Business Dynamism, Educational Attainment, and Residential Location Choice

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Abstract: Using individual-level, geocode data from the National Longitudinal Survey of Youth's 1997 cohort, I ask whether business dynamism in local labor markets, defined as the rates of job creation and establishment entry, affects the location decisions of labor force participants, and I examine how effects differ for highly and less educated labor force participants. I find that a one standard deviation increase in business dynamism is associated with a 2 to 4 percent increase in probability a college graduate chooses a metropolitan statistical area and an 8 to 15 percent decrease for high school graduates with no college experience. These results support recent findings documenting a decrease in responsiveness to local labor market conditions and suggest that incentivizing job creation in local labor markets may not be enough to offset the trend of declining internal migration in the United States.

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1. Introduction

The idea that an individual or household can pack up and move to a different part of the country in search of new opportunities is widely regarded as a key component of the "American dream." However, declining rates of internal migration in the United States in recent decades call into the question whether the willingness to move from one part of the country to another is still an enduring feature of the United States economy. The departure from the previous upward trend in internal migration rates since 1980 and the acceleration of the decline after 2000 caused economists to investigate explanations for the reversal, yet no existing hypothesis accounts for it completely.

Molloy, Smith, and Wozniak (2014, 2017) argue that declining rates of internal migration are related to a concurrent secular decline in labor market transitions, as the decision to change residences is closely tied to the decision to change jobs or exit the labor force, and Bosler and Petrosky-Nadeau (2016) show that this decline in job-to-job transitions is most pronounced among young workers, who are typically more geographically mobile and responsive to spatial variation in local labor market conditions than their more tenured colleagues (Millington 2000). This evidence of a link between declining internal migration rates and declining job changing provides a compelling reason to ask why individuals, especially young workers, no longer change jobs as readily as they used to. Molloy, Smith, and Wozniak (2014) and Konczal and Steinbaum (2016) argue that the distribution of wage offers has changed so that wage gains associated with changing employers have decreased over time, making labor market transitions less attractive.[1] So, if internal migration rates and job changing are declining because young

[1] Relatedly, Kaplan and Schulhofer-Wohl (2017) document a decline in job-related moves over the same period and argue this is because job opportunities have become more similar across locations, reducing the need for workers to move where their skills are most productive.

workers are facing fewer desirable outside offers in the labor market, why are young workers receiving fewer desirable wage offers?

Molloy, Smith, and Wozniak (2017) suggest that the downward trend in new firm startup rates may be another piece of the puzzle. Decker et al. (2014) show that business dynamism in the United States, measured by the rate of new firm formation, has also declined over recent decades, and Figure 1 documents these concurrent declines in internal migration and business dynamism using data from the U.S. Census Bureau. It shows declines in the number of inmigrants to and outmigrants from U.S. metropolitan areas along with accompanying declines national job creation and establishment entry rates from 1984 to 2016. Consequences of the diminishing startup rate include a decline in the share of young firms in the economy, a decline in the share of economic activity and employment accounted for by young firms, and downward trends in job creation and job destruction rates, as these rates are higher at younger firms (Decker et al. 2014). Moreover, the labor market outcomes of young workers may be disproportionately affected by declining business dynamism because young firms disproportionately employ young workers (Ouimet and Zarutskie 2014).

While the trends of decreasing internal migration and business dynamism in the United States have been documented at an aggregate level, no studies to my knowledge examine their relationship using individual-level data on young workers, by modeling the location choice decision, and by investigating its determinants, which would allow for a closer examination of the relationships between the trends observed in the aggregate data. Using individual-level data, I ask whether dynamic business environments attract young labor force participants and whether the likelihood of doing so depends on the individual's level of educational attainment. Understanding the extent to which the level of business dynamism in a local labor market affects an individual's propensity to reside there will provide insight into the relationship between the trends visible in the aggregate data and could help policymakers understand how incentivizing business dynamism affects human behavior.

