may differ in each city, they are otherwise identical, and as such we will only consider workers born in $b$ who may move to $m$. Regardless of location, productive workers produce $\theta$, while unproductive workers produce 0.[2] Movers incur a migration cost $\zeta_i$ which is independently and identically distributed with uniform probability distribution $f(\zeta_i)$ over $[-\theta, \theta]$. This accounts for both the explicit and implicit costs (including psychic costs) of migration, as well as nonwage preferences for moving that vary across individuals.[3] The boundary ensures that the number of migrants and non-migrants from each group is always positive.[4]

Firms cannot observe a worker's productivity or cost of migrating, but they can observe each worker's city of birth. In the next subsections, we vary firms' ability to observe a worker's group in order to derive our main predictions. Firms use all information available to them to form beliefs about each worker's type. There is an infinite number of identical potential entrant firms in $b$ and $m$ which may costlessly enter and exit the market.

We emphasize that this is a one-period model, in which firms never observe a worker's productivity; thus, a worker's wages depend solely on his group and whether he chooses to migrate. This modeling choice was made for simplicity: it is trivial to show that our main predictions hold in a two-period model in which workers' types are revealed after one period.[5] As long as there is an initial period in which information is asymmetric across cities–-and workers care about their earnings in this initial period–-migration behavior will be affected by these information asymmetries.

Before we introduce our main results, it is useful to specify our concept of equilibrium.

**Definition 1**

Let $M \in \{0,1\}$ represent the binary migration decision and $k \in \{A, D\}$ represent the worker's group. A Bayesian equilibrium is a mapping $G : (k, \zeta) \rightarrow M$, a vector of wages $W$, and a set of beliefs $R$ that satisfy the following conditions:

1. All migration decisions maximize expected lifetime utility given $W$.
2. The excess supply and excess demand for workers is nonpositive for all observable types in $b$ and $m$ given $W$ and $R$.
3. All beliefs $R$ are determined by Bayes' rule whenever possible.

Condition 2 combined with free entry ensures that all labor markets are perfectly competitive, so that workers earn their expected product.

## 2.2 Locally Limited Information

### 2.2.1 Expected Wages

We first consider the case of "locally limited information." Group membership is observable only to employers in a worker's birth city. That is, employers in $b$ can form beliefs about local workers that condition on whether they are advantaged, but employers in $m$ can only form beliefs based on a migrant's birth city.

Suppose a worker does not migrate. Firms observe the worker's group membership and use this to form beliefs about his productivity. Beliefs about a the probability that a worker from group $k$ who remains in city $b$ is productive are denoted $r_{bk}$. This worker's wage is

$$w_{bk} = r_{bk}\theta \tag{1}$$

which is simply the expected productivity of a worker from $k$ who does not migrate to $m$.

Employers in $m$ do not observe the advantaged/disadvantaged status of a worker from $b$. Therefore, expectations are conditional only on being a migrant, so $r_{mA} = r_{mD} \equiv r_m$. The wage of a worker who migrates to $m$ will be

$$w_m = r_m\theta \tag{2}$$

which is simply the expected productivity of a worker conditional on being born in $b$ and moving to $m$.

### 2.2 Mobility Decision

In equilibrium, workers move when their expected income in the migration city is larger than their expected income in the birth city less the cost of migrating. This occurs when

$$w_m \geq w_{bk} + \zeta_i \tag{3}$$

We can thus define a cutoff migration cost $\zeta_k^*$, whereby all workers from group $k$ with $\zeta_i \leq \zeta_k^*$ will migrate, as

$$\zeta_k^* \equiv w_m - w_{bk} \tag{4}$$

Since migration costs are independently and identically distributed, the total number of migrants from $k$ is $F(\zeta_k^*)$.

### 2.3 Equilibrium

It is straightforward to derive equilibrium beliefs about workers in city $b$.

**Lemma 2**
*In the locally limited information case, $r_{bA} = q + \alpha$ and $r_{bD} = q - \alpha$.*[6]

Wages are independent of group membership in the migration city; the overall mixture of types influences the wage of each worker, but his own skill is not directly observed by his employer. Thus, there is no selective migration within groups, and the beliefs remain equal to the initial distribution.

Beliefs in the migration city will depend on the relative fraction of workers from each group who choose to migrate. Applying Bayes' rule, we can express beliefs in $m$ as

$$r_m = \frac{(q+\alpha)F(\zeta_A^*)+(q-\alpha)F(\zeta_D^*)}{F(\zeta_A^*)+F(\zeta_D^*)} \tag{5}$$

The numerator represents the total number of high types who migrate, which is the fraction of workers from each group who migrate multiplied by the fraction of high types in that group. The denominator is the measure of the total set of workers who migrate. This simplifies to

$$r_m = q + \frac{\alpha[F(\zeta_A^*)-F(\zeta_D^*)]}{F(\zeta_A^*)+F(\zeta_D^*)} \tag{6}$$

which simply states that the average quality of migrants will depend on the differences in the number of migrants from each group and the differences in quality across groups.

To derive these beliefs, we first need to find the cutoff values of $\zeta$ that trigger mobility.

**Lemma 3**
*In the locally limited information case, $\zeta_D^* > \zeta_A^*$.*

The intuition behind this result is straightforward. Migrants from the disadvantaged group have worse opportunities in their birth city than those from the advantaged group, and so they will always be willing to pay a higher cost to migrate.

**Proposition 4**
*For any set of parameters $\alpha$, $q$, and $\theta$, there exists a unique Bayesian equilibrium in the locally limited information case*

### 2.4 Comparative Statics

Our main parameter of interest is $\alpha$, which represents the level of group inequality in city $b$. As $\alpha$ increases, holding $q$ fixed, the advantaged group gains a higher concentration of productive types relative to the disadvantaged group.

**Proposition 5**
*In equilibrium, $r_m$ is a strictly decreasing function of $\alpha$.*

**Corollary 6**
*In the locally limited information case, the average wage for migrants is a decreasing function of $\alpha$.*

An increase in $\alpha$ both increases the home city wages of workers from the advantaged group and decreases the home city wages for workers from the disadvantaged group. This induces a decrease in migration from the advantaged group and an increase in migration from the disadvantaged group, which decreases average productivity among migrants. The migration wage then declines, as it is an increasing function of beliefs about worker productivity.