This paper focuses on the location decisions of recent labor market entrants because of the larger secular trend in declining mobility documented among young workers (Bosler and Petrosky-Nadeau 2016). Using restricted geocode data from the National Longitudinal Survey of Youth's 1997 cohort (NLSY97) and data from the U.S. Census Bureau's Business Dynamics Statistics (BDS), I estimate a conditional logit model of the yearly choice of local labor market, defined as a metropolitan statistical area (MSA). My covariate of interest is the time-varying, MSA-specific level of business dynamism, measured by job creation and establishment entry rates. This approach allows me to identify the change in the probability of an MSA attracting a young labor force participant that is attributable to changes in business dynamism in the MSA. By interacting the business dynamism variables with indicators of educational attainment, I examine how the effects of business dynamism on choice of MSA differ for individuals with varying levels of education.

I find that college graduates choose local labor markets with higher rates of job creation, but an increase in the job creation rate is associated with a *decrease* in the odds high school graduates and GED recipients with no college experience choose an MSA. However, the magnitudes of these effects are relatively small. A one standard deviation increase in the job creation rate is associated with a 4 percent increase in the odds a college graduate chooses an MSA and an 8 percent decrease in the odds a high school graduate with no college experience chooses an MSA. In contrast, I find no statistically significant effect of job creation rates on the location choices of high school dropouts and or high school graduates and GED recipients with some college experience. Similarly, I find that a one standard deviation increase in the establishment entry rate is associated with a 15 percent decrease in the odds a high school graduate with no college chooses an MSA, a 2 percent decrease for people with some college experience, and a 2 percent increase for college graduates.

This paper provides a more nuanced view of the relationship between internal migration and business dynamism than can be obtained from aggregate trends. These results suggest that reversing declines in business dynamism may only increase internal migration among college-educated labor force participants and will fail to do so for high school graduates with no college experience due to negative effects for this group that are over 50 percent larger than the positive effects for college graduates. As such, implementing policies aimed at reversing declines in business dynamism may not fully reverse the aggregate trend of declining internal migration and could contribute to the persistence of inequality across space with respect to educational attainment. Overall, the relatively small magnitude of these effects supports the findings of recent studies that document a decrease in the responsiveness of the population to local labor demand shocks since 2000 using aggregate data (Partridge et al. 2012; Dao, Furceri, and Loungani 2017) and suggests that implementing policies to incentivize business dynamism in local labor markets may not do much to combat the downward in trend in internal migration in the United States.

This paper relates to the literature on local labor market conditions and location decisions of recent labor market entrants but differs from existing studies in three important ways. First, I introduce a novel measure of local labor market conditions: business dynamism measured by the MSA-specific job creation and establishment entry rates. Second, the use of longitudinal data allows me to include individual fixed effects in my empirical analyses, something that no existing studies that examine the choice of local labor market have implemented to my knowledge. Individual fixed effects allow me to control for time-invariant individual heterogeneity that affect the choice of local labor market, like preferences for living in or near certain places. Third, many papers that examine individual migration decisions of labor force participants in the United States analyze moves across states (Davies, Greenwood, and Li 2001; Dahl 2002; Wozniak 2010), but examining migration decisions across MSAs is relatively less common.[2] I define local labor markets as MSAs as opposed to states because doing so allows me to more accurately characterize the distribution of employment opportunities across space since many MSAs cross state borders and because of evidence heterogenous business cycles across cities within the same state (Moretti 2012; Ransom 2021).

2. Literature Review

This study relates most directly to the literature on residential location choice and migration. The literature on migration is vast, and many studies use aggregate data to examine the determinants of migration flows from one place to another. Fewer use individual level data to examine how certain location- and individual-specific characteristics affect an individual's choice of location or decision to migrate, and studies that do use individual level data typically take one of four approaches.

The first is a static, discrete choice approach where researchers estimate the probability of moving using a linear probability model (Winters 2017) or a multinomial logit model (Linneman and Graves 1983; Détang-Dessendre, Goffette-Nagot, and Piguet 2008; Abreu, Faggian, and McCann 2015; Kazakis and Faggian 2017). This approach allows the authors to isolate the effects of individual- and location-specific characteristics on the probability of migrating, but the

[2] A MSA is a core, urbanized area and adjacent communities that have "a high degree of economic and social integration with that core," together containing at least 50,000 inhabitants (U.S. Census Bureau 2013).

window of time over which individuals make the decision to migrate is fixed and often arbitrary or determined by data limitations. The second, a dynamic discrete time hazard function approach, address this problem directly (Bailey 1993; Clark and Davies Withers 1999; Détang-Dessendre and Molho 1999; van Ommeren, Rietveld, and Nijkamp 1999; Huffman and Feridhanusetyawan 2007; Busch and Weigert 2010). The coefficients generated from the estimation of discrete time hazard models represent the effects of individual- and location-specific characteristics on the hazard of migrating i.e., on the likelihood of migrating in the next period conditional not having migrated in any previous period.