**Proposition 7**
*The difference between the observed return to migration for disadvantaged and advantaged workers is increasing in $\alpha$.*

Increasing group inequality increases the wages of advantaged workers who do not migrate, which leads to a decrease in their return to migration, defined as the difference between wages in the destination and wages at home. The effect on the return to migration for disadvantaged workers is ambiguous. As there are fewer migrants from the advantaged group, wages for migrants decrease, which in turn decreases the return to migration. However, an increase in group inequality has a direct negative effect on the wages of disadvantaged workers who do not migrate. While it is unclear which effect will dominate, the fact that there is a countervailing effect ensures that the *gap* between the observed return to migration for disadvantaged and advantaged workers will increase.

### 2.3 Symmetric Information

In this subsection, we analyze the alternative case in which employers in both the home and migration city can observe group membership. It is straightforward to show that the equilibrium is efficient in that workers migrate only when their cost of moving is negative.

**Proposition 8**

*In the symmetric information case,* $r_{bA} = r_{mA} = q + \alpha$, $r_{bD} = r_{mD} = q - \alpha$, *and* $\zeta^*_A = \zeta^*_D = 0$

In the locally limited information case, disadvantaged workers have two reasons to migrate: (i) the costs are low (negative) and (ii) firms in the migration city have coarser beliefs about their productivity, which may increase the worker's wage. When information is symmetric, that second mechanism is shut down, and workers consider only migration costs when making mobility decisions. As such, they will only move when the costs of doing so are negative.

**Proposition 9**

*In the symmetric information case, the average wage of migrants is independent of* $\alpha$.

In the symmetric case, there is no selection into migration, and firms' beliefs about workers are the same in both cities. Thus, the average wage of migrants is identical in the migration and birth cities. This wage depends only on the mean type $q$; the group inequality parameter $\alpha$ does not enter the equation. Thus, each of our comparative statics in Section 2.2.4 represents a test against the null hypothesis that information is not local.

### 2.4 Empirical Applications and Income Segregation

In practice, there are many possible characteristics that could constitute local information. Things like accents, mannerisms, or surnames may carry important connotations to local employers but offer little information to those who are not familiar with the local culture.[7] The problem is that in most instances, insofar as it is difficult for non-local employers to observe these characteristics, it is also difficult for researchers.

For our empirical exercises, we will focus on neighborhood quality for several reasons. First, one's location within a city is an important correlate of worker productive both because worker skills are not randomly distributed spatially, and because neighborhood quality itself can have an impact on productivity (Chetty and Hendren 2017; Chetty, Hendren, and Katz 2016). Second, qualitative evidence from Kirschenman and Neckerman (1991) and Kasinitiz and Rosenberg (1996) shows both that employers discriminate on the basis of residential address, and that workers know that they face such discrimination. Third, home neighborhood quality will be difficult to observe for migrants. It will be easy to ascertain from a resumé that an individual was educated somewhere different from where they currently live, for instance, but it is unlikely that an individual would list a former address.[8] Even if such information were available to a non-local employer – for example, through background checks – it is unlikely most non-local employers have direct knowledge of the nuances of different addresses in different cities. At the very least, it will be more costly for non-local employers to process such information, meaning it is more likely to be ignored. Finally, we can use data from the United States Federal Census to measure group-level inequality ($\alpha$) through income segregation. We can also obtain a coarse measure of group membership (Public Use Microdata Area (PUMA), discussed below) from the same source.

Given the predictions of our model, we expect to find the following in the cross-section:

1. Migrants from cities with higher levels of income segregation will earn lower wages, conditional on mean income in their birth city.

2. The difference in wages between migrants and nonmigrants from poorer areas within a city will increase relative to the difference in wages for those from wealthier areas as income segregation in that city increases.

The first prediction follows from Corollary 6, where mean income in the birth city measures possible differences in $q$ across municipalities. The second prediction follows from Proposition 7.

## 3 Data

To test our model, we use data from the 2000 United States Federal Census 5% public use file (Ruggles et al. 2017), which includes information on the respondent's location of residence in 1995. As we are interested in individuals for whom neighborhood could be a strong signal of productivity, we restrict our samples to individuals aged 16–30; these workers will not, for example, possess long and observable work histories. To avoid issues related to labor force participation and attachment, we further restrict our sample to men who worked between 30 and 80 hours during a regular work week, and who do not identify as self-employed.

We are interested in the decision of a worker born in one city to move to another city, where firms have less information about his background. Ideally, we would restrict our sample to include only individuals making their first move from their birth city to a new location. Our model has nothing to say about the decision of a man from, for example, South Boston to move from Detroit to Los Angeles. Unfortunately, the Census does not include information on birth city, only birth state. We therefore limit our sample to individuals who migrated from a primary metropolitan statistical area (PMSA) located in their state of birth. To the extent that this includes individuals who move from non-birth cities in their birth states, our results will be attenuated.

Table 1 compares summary statistics for migrants and nonmigrants in the Census. Approximately two-thirds of all men aged 16–30 residing in a PMSA in 1995 were living in their state of birth. Of these, just over half are full-time workers earning positive income in the last year.[9] More than a quarter of these migrated between 1995 and 2000. It is evident from Table 1 that young male migrants are generally positively selected: they are more educated, and they typically earn more per hour than stayers. In the analysis to follow, we will focus on differences in the outcomes of migrants–-and of migrants relative to stayers–-from different home cities.

We measure income segregation using the rank-order information theory index used by Chetty et al. (2014) and originally developed by Reardon (2011). The measure extends standard measures of segregation between two groups (e.g. racial segregation) to continuous dimensions (e.g. income). Denote $p$ as a percentile in the income distribution. Then, the rank-order information theory index, $H^R$, is defined as

$$H^R = 2\ln(2)\int_0^1 E(p)H(p)dp \tag{7}$$

Here, $H(p)$ is the conventional binary segregation index between the bottom and top $p$th percentile income groups:

$$H(p) = 1-\sum_j \frac{t_j E_j(p)}{TE(p)} \tag{8}$$

where $T$ is the population of the metropolitan area and $t_j$ is the population of neighborhood $j$, and $E(p)$ is the entropy of the population when divided into these percentile groups,

$$E(p) = p\log_2\frac{1}{p}+(1-p)\log_2\frac{1}{1-p} \tag{9}$$

In words, $H^R$ is the sum of all the possible binary segregation indices weighted by the entropy of the population using each of these indices. $H^R$ is defined over [0,1] where 0 represents complete integration and 1 represents complete segregation. The advantage of this measure is that it relies only on ranks of income within a metropolitan area, and is thus independent of income inequality, which will allow us to test our theory separately from other theories of selective migration.

We compute this index for each PMSA using publicly available tract-level tabulations from the 2000 census. These data contain the number of families residing in each census tract whose income lies within 16 income categories.[10] Following Reardon (2011), we calculate $H(p)$ for each of these categorical cutoffs. We then estimate the $H$ function using a sixth-degree polynomial and use this estimate to evaluate $H^R$ from the formula provided by Reardon (2011). We standardize this measure to be mean 0 standard deviation 1 across PMSAs.

In addition to measuring segregation in a worker's home city, we classify workers as "advantaged" and "disadvantaged" using information about their PUMA of residence in 1995. Here, we restrict our focus to PMSAs having at least two distinct PUMAs. We classify "advantaged" workers as those originating from a PUMA with a mean full-time, full-year hourly wage above the median for the PMSA; "disadvantaged" workers are those who originate from a PUMA with a mean wage below the median. While PUMAs are much larger than census tracts, containing at least 100,000 people, they are the finest geographic information publicly available for analysis of census microdata. Every PUMA likely contains a mix of good and bad neighborhoods, but it seems reasonable to assume that, in general, low-income PUMAs contain poorer neigbhorhoods than high-income PUMAs.[11]

Table 2 and Table 3 contain background information about PMSAs. Table 2 lists summary statistics about the 283 PMSAs in our sample, weighted by PMSA population. We include information about a variety of city-level economic characteristics, which are computed using the IPUMS 5% sample from the 2000 census. These include a Gini coefficient measuring wage inequality, the mean full-time, full-year log hourly wage, percent black, percent foreign born, the unemployment rate, percent with a college degree, the rate of household home ownership, the mean log value of owner-occupied homes, and the mean student–teacher ratio.[12] We also include the correlation between the segregation index ($H^R$) and each of these variables. Clearly, segregation is highly correlated with other characteristics. As such, we take care to control for as many other city characteristics as possible in our regressions. We are particularly interested in the degree to which income segregation is distinct from income inequality: this allows us to distinguish our model from the conventional Borjas (1987) selective migration model, in which wage inequality is the primary determinant of migrant composition.[13] In Table 3, we list the 15 most and least segregated and unequal PMSAs, highlighting PMSAs that appear at the top or bottom of both lists. While there is some overlap, the most segregated PMSAs tend to be large cities like New York, Dallas, Houston, Los Angeles, and Philadelphia. The most unequal PMSAs (measured by Gini coefficient) are very often college towns (College Station, TX; Gainesville, FL; Athens, GA; Iowa city, IA; Bloomington, IN, etc.). In general, while segregation is correlated with overall inequality, they are two distinct measures.

## 4 Empirical Approach and Results

We evaluate the impact of home city segregation on the labor market performance of young male migrants. Our model predicts that migrants from more segregated cities will be more negatively selected. Increasing segregation decreases wages in the home city for workers from (only locally observable) disadvantaged groups while increasing wages for workers from advantaged groups. As employers from outside cities do not observe group membership, this increases the incentive for disadvantaged workers to migrate, while diminishing this incentive for advantaged workers. This leads to a decrease in the overall skill level of migrants. The difference between the wages of migrants and non-migrants from the disadvantaged group should be greater than the analogous difference in the advantaged group when the level of segregation in the home city is greater. This is driven by the fact that group inequality inflates the wage gap between advantaged and disadvantaged workers in the home city faster than it depresses the wages of migrants in the destination city.

We begin by testing the prediction that migrants from more segregated cities earn lower wages, conditional on destination city. Using our sample of migrants from the 2000 census, we estimate

$$\log W_{ijk} = \alpha + \beta SEG_j + \psi Z_j + \gamma X_i + \delta_k + u_{ijk} \tag{10}$$

Here, $W_{ijk}$ denotes the hourly wage earned by person $i$ from city $j$ in city $k$; $SEG_j$ is our measure of income segregation in city $j$; $Z_j$ is a vector of home city characteristics, which includes every city characteristic summarized in Table 2, as well as log population of the home city;[14] $X_i$ is a vector of socioeconomic and demographic characteristics of person $i$, including years of education, race indicators, and a cubic in age; $\delta_k$ is a destination city-fixed effect. Geographic detail is obscured for individuals who move to places other than metropolitan areas; we use a state-specific "rural" fixed effect for those who migrate outside of PMSA. Our model predicts $\beta < 0$ : migrants from cities will high levels of income segregation will earn lower wages.

We note that a typical empirical study such as ours would seek to identify the impact of income segregation on migration through changes in the level of segregation within the same city over time (by controlling for birth city fixed effects with multiple years of migration outcomes). We eschew this approach for several reasons. First, there is very little within-city, between-year variation in segregation (Chetty et al. 2014). It is also not clear precisely when segregation should be measured for such an analysis. Would a small change in segregation this year affect the beliefs of employers about workers who are 20 years old today, or workers who would be 20 years old 20 years from now? Therefore, for our purposes, we view comparisons between cities that have "permanently" different levels of segregation as being more useful. Still, it is important to recognize that our use of cross-sectional variation in segregation introduces certain issues. We emphasize the importance of appropriately selecting $Z_j$ to account for other city characteristics that may be correlated with segregation and affect the outcomes of migrants.

In Table 4, we estimate the effect of home city income segregation on log hourly wages. In column (1), we include only destination-fixed effects in the regression, and we estimate a negative but only marginally significant effect. As discussed above, however, it is important for our cross-sectional approach to include a full set of city characteristic controls to account for potential confounding factors. We include these controls in column (2), which causes our estimated coefficient to nearly double in magnitude, and to become significant at the 1% level.[15] This is because segregated cities also tend to be higher income, more educated cities, which puts upward pressure on wages of migrants from these areas. Note that these controls include birth city Gini coefficient, which has a negative and significant effect on migrant wages. This is consistent with the standard Roy model of migrant selection (Borjas 1987; Grogger and Hansen 2011; Salisbury 2014). However, despite being highly correlated, our segregation index also has a strong, negative, and significant effect on wages, suggesting it represents a distinct type of migrant selection.[16]

We include a standard set of individual-level Mincer controls in column (3). Given that our predictions are based on selection patterns, it is not surprising that accounting for migrants' observable characteristics causes a reduction in the magnitude of our point estimate. Nonetheless, the result remains highly statistically significant. Our preferred estimate in column (4), which also includes migration distance and home region fixed effects, indicates that a one standard deviation increase in home city segregation is associated with roughly a 1.1% drop in hourly wages.[17] The most and least segregated cities in our data–-Newark, New Jersey and Joplin, Missouri, respectively–-differ in the degree of income segregation by 4.7 standard deviations. Thus, our results imply that a migrant from Newark should earn around 5.2% less than a migrant from Joplin, through the "local information" mechanism alone. While this difference is substantially smaller than the gender wage gap or the black–white wage gap, it is nontrivial and larger in magnitude than any other city characteristic we include other than mean income.