The third approach, which is both dynamic and structural, has become prevalent in the literature as recent advances have made these estimating models more feasible (Kennan and Walker 2011). Behavioral models of migration are fully specified and solved numerically, and the estimates obtained are then used to quantify responses to shocks or policy interventions. The fourth and final approach involves estimating a conditional logit model of location choice (Davies, Greenwood, and Li 2001; O'Keefe 2004; Scott, Coomes, and Izyumov 2005; Dahl and Sorenson 2010; Wozniak 2010). With this this non-structural dynamic discrete choice approach, individuals choose a residential location out of a set of clearly defined alternatives, and the estimated coefficients give the effect of either individual- or location-specific characteristics on the probability of choosing a location.

Studies that examine the determinants of the probability of migrating or the hazard rate do not adequately account for differences across alternative locations. These studies examine the effects of individual- and location-specific characteristics on the decision to move without taking into account the fact that the decision to migrate is based on the consideration of the current location relative to other alternative locations. Although alternatives are considered in many of the structural studies, the structure imposed on the location decision problem is often restrictive, and the computational burden associated with solving the decision problem is great. Therefore, in this paper I estimate a model of residential location choice using the conditional logit approach.

Before describing the conceptual framework and empirical strategy implemented this paper, I briefly discuss the literature that examines the effects of labor market characteristics on residential location choice. Local labor market conditions have been shown to be an important determinant of migration flows (Blanchard et al. 1992; Gabriel, Mattey, and Wascher 1995; Bound and Holzer 2000; Sasser 2010) and of individual residential location decisions Davies, Greenwood and Li 2001; O'Keefe 2004; Scott, Coomes, and Izyumov 2005; Wozniak 2010). In doing so, almost all studies measure labor market conditions using the unemployment rate or a Bartik-type shift-share measure to isolate labor demand shocks purged of any labor supply responses. Davies, Greenwood, and Li (2001) find that migrants are significantly less likely to move to a state with a relatively higher unemployment. Similarly, O'Keefe (2004) finds a negative effect of unemployment rates on the choice of county for AFDC recipients in California. In addition to using the unemployment rate as a measure of labor market conditions, Wozniak (2010) derives an exogenous demand-based measure of employment growth using a Bartik-type measure of employment rates to investigate the effect of labor demand shocks on a college graduate's choice of state. She finds a positive and significant effect, suggesting that better entry labor market conditions attract college graduates. One exception is Scott, Coomes, and Izyumov (2005), who include job growth in goods-producing and service-producing industries, measured by job growth over the previous 5 years, as an indicator for the strength of the local economy when examining the determinants of location decisions of those immigrating into the United States. They find mixed effects of these variables on location choice across immigrant populations.

No studies to my knowledge examine the effects of business dynamism at the local labor market level, measured by the rate of job creation or establishment entry, on the location choice of individuals. Instead of examining the effects of shocks to labor demand, which could be driven by either firm-specific or external factors, these measures allow me to assess the effects of actions taken by firms that directly contribute to the dynamism of local labor markets. This paper adds to the existing literature by introducing a novel measure of local labor market conditions and by examining its effects on residential location choice over a period when aggregate trends in this variable are deteriorating.

3. Conceptual Framework

3.1 A Model of Residential Location Choice

In this section, I describe the theoretical foundation for the relationship between business dynamism and residential location choice, which is based on the framework from Rosen (1979) and Roback (1982). In this model, individuals obtain utility from living in a location in each year. I assume that the level of utility individual i receives from location j at time t is a function of three sets of location-specific variables: labor market characteristics, housing prices, and amenities. I assume that more favorable labor market characteristics reflect a higher likelihood of finding a higher-paying job. Therefore, location-specific labor market characteristics can be summarized by two variables: the average wage and the wage offer arrival rate, the latter of which describes the frequency with which an individual receives wage offers from firms in a given location.[3] Wage offers are given to individuals by firms and reflect the quality of the match

[3] I allow wages and the wage offer arrival rate to have independent effects on indirect utility because differences in wage offer arrival rates are not fully captured by differences in average wages across MSAs. For example, in 2010

between the worker-firm pair. I assume the wage offer arrival rate for individual i depends not only on her individual-specific characteristics, such as educational attainment, but also on time-varying characteristics of the business environment in location j. As a result, the indirect utility individual i receives from location j at time t is

$$V(\lambda_{ijt}, w_{ijt}, H_{jt}, A_j, \rho_t, \alpha_i) \tag{1}$$

where λ_{ijt} is individual i's wage offer arrival rate in location j at time t, w_{ijt} is the wage individual i receives in location j at time t, H_{jt} is the average price of housing in location j at time t, A_j represents time-invariant amenities associated with living in location j, ρ_t represents year-specific factors common to all individuals and locations (the national business cycle, for example), and α_i represents time-invariant, individual-specific preferences for certain locations.

Wage offer arrival rates will be higher in locations with higher business dynamism. Because wage offers are more frequent, individuals have a higher likelihood of finding the best quality worker-firm match by locating in areas where business dynamism is high. Put differently, for any individual, the average worker-firm match quality is higher in a more dynamic business environment than in a less dynamic business environment. Within the context of job search and matching models, the worker-firm match represents the marginal productivity of a given worker-firm pairing. Because workers seek the best opportunity to maximize the expected present value of lifetime earnings, they search for the best quality worker-firm match available to them. Therefore, location-specific utility is increasing in the wage offer arrival rate because higher

the job creation rate was 14.6 in Charlotte, NC and only 11.9 in Boston, MA (see Table A.1), but the annual average pay was $62,460 in Boston compared to just $48,271 in Charlotte according to the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). Therefore, despite having lower average wages, the relocation rate of labor was higher in Charlotte than in Boston, with jobs created and destroyed at faster rates. This means that wage offer arrival rates were likely higher in Charlotte on average i.e., workers were getting more wage offers than they would have gotten in Boston, but those wage offers were lower on average than what they would have received in Boston due to differences in amenities between the two cities (Rosen 1979, Roback 1982, Albouy 2015).

wage offer arrival rates are associated with a higher likelihood of finding the best possible worker-firm match. Finally, an individual will migrate if the utility she receives from location k net of any moving costs is higher than the utility she currently receives from location j.

Formally, the choice problem for individual i residing in location j^* in a given period t is written as

$$\max_{j \epsilon J} V(\lambda_{ijt}, w_{ijt}, H_{jt}, A_j, \rho_t, \alpha_i) - c_{i(j^*,j)t} \tag{2}$$

where $c_{i(j^*,j)t}$ denotes the cost associated with moving from location j^* to location j at time t with $j \neq j^*$, which takes the value of zero when $j = j^*$. The framework McFadden (1974) uses to describe individual choice behavior can be applied to this choice problem to gain insight into how changes in the wage offer arrival rate affect the probability a utility-maximizing individual chooses a location j in any given period t. Following McFadden (1974), the probability an individual chooses to reside in location $j \neq j^*$ depends on her wage offer arrival rate, her wage level, the average price of housing, and the level of amenities in both location j and all other locations $k \neq j$ along with individual preferences as follows:

$$\Pr(choose\ j \neq j^*) = \Pr\,[V(\lambda_{ijt}, w_{ijt}, H_{jt}, A_j, \rho_t, \alpha_i) - c_{i(j^*,j)t} > V(\lambda_{ij^*t}, w_{ij^*t}, H_{j^*t}, A_{j^*}, \rho_t, \alpha_i)$$
$$and\ V(\lambda_{ijt}, w_{ijt}, H_{jt}, A_j, \rho_t, \alpha_i) - c_{i(j^*,j)t} > V(\lambda_{ikt}, w_{ikt}, H_{kt}, A_k, \rho_t, \alpha_i) - c_{i(j^*,k)t}] \tag{3}$$

Expression (3) says that the probability an individual chooses a location other than her current location is equal to the probability her utility from the new location net of moving costs outweighs utility from her current location and utility from all other alternative locations net of moving costs.