In Table 5, we test the sensitivity of our baseline results to additional sample restrictions. All specifications include a full set of controls. In column (2), we omit all individuals who have ever attended a 4-year college. As we are interested in young workers who migrate from their birth city, college students are empirically problematic. Much of the migration we see in the data will represent students moving from their college town to their first full-time job, a migration decision about which our model has nothing to say. Reassuringly, our estimated coefficient is not sensitive to this restriction. We are also concerned that our results may be driven by race discrimination, as many cities that are segregated by income are also segregated by race. If there is variation in the degree of race discrimination in different parts of the country, and if racial segregation is symptomatic of discrimination, then African-American migrants from more and less segregated cities may be differently selected (although it is not obvious whether this selection should be positive or negative).[18] While interesting in its own right, this is a very different mechanism from the one analyzed in this paper, in part because race is often globally observable. In column (3) of Table 5, we restrict the sample to whites only, and we find that our results are not sensitive to this sample restriction. Finally, the youngest movers in our sample may have moved due to decisions by their parents, rather than their own labor market calculations. In column (4), we restrict the sample to men between the ages of 19 and 30. Our results are not sensitive to this restriction.

Next, we test our prediction that the cross-sectional observed return to migration for disadvantaged relative to advantaged workers is increasing in home city segregation. Using our sample of both migrants and stayers from the 2000 census, we estimate:

$$\begin{aligned}\log W_{ijk} =& \alpha + \beta_1 MIG_{ij} + \beta_2 LOW_{ij} + \eta_1 MIG_{ij} \times LOW_{ij} + \eta_2 MIG_{ij} \times SEG_j \\ &+ \eta_3 LOW_{ij} \times SEG_j + \phi MIG_{ij} \times SEG_j \times LOW_{ij} + \gamma X_i + \psi Z_k + u_{ijk}\end{aligned} \tag{11}$$

Here, $MIG_{ij}$ is an indicator equal to one if person $i$ migrated from city $j$; $LOW_{ij}$ is an indicator equal to one if person $i$ originated from a below-median income PUMA in city $j$; and other variables are defined as above.[19] In this case, our model predicts that $\phi > 0$.

We estimate this equation in Table 6. In the first column, we include our key variables (a migrant indicator, a low PUMA of origin indicator, home city segregation, a full set of interactions) and home metro area fixed effects. Home metro area fixed effects are critical here because we want to draw comparisons between migrants and stayers from the same place. As predicted, we estimate a positive coefficient on the three-way interaction between our migrant indicator, our low-income PUMA of origin indicator, and home city segregation; however, it is not quite significant at conventional levels. In column (2), we add controls for individual worker characteristics: this does not affect our coefficient estimate, but it reduces the standard error so that the estimate is significant a the 5% level. In column (3), we add migration distance and destination state fixed effects, which has little impact on our results. In column (4), we add a full set of interactions between the migrant indicator, the low-income PUMA of origin indicator, and the city-level controls listed in Table 2. This accounts for the possibility that some other city characteristic that is correlated with home city segregation is driving the effect on the triple interaction. This does not appear to be the case; the result remains positive and statistically significant.[20]

In Table 7, we perform the same sensitivity analysis of these estimates as we did in Table 5 for eq. (7). Here, we are using the specification in column (3) of Table 6 with different sample restrictions. Our estimates are not particularly sensitive to these alternate specifications.

## 5 Discussion and Conclusion

We developed a model of the impact of geographic information asymmetries on migration decisions. Local firms observe a characteristic of workers who were born in their home city that is unboservable to firms outside their locality. Our model generates predictions which we apply to neighborhood quality and income segregation and confirm using data from the US Census. Within a destination city, migrants who originate from more segregated cities have lower wages, indicating that they are more negatively selected than migrants originating from less segregated cities. We also show that, as income segregation increases, the difference between migrants' and nonmigrants' wages among individuals from poorer neighborhoods grows relative to the same difference among workers from wealthier neighborhoods of the same city.

Heterogeneity in access to information across geographic areas remains an understudied topic in labor economics. Incomplete (negative) information on those with poor backgrounds may have positive impacts on themselves and their children. Policies that improve information access may have positive effects on efficiency but unintended consequences for inequality.

**Table 1:** Summary statistics.

| | **Migrants** | **Stayers** |
|---|---|---|
| Age | 24.73 | 24.52 |
| White | 0.81 | 0.76 |
| | 0 | 0 |
| < High school | 0.11 | 0.19 |
| High school | 0.25 | 0.36 |
| Some college | 0.37 | 0.32 |
| College or higher | 0.27 | 0.13 |
| | 0 | 0 |
| Hourly wage (2,000 dollars) | 14.19 | 13.25 |
| Usual weekly hours | 44.83 | 43.19 |
| | 0 | 0 |
| Observations | 88,492 | 230,799 |

Note: Sample is drawn from the 2000 United States Federal Census and consists of men aged 16–30, residing in an MSA in their state of birth in 1995, who are full-time workers.

**Table 2:** Summary statistics for home cities.

| | **Mean** | **SD** | **Minimum** | **Maximum** | **Corr (Seg. index, X)** |
|---|---|---|---|---|---|
| Segregation index | 0.11 | 0.03 | 0.02 | 0.16 | 1.00 |
| Gini coefficient | 0.89 | 0.02 | 0.70 | 0.92 | 0.29 |
| Mean log wage | 2.87 | 0.15 | 2.22 | 3.43 | 0.33 |
| % Black | 0.14 | 0.09 | 0.00 | 0.5 | 0.45 |
| % Immigrant | 0.14 | 0.10 | 0.01 | 0.39 | 0.54 |
| Unemployment rate | 0.06 | 0.02 | 0.03 | 0.13 | 0.52 |
| % College degree | 0.27 | 0.07 | 0.10 | 0.49 | 0.12 |
| % Home owner | 0.64 | 0.09 | 0.32 | 0.84 | −0.60 |
| Mean log home value | 11.76 | 0.41 | 10.69 | 12.97 | 0.29 |
| Mean student–teacher ratio | 17.81 | 2.41 | 12.83 | 23.94 | −0.01 |

Note: Summary statistics for 238 MSAs in total. Weighted by MSA population.