3.2 Implications for Empirical Strategy

Not only does McFadden (1974) characterize choice problems of this kind, but he describes a tractable empirical strategy that can be used to examine choice behavior: the conditional logit model. Following Davies, Greenwood, and Li (2001), O'Keefe (2004), and Wozniak (2010), I estimate the individual's choice problem described by equation (2) using the conditional logit approach.

With this approach, individual i chooses one location j from J possible unordered alternatives at time t. I observe each individual's choice during each time period, so the dependent variable, y_{ijt}, takes on the value of 1 if individual i chooses location j in time t and 0 otherwise. Rewriting (1) as a linear function of the wage offer arrival rate, the wage, location-specific amenities, and individual preferences, the utility level individual i obtains from choosing location j in time t is

$$\begin{aligned} U_{ijt} &= V(\lambda_{ijt}, w_{ijt}, H_{jt}, A_j, \rho_t, \alpha_i) - c_{i(j^*,j)t} + \varepsilon_{ijt} \\ &= \beta\lambda_{ijt} + \theta w_{ijt} + \gamma H_{jt} + A_j + \rho_t + \alpha_i - c_{i(j^*,j)t} + \varepsilon_{ijt} \end{aligned} \tag{4}$$

where is ε_{ijt} a random component of utility that is assumed to be independent and identically distributed with an extreme-value distribution. The probability of choosing location $j \neq j^*$ in period t is

$$\Pr(y_{ijt} = 1) = \frac{e^{\beta\lambda_{ijt}+\theta w_{ijt}+\gamma H_{jt}+A_j+\rho_t+\alpha_i-c_{i(j^*,j)t}}}{\sum_{k=1}^{J} e^{\beta\lambda_{ikt}+\theta w_{ikt}+\gamma H_{kt}+A_k+\rho_t+\alpha_i-c_{i(j^*,k)t}}} \tag{5}$$

where $c_{i(j^*,k)t} = 0$ if $j^* = k$. McFadden (1974) shows that (5) is equal to the probability that location j provides higher utility to individual i at time t than all other locations at time t. To estimate coefficients in (5), the conditional probability of observing $y_{ijt} = 1$ is maximized using the following log-likelihood function:

$$\ln L = \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{J} y_{ijt} \ln \Pr(y_{ijt} = 1) \tag{6}$$

I describe the data used in the analysis and the measurement of the variables in equation (5) in the section 4, and the estimation results from this exercise are presented and discussed in section 5.

4. Description of the Data

I use restricted access geocode data from the National Longitudinal Survey of Youth 1997 Cohort (NLSY97) and data from the U.S. Census Bureau's Business Dynamics Statistics (BDS) to investigate whether more dynamic business environments differentially attract labor market participants by educational attainment. The NLSY97 is a longitudinal survey containing rich demographic, geographic, education history, and job history information for a nationally representative sample of 8,984 youths. Respondents were between 12 and 16 years old at the end of 1996 and were interviewed every year from 1997 until 2011, at which point interviews began being conducted biennially. Since location information for respondents is only available at the date of each interview, I use data from 1997 through 2011 to avoid inconsistencies due to the interview schedule change.[4] Following Kennan and Walker (2011), I define migration as a change in location from one interview to the next, and I define locations as MSAs in the United States.