**Table 3:** Cities ranked by segregation and inequality, 2000.

| **Rank:** | **Most segregated PMSAs** | **Most unequal PMSAs** |
|---|---|---|
| 1 | Newark, NJ | Bryan-College Station, TX |
| 2 | Dallas-Fort Worth, TX | Stamford, CT |
| 3 | **New York-Northeastern NJ** | **New York-Northeastern NJ** |
| 4 | Houston-Brazoria, TX | Gainesville, FL |
| 5 | Memphis, TN/AR/MS | Athens, GA |
| 6 | Austin, TX | Iowa City, IA |
| 7 | **Los Angeles-Long Beach, CA** | Bloomington, IN |
| 8 | Philadelphia, PA/NJ | Savannah, GA |
| 9 | Oakland, CA | Greenville, NC |
| 10 | Trenton, NJ | Lexington-Fayette, KY |
| 11 | Washington, DC/MD/VA | Naples, FL |

| | | |
|---|---|---|
| 12 | Chicago-Gary-Lake, IL | Beach-Boca Raton-Delray Beach, FL |
| 13 | San Antonio, TX | **Los Angeles-Long Beach, CA** |
| 14 | Tallahassee, FL | Lawrence-Haverhill, MA/NH |
| 15 | Bridgeport, CT | San Francisco-Oakland-Vallejo, CA |
| Rank: | Least segregated PMSAs | Least unequal PMSAs |
| 1 | Joplin, MO | Appleton-Oskosh-Neenah, WI |
| 2 | Glens Falls, NY | Sheboygan, WI |
| 3 | Williamsport, PA | Jacksonville, NC |
| 4 | Punta Gorda, FL | York, PA |
| 5 | **Dover, DE** | Clarksville-Hopkinsville, TN/KY |
| 6 | San Luis Obispo-Atascad-P Robles, CA | Janesville-Beloit, WI |
| 7 | Jamestown-Dunkirk, NY | Nashua, NH |
| 8 | Hickory-Morgantown, NC | Lancaster, PA |
| 9 | Elkhart-Goshen, IN | **Dover, DE** |
| 10 | Bellingham, WA | Kenosha, WI |
| 11 | Fayetteville-Springdale, AR | Brazoria, TX |
| 12 | Myrtle Beach, SC | Brockton, MA |
| 13 | Altoona, PA | Racine, WI |
| 14 | Eau Claire, WI | Lima, OH |
| 15 | Johnstown, PA | Anchorage, AK |

Note: See text for definition of PMSA segregation. PMSA inequality is measured using a Gini coefficient. Bolded entries appear in both columns.

**Table 4:** Home city income segregation and wages, migrants.

| **Dependent variable** | **(1)** *Loghourly wage* | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| Home city segregation | −0.010* | −0.018*** | −0.011*** | −0.011*** |
| | (0.006) | (0.007) | (0.004) | (0.004) |
| Home city mean FTFY log wage | | 0.010 | 0.013** | 0.013** |
| | | (0.010) | (0.006) | (0.005) |
| Home city Gini coefficient | | −0.018*** | −0.006 | −0.007* |
| | | (0.006) | (0.004) | (0.004) |
| Home city % black | | −0.005 | 0.010** | 0.009 |
| | | (0.006) | (0.004) | (0.006) |
| Home city % immigrant | | −0.035*** | 0.001 | −0.000 |
| | | (0.007) | (0.005) | (0.005) |
| Home city unemployment rate | | −0.005 | −0.011** | −0.009* |
| | | (0.006) | (0.004) | (0.005) |
| Home city % with college degree | | 0.047*** | −0.002 | −0.003 |
| | | (0.007) | (0.004) | (0.005) |
| Home city % home owners | | −0.033*** | −0.009*** | −0.008*** |
| | | (0.005) | (0.003) | (0.003) |
| Home city mean log home value | | −0.004 | 0.006 | 0.008 |
| | | (0.016) | (0.009) | (0.009) |
| Home city mean student–teacher ratio | | 0.012** | 0.009** | 0.004 |
| | | (0.005) | (0.003) | (0.004) |
| Log population of home city | | −0.008 | −0.000 | 0.003 |
| | | (0.006) | (0.004) | (0.004) |
| Migration distance (hundreds of miles) | | | | −0.004*** |
| | | | | (0.000) |
| Destination FEs | X | X | X | X |

| | | | | |
|---|---|---|---|---|
| Demographic controls | | | X | X |
| Home region FEs | | | | X |
| Observations | 68,598 | 68,598 | 68,598 | 68,598 |
| *R*-squared | 0.092 | 0.100 | 0.300 | 0.301 |

Notes: Sample includes men aged 16–30 who migrated from an MSA in the last 5 years. Full-time workers only. Taken from the 5% sample of the 2000 United States Federal Census. All city characteristics are standardized. Demographic controls include a quadratic in age, race-fixed effects, and fixed effects for educational categories. Standard errors, clustered at the home MSA level, in parentheses: * *p<0.10*, ** *p<0.05*, *** *p<0.01*.

**Table 5:** Home city segregation and wages, migrants: sensitivity analysis.

| **Dependent variable** | **(1)** ***Loghourly wage*** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| Home city segregation | −0.011*** | −0.012* | −0.010** | −0.012*** |
| | (0.004) | (0.006) | (0.005) | (0.004) |
| Home city mean FTFY log wage | 0.013** | 0.014* | 0.007 | 0.011** |
| | (0.005) | (0.008) | (0.007) | (0.005) |
| Home city Gini coefficient | −0.007* | −0.015*** | −0.005 | −0.007* |
| | (0.004) | (0.005) | (0.004) | (0.004) |
| Home city % black | 0.009 | 0.009 | 0.005 | 0.010* |
| | (0.006) | (0.008) | (0.006) | (0.006) |
| Home city % immigrant | −0.000 | −0.001 | 0.001 | −0.000 |
| | (0.005) | (0.008) | (0.006) | (0.006) |
| Home city unemployment rate | −0.009* | −0.013** | −0.012** | −0.009* |
| | (0.005) | (0.006) | (0.006) | (0.005) |
| Home city % with college degree | −0.003 | −0.008 | −0.003 | −0.002 |
| | (0.005) | (0.008) | (0.005) | (0.005) |
| Home city % home owners | −0.008*** | −0.007 | −0.010*** | −0.008*** |
| | (0.003) | (0.004) | (0.003) | (0.003) |
| Home city mean log home value | 0.008 | 0.005 | 0.008 | 0.009 |
| | (0.009) | (0.012) | (0.010) | (0.009) |
| Home city mean student–teacher ratio | 0.004 | 0.008 | 0.004 | 0.005 |
| | (0.004) | (0.006) | (0.005) | (0.005) |
| Log population of home city | 0.003 | 0.004 | 0.005 | 0.003 |
| | (0.004) | (0.006) | (0.004) | (0.004) |
| Migration distance (hundreds of miles) | −0.004*** | −0.004*** | −0.004*** | −0.004*** |
| | (0.000) | (0.001) | (0.001) | (0.000) |
| Ex. college attendees | | X | | |
| Whites only | | | X | |
| Ex. children < 18 | | | | X |
| Observations | 68,598 | 28,150 | 55,122 | 67,801 |
| *R*-squared | 0.301 | 0.197 | 0.319 | 0.296 |

Notes: Sample includes men aged 16–30 who migrated from an MSA in the last 5 years. Full-time workers only. Taken from the 5% sample of the 2000 United States Federal Census. All regressions include destination-fixed effects; age, race, and education controls; and indicators for region of residence in 1995. City characteristics are standardized. In column (2), college attendees are defined as anyone who has attended some college, save persons holding an associate’s degree. Standard errors, clustered at the home MSA level, in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

**Table 6:** Home city income segregation and the return to migration.

| Dependent variable | (1) *Loghourly wage* | (2) | (3) | (4) |
|---|---|---|---|---|
| Migrant × home city segregation × from low-income PUMA | 0.015 | 0.015** | 0.017*** | 0.039*** |
| | (0.014) | (0.007) | (0.006) | (0.012) |
| Migrant × from low-income PUMA | −0.030* | −0.031*** | −0.026*** | −1.777*** |
| | (0.016) | (0.010) | (0.009) | (0.514) |
| Migrant × home city segregation | −0.037** | −0.025** | −0.022*** | −0.033*** |
| | (0.015) | (0.009) | (0.007) | (0.012) |
| Home city segregation ×from low-income PUMA | −0.011 | −0.001 | −0.004 | −0.013* |
| | (0.012) | (0.007) | (0.007) | (0.008) |
| Migrant | −0.007 | −0.050*** | −0.006 | 1.215** |
| | (0.015) | (0.010) | (0.008) | (0.591) |
| From low-income PUMA | −0.011 | 0.003 | 0.004 | 0.876** |
| | (0.011) | (0.007) | (0.007) | (0.367) |
| Home metro area-fixed effects | X | X | X | X |
| Demographic controls | | X | X | X |
| Destination state-fixed effects and distance | | | X | X |
| Interactions with other home city characteristics | | | | X |
| Observations | 201,338 | 201,338 | 201,338 | 201,338 |
| *R*-squared | 0.025 | 0.254 | 0.257 | 0.257 |

Notes: Sample includes men aged 16–30 who lived in an MSA located in their state of birth in 1995. Full-time workers only. Taken from the 5% sample of the 2000 United States Federal Census. Home city segregation is standardized. Demographic controls include a quadratic in age, race-fixed effects, and fixed effects for educational categories. Standard errors, clustered at the home MSA level, in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

**Table 7:** Home city income segregation and the return to migration: sensitivity analysis.

| Dependent variable | (1) *Loghourly wage* | (2) | (3) | (4) |
|---|---|---|---|---|
| Migrant × home city segregation × from low-income PUMA | 0.017*** | 0.011 | 0.016** | 0.018*** |
| | (0.006) | (0.011) | (0.007) | (0.006) |
| Migrant × from low-income PUMA | −0.026*** | −0.029** | −0.027*** | −0.026*** |
| | (0.009) | (0.015) | (0.009) | (0.009) |
| Migrant × home city segregation | −0.022*** | −0.018* | −0.028*** | −0.025*** |
| | (0.007) | (0.010) | (0.007) | (0.007) |
| Home city segregation × from low-income PUMA | −0.004 | 0.003 | −0.001 | −0.004 |
| | (0.007) | (0.005) | (0.008) | (0.007) |
| Migrant | −0.006 | 0.021* | −0.005 | −0.005 |
| | (0.008) | (0.012) | (0.008) | (0.008) |
| From low-income PUMA | 0.004 | 0.002 | −0.001 | 0.003 |
| | (0.007) | (0.006) | (0.008) | (0.008) |
| Ex. college attendees | | X | | |
| Whites only | | | X | |
| Ex. children < 18 | | | | X |

| | | | | |
|---|---|---|---|---|
| Observations | 201,338 | 113,989 | 162,613 | 196,865 |
| $R$-squared | 0.257 | 0.195 | 0.274 | 0.242 |

Notes: Sample includes men aged 16–30 who lived in an MSA located in their state of birth in 1995. Full-time workers only. Taken from the 5% sample of the 2000 United States Federal Census. All regressions include home metro area-fixed effects; age, education, and race controls; migration distance and state of residence indicators for 2000. Home city segregation is standardized. In column (2), college attendees are defined as anyone who has attended some college, save persons holding an associate's degree. Standard errors, clustered at the home MSA level, in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

# 6 Theoretical Appendix

## 6.1 Proof of Lemma 2

**Proof**

The total number of workers from group $k$ who do not migrate is simply $1 - F(\zeta_k^*)$.

$$r_{bA} = \frac{(q+\alpha)F(\zeta_A^*)}{F(\zeta_A^*)} \tag{12}$$

$$r_{bD} = \frac{(q-\alpha)F(\zeta_D^*)}{F(\zeta_D^*)} \tag{13}$$

for the advantaged and disadvantaged groups, respectively. Simplification proves the lemma. □

## 6.2 Proof of Lemma 3

**Proof**

Notice that since $w_m$ does not vary with group membership, we need only to inspect $w_{bA}$ and $w_{bD}$. From Lemma 2, $w_{bA} = (q+\alpha)\theta$ and $w_{bD} = (q-\alpha)\theta_H$, so $w_{bA} > w_{bD}$ and $\zeta_D^* > \zeta_A^*$. □

## 6.3 Proof of Proposition 4

**Proof**

First note that $r_m$ is bounded between $(q-\alpha)$ and $(q+\alpha)$. Suppose that the migration city believed that a fraction less than $(q-\alpha)$ were of the high type. Given the bounds on $f$, there is always individuals from the advantaged group with sufficiently negative migration costs that they will still move. As there is no selective migration on type within a group and there will always be migrants from both groups, the true fraction of high type migrants must be above $(q-\alpha)$. The reverse holds for beliefs above $(q+\alpha)$ since there will always be some migrants from the disadvantaged group

Now, note that we can rewrite eq. (5) as

$$r_m = q + \alpha\left(\frac{2F(\zeta_A^*)}{F(\zeta_A^*)+F(\zeta_D^*)} - 1\right) \tag{14}$$

Differentiating the right-hand side with respect to $r_m$ yields

$$-2\alpha\theta\frac{f(\zeta_A^*)F(\zeta_D^*) - f(\zeta_D^*)F(\zeta_A^*)}{\left[F(\zeta_A^*) + F(\zeta_D^*)\right]^2} \tag{15}$$