To reduce the computational burden associated with estimating a model where individuals choose from one of over 300 locations in each of up to 13 years and to more appropriately define the choice set since individuals may not truly consider *all* MSAs when deciding where to live, I restrict the choice set to the 50 most frequently observed MSAs in the NLSY97, which are listed in Table A.1, following Ransom (2021). This assumption is not overly

[4] As a robustness check, I reestimated the model after adding data from the 2013 and 2015 interviews to the analysis sample and controlling for the number of years between interviews, and the results presented in section 5 do not change.

restrictive because 48% of the U.S. population lived in one of these 50 MSAs in 2010 and because the results presented in section 5 are robust to defining the choice set as all MSAs ever observed in the NLSY97.[5]

Changes to the sample due to the following selection criteria are described in detail in Table A.2. I begin by defining the date of labor market entry for all respondents. For respondents who obtain a high school degree, GED, or any degree higher and do not go back to school after obtaining their highest degree, I define date of labor market entry as the date of highest degree receipt. For respondents who obtain a high school degree, GED, or any degree higher and do go back to school, I define the date of labor market entry as last month the respondent reports being enrolled in school. Finally, for high school dropouts I define labor market entry as occurring at the date of high school exit. I exclude from the sample any high school dropouts whose high school exit date is not reported.

Next, I identify the date of the closest interview following the date of labor market entry for each respondent and call this the start of the respondent's observation period. The observation period ends at the interview date preceding the first interview where location information is missing or at the 2011 interview date. Because I am interested in residential location choice within local labor markets, I exclude individuals who do not reside in one of the 50 MSAs in the choice set at the start of the observation period. I exclude individuals who are

[5] Migration researchers and modelers of residential location choice decisions have long struggled with how to appropriately define choice sets in this context, where they are both unobserved and heterogenous, and there is no consensus about how to do so in the literature. A common approach proposed by Manski (1977) involves modeling both the choice set generation process and the choice itself by estimating the joint probability of being matched to a certain choice set and of making a specific choice within that choice set. However, this approach becomes computationally infeasible when the number of choices is large, so many researchers select the choice set by imposing constraints on attributes of alternatives, thereby creating a feasible choice set consisting of relevant alternatives only, or use sufficient sets based on combinations of observed choices (Hicks and Schnier 2010; Crawford, Griffith, and Iaria 2021). See Zolfaghari, Sivakumar, and Polak (2013) for a review of approaches to residential choice set formation.

not interviewed within 12 months of labor market entry and those for whom the start of the observation period begins after 2011. I assume that permanent labor for attachment begins no earlier than age 18 and consequently exclude those who were younger than age 18 at labor market entry. Following Kennan and Walker (2011), I exclude anyone who has ever served in the military and anyone who reports being out of the labor force for more than 1 year during the observation period. Restricting the sample to labor force participants allows me to examine the location decisions of individuals who are either in the labor or force or are searching for a job i.e., of those for whom job creation rates should matter the most when choosing a local labor market. Lastly, I exclude individuals for whom the observation period is only one year in length.

The sample contains 1,906 individuals who are followed continuously for at least two years, resulting in a total of 8,963 person-years after excluding the first year of the observation period, in which I take residential location as given, and the years following the first gap in location history. In each period, individuals choose from 50 MSAs, which yields 448,150 MSA-person-year observations in total.

In addition to the NLSY97, I collect job creation and establishment entry rates from the U.S. Census Bureau's Business Dynamics Statistics (BDS). The BDS provides annual measures of business dynamics at the state, MSA, and county levels. These data are created from the Longitudinal Business Database, a confidential database maintained by the U.S. Census Bureau with detailed establishment- and firm-level data. I use these data to match annual job creation and establishment entry rates to the MSA in which each respondent resides in each survey round during the observation period. The job creation rate is defined by the BDS as the count of all jobs created within the MSA over the last 12 months divided by the Davis-Haltiwanger-Schuh (DHS) denominator and multiplied by 100. The DHS denominator is the average of employment for the current year and previous year. The establishment entry rate is the count of establishments born in the MSA over the last 12 months divided by the average number of establishments in the MSA in the current year and previous year, all multiplied by 100.

I obtain the annual average weekly wage in each MSA and year from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW) and the MSA- and year-specific House Price Index (HPI), which is a measure of the movement of single-family house prices based on price changes from repeat sales or repeat occurrences of refinancing for the same properties, from the Federal Housing Finance Agency (FHFA). Finally, I obtain unsuppressed employment by industry, year, and county from the W.E. Upjohn Institute for Employment Research's WholeData (Bartik, Biddle, Hershbein, and Sotherland, 2018), which I aggregate to the MSA level to create Bartik-style industry mix variable used to control for changes in the industrial composition of MSAs over time that are correlated with business dynamism and with residential location choice. I create this variable by multiplying the share of employment in industry d in MSA j at time t by the national employment growth rate in industry d from time $t-1$ to time t and then summing these values across all industries.