We can then apply the uniform distribution to $f$ to get,

$$-\alpha\frac{\zeta_D^* - \zeta_A^*}{(\zeta_D^* + \zeta_A^* + 2\theta)^2} \tag{16}$$

Since $\zeta_D^* > \zeta_A^*$, the numerator of the fraction is positive and thus the entire expression is negative. The average quality of the workers is a strictly decreasing function of beliefs. This combined with boundedness is a sufficient condition for the existence of a unique equilibrium. □

### 6.4 Proof of Proposition 5

**Proof**

Implicitly differentiating equilibrium $r_m$ from eq. (9),

$$\frac{\partial r_m}{\partial \alpha} = 2\chi - 1 + \alpha\left(\frac{\partial \chi}{\partial r_m}\frac{\partial r_m}{\partial \alpha} + \frac{\partial \chi}{\partial \alpha}\right) \tag{17}$$

where,

$$\chi \equiv \frac{F(\zeta_A^*)}{F(\zeta_A^*) + F(\zeta_D^*)} \tag{18}$$

Rearranging terms,

$$\frac{\partial r_m}{\partial \alpha} = \left(2\chi - 1 + \alpha\frac{\partial \chi}{\partial \alpha}\right)\left(1 - \alpha\frac{\partial \chi}{\partial r_m}\right)^{-1} \tag{19}$$

Since $\zeta_A^* < \zeta_D^*$, $2\chi - 1 < 0$. We know from eq. (11) that $\frac{\partial \chi}{\partial r_m} < 0$ and taking the partial derivative of $\chi$ with respect to $\alpha$ yields

$$\frac{\partial \chi}{\partial \alpha} = -\theta\frac{f(\zeta_A^*)F(\zeta_D^*) + f(\zeta_D^*)F(\zeta_A^*)}{\left[F(\chi_A) + F(\chi_D)\right]^2} \tag{20}$$

which is less than zero, and thus the overall sign of the derivative is unambiguously negative. □

### 6.5 Proof of Corollary 6

**Proof**

The corollary follows directly from the proposition. All migrants earn $w_m$. Taking the derivative of eq. (2) then with respect to $\alpha$,

$$\frac{\partial w_m}{\partial \alpha} = \theta\frac{\partial r_m}{\partial \alpha}$$

which is less than zero, since $\frac{\partial r_m}{\partial \alpha} < 0$. □

### 6.6 Proof of Proposition 7

**Proof**

First, the difference in wages between migrants and stayers from the advantaged group is

$$r_m\theta - (q + \alpha)\theta \quad < 0 \tag{21}$$

For the disadvantaged group, the difference in wages between migrants and stayers is

$$r_m\theta - (q - \alpha)\theta \quad > 0 \tag{22}$$

The difference in observed return between advantaged and disadvantaged workers then is

$$r_m\theta - (q + \alpha)\theta - r_m\theta + (q - \alpha)\theta \quad = -2\alpha\theta \tag{23}$$

which is a decreasing function in $\alpha$. □

### 6.7 Proof of Proposition 8

**Proof**

Since firms in the migration city can condition their beliefs on group membership, workers who migrate earn $w_{mk} = r_{mk}\theta$. Workers who do not migrate earn $w_{bk} = r_{bk}\theta$. They thus will migrate provided that

$$\zeta_i \quad \leq w_{mk} - w_{bk} \tag{24}$$

and the cutoff value for migration for each group will be

$$\zeta_k^* \quad = (r_{mk} - r_{bk})\theta \tag{25}$$

which is independent of worker type. Thus there is no selective migration and beliefs in each city for each group must be the true distribution of types in the group's population. That is $r_{bA} = r_{mA} = q+\alpha$ and $r_{bD} = r_{mD} = q-\alpha$. Substituting for beliefs in the above expression yields

$$\zeta_k^* \quad = 0 \tag{26}$$

which proves the proposition. □

## 7 Proof of Proposition 9

**Proof**

Since in the symmetric case, migrants earn heterogeneous wages depending on whether they are advantaged or disadvantaged, the average wage will be a weighted average of these two group wages,

$$\bar{w}_m \quad = \frac{F(\zeta_A^*)w_{mA} + F(\zeta_D^*)w_{mD}}{F(\zeta_A^*) + F(\zeta_D^*)} \tag{27}$$

where $F$ is the cumulative distribution function (CDF) of moving costs. Since $\zeta_A^* = \zeta_D^* = 0$, we can rewrite this as

$$\bar{w}_m \quad = \frac{F(0)(w_{mA} + w_{mD})}{2F(0)} = \frac{q\theta}{2} \tag{28}$$

which is not a function of $\alpha$. □

## Acknowledgements

We are grateful to Alberto Davila, Kevin Mumford, Joshua Pinkston, Tyler Ransom and conference and seminar participants at Purdue University, the Midwest Economic Association Annual Meetings, and the Southern Economic Association Annual Meetings for their helpful comments. All mistakes are our own.

## Notes

1 Bounding $q$ at $\frac{1}{2}$ is only necessary to precisely bound $\alpha$ so that the probabilities are always positive. When $q > \frac{1}{2}$, the upper boundary of $\alpha$ becomes $1 - q$ and all the results remain the same.
2 By assuming that the two cities are identical, we are able to isolate the effects of the information asymmetry on the migration decision. We will account for possible heterogeneity in the migration city by using destination city fixed effects in our empirical section. We will thus be comparing migrants who currently work in the same local labor market, but differ in the characteristics of their origin city.
3 For example, an individual born into a city for which he has a strong distaste could experience negative migration costs. We obtain identical results when costs are bounded below by 0 (i.e. all costs are positive) and there are some exogenous movers. Under this framework, advantaged workers never voluntarily move, and thus all of the predictions are generated by differences in the fraction of disadvantaged movers.
4 The uniform distribution allows for a tractable characterization of equilibrium. Other distributions will generally yield the same predictions, but there may be multiple equilibria, and thus the predictions are valid only locally.
5 The results will hold generally in multiperiod models so long as the rates of learning are more or less similar across cities. We have no strong prior about whether learning should be faster or slower in a destination city than a home city. Even if there were large differences in this facet, the results would still hold so long as workers discount future income at a high enough rate.
6 The proof of this and all other results may be found in the theoretical appendix.
7 To use an example from the popular press, the idea was recently presented in a *Psychology Today* piece on American perceptions of British accents (Bennett 2016). The author notes that, "Right or wrong, we use the information that accents provide to make social judgements. Accents can provide clues to geography which then fuels biased decision-making. We make both positive and negative assumptions about

socioeconomic status, intelligence, and personality that may not be grounded in statistical reality." The piece goes on to point out that "not all British accents are identical. They indicate geographic regions with very different cultural stereotypes attached to them. If you grew up in England, you would be sensitive to these distinctions just like in the U.S. we can hear voices from Boston, Chicago, Brooklyn, and Texas. However, since many Americans can't tell the difference between BBC, Cockney, or even Australian... voices we just lump them under one generic 'British accent' label."

8 A resumé might include the name of one's high school, which at best aggregates several different neighborhoods, and in the case of many major cities in the United States that offer school choice, school lotteries, or magnet schools, may contain no specific geographic information at all.

9 These are the authors' calculations and are not included in the table.

10 A census tract is the finest geography at which aggregated information is publicly available. Census tracts typically encompass 2,500 to 8,000 people.

11 We also note that PUMA need not be a measure of neighborhood directly; if, for example, local accents contain local information and individuals with the same accent live in similar geographic locations, this could be captured by PUMA of residence.

12 Data on student–teacher ratios come from the National Center for Education Statistics Common Core of Data. Data reported at the school level are aggregated up to the MSA level, weighting by school size. We include this control to address the concern that more segregated cities may have lower average school quality, which would cause migrants from these cities to earn lower wages on average. Note that we do not find much evidence that this is the case. While we expect segregation to be highly related to *within* MSA variation in school quality, it need not be related to *between* MSA variation in school quality.

13 In brief, the argument is that unskilled workers tend not to stay in places where the return to skill is high.

14 Baum-Snow and Pavan (2012) have previously shown that city size is an important determinant of wages.

15 To ease comparison of magnitudes, we standardize each of our city controls to be mean 0, standard deviation 1 across PMSAs.

16 In general, the coefficients on home city controls in column (2) have the anticipated sign. An exception is the average home city student–teacher ratio, which appears to be associated with higher wages. We should expect the student–teacher ratio in an individual's own school to negatively impact his wages. However, there is substantially more within- than between-MSA variation in school quality, making it difficult to infer much about an individual's own school quality from his home MSA's average. We also note that the positive and significant association between wages and the average home city student–teacher ratio is not robust to the inclusion of all additional controls (the MSAs with the highest student–teacher ratios are all in the West).

17 Migration distance is calculated as the distance between the centroid of a person's PUMA of residence in 1995 and the centroid of his PUMA of residence in 2000. PUMA centroids are calculated using GIS from boundary files supplied by IPUMS (Ruggles et al. 2017).

18 For discussions about the link between discrimination and racial segregation, see Cutler, Glaeser, and Vigdor (1997) and Shertzer and Walsh (2016).

19 We do not include $SEG_j$ in this regression model because it is absorbed by our home metro area-fixed effects.

20 We note that the coefficients on the uninteracted variables are not directly comparable from (3) to (4) due to the additional interaction terms. While we normalized all of our city characteristics to be mean 0 across PMSAs, due to differences in PMSA size, the average worker lives in an PMSA that looks much different than the average PMSA. For example, the average worker lives in a PMSA that has 0.67 standard deviation higher mean log wage and a 0.71 standard deviation higher fraction of immigrants than the mean.

## References


Bennett, Kevin. September 9, 2016. "Why do British Accents Sound Intelligent to Americans?" *Psychology Today*. Accessed on October 25, 2016. https://www.psychologytoday.com/blog/modern-minds/201609/why-do-british-accents-sound-intelligent-americans

Borjas, George. 1987. "Self-selection and the Earnings of Migrants." *American Economic Review* 77 (4): 531–553.

Baum-Snow, Nathaniel, and Ronni Pavan. 2012. "Understanding the City Size Wage Gap." *Review of Economic Studies* 79 (1): 88–127.

Chetty, Raj, and Nathaniel Hendren. 2017. "The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects and County-Level Estimates." NBER Working Paper No. 23001.

Chetty, Raj, Nathaniel Hendren, and Lawrence F. Katz. 2016. "The Effect of Exposure to Better Neighborhoods on Children: Evidence from the Moving to Opportunity Experiment." *American Economic Review* 106 (4): 855–902.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *Quarterly Journal of Economics* 129 (4): 1553–1623.

Cutler, David M., Edward L. Glaeser, and Jacob L. Vigdor. 1997. "The Rise and Decline of the American Ghetto." *Journal of Political Economy* 107: 455–506.

Dequiedt, Vianney, and Yves Zenou. 2013. "International Migration, Imperfect Information, and Brain Drain." *Journal of Development Economics* 102: 62-78.

Grogger, Jeffrey and Gordon H. Hansen. 2011. "Income Maximization and the Selection and Sorting of International Migrants." *Journal of Development Economics* 95: 42–57.

Kasinitiz, Philip, and Jan Rosenberg. 1996. "Missing the Connection: Social Isolation and Employment on the Brooklyn Waterfront." *Social Problems* 43 (2): 180–196.

Katz, Eliakim, and Oded Stark. 1984. "Migration and Asymmetric Information: Comment." *American Economic Review* 74 (3): 533–535.

Katz, Eliakim, and Oded Stark. 1986. "Labor Mobility Under Asymmetric Information with Moving and Signaling Costs." *Economics Letters* 21 (1): 89–94.

Katz, Eliakim, and Oded Stark. 1987a. "International Migration under Asymmetric Information." *Economic Journal*. 97: 718-726.

Katz, Eliakim, and Oded Stark. 1987b. "Migration, Information, and the Costs and Benefits of Signaling."*Regional Science and Urban Economics* 17 (3): 323–331.

Katz, Eliakim, and Oded Stark. 1989. "International Labour Migration under Alternative Informational Regimes: A Diagrammatic Analysis." *European Economic Review* 33 (1): 127–142.

Kirschenman, Joleen and Katrhyn M. Neckerman. 1991. "'We'd Love to Hire Them, But...' The Meaning of Race for Employers." In *The Urban Underclass*, edited by Christopeher Jencks, and Paul E. Peterson, 203–232. Washington DC: Brookings Institute.

Kwok, Viem, and Hayne Leland. 1982. "An Economic Model of the Brain Drain." *American Economic Review* 72 (1): 91–100.
Reardon, Sean F. 2011. "Measures of Income Segregation." unpublished.
Ruggles, Stevn, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. Integrated Public Use Microdata Series: Version 7.0 [dataset]. Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D010.V7.0.
Salisbury, Laura. 2014. "Selective Migration, Wages, and Occupational Mobility in Nineteenth Century America." *Explorations in Economic History* 53: 40–63.
Shertzer, Allison, and Randall P. Walsh. 2016. "Racial Sorting and the Emergence of Segregation in American Cities." NBER Working Paper no. 22077.