The top two panels of Table 1 provide migration history information for the sample. To examine how location decisions differ for individuals with varying levels of educational attainment, I stratified the sample into four groups: high school dropouts, high school graduates and GED recipients who never attend college, high school graduates and GED recipients who attend some college, and college graduates.

College graduates are the most mobile group with almost 15.4 percent moving at least once during the observation period, and the share of movers in each group increases with educational attainment, a finding that is consistent with evidence from previous studies (Faggian, McCann, and Sheppard 2007a,b). Table 1 reports average moves per mover for each group, but since the length of the observation varies for each individual, I also include a normalized measure which gives the expected number of moves per mover if every individual in that education group were observed for 4.7 years, the average length of the observation period for the full sample. College graduate movers move the most, as expected, and high school dropout movers move the least with less than 1 normalized move per mover on average. Finally, Table 1 shows average origin and destination job creation rates for movers in each educational group. All movers move to MSAs with job creation rates equal to or higher than their origin MSAs on average, despite the fact that dynamism is declining nationally over this period (see Figure 1). However, movers with no college experience (including high school dropouts) enter the labor market in MSAs with higher business dynamism on average, and the gaps between origin and destination job creation rates is larger for these groups than the analogous gaps for individuals with college experience.

The middle panel of Table 1 shows data for non-movers, which make up a majority of the full sample. These statistics show that business dynamism declines throughout the observation period for all educational groups on average, consistent with the aggregate trend described in the introduction of the paper and shown in Figure 1. In addition, the magnitudes of the declines in dynamism are similar across groups on average.

The bottom panel of Table 1 shows basic demographic information for sample members in each educational group. More educated labor force participants are older at the start of the observation period compared to those with less education because it takes time to obtain additional years of schooling. They are also more likely to be female and less likely to be Black or Hispanic. High school dropouts and high school diploma and GED recipients who do not attend college enter the labor market in 2002 on average and are observed for 5.3 to 6.3 years. In contrast, individuals who attend some college and college graduates enter the labor market between 2005 and 2006 on average and are observed for 4 to 4.6 years.

5. Results

The results from the estimation of the conditional logit model in equation (5) above are presented in Tables 2 and 3. My proxy for λ_{ijt}, the wage offer arrival rate, is the level of business dynamism in the local labor market measured by the time-varying, MSA-specific job creation rate (Table 2) or establishment entry rate (Table 3). I measure w_{ijt} using the time-varying, MSA-specific annual average weekly wage from the QCEW and H_{jt} using the HPI from the FHFA. I also include the Bartik-style industry mix variable described in section 4 to control for changes in the industrial composition of MSAs over time that are correlated with business dynamism and with an individual's residential location choice. The two measures of business dynamism, the annual average weekly wage, the HPI, and the Bartik-style industry mix variable are lagged by one year to more accurately reflect the information known at the time the location decision is made and to alleviate concerns about reverse causality.

I include MSA fixed effects as a measure of amenities, A_j, and other time-invariant unobservable MSA-specific attributes that are correlated with the job creation and establishment entry rates and affect an individual's choice of location, like city size or cost of living. To capture the cost of moving, $c_{i(j^*,j)t}$, I include a variable with the distance between the previous year's MSA of residence and each alternative MSA in miles, and time-invariant preferences, α_i, are measured using individual fixed effects. Including individual fixed effects in all specifications allows me to address selection issues resulting from time-invariant individual heterogeneity, like preferences for residing in certain MSAs.[6] Finally, I include year fixed effects, ρ_t, in each specification to address the correlation between internal migration and the national business cycle documented by Saks and Wozniak (2011).

Odds ratios and standard errors are reported in Tables 2 and 3. I report odds ratios instead of marginal effects because the conditional fixed effects logit estimator does not provide estimates of the individual fixed effects, which are necessary to compute marginal effects. Note that an odds ratio equal to one indicates that the variable has no effect on the odds of an individual choosing an MSA. Each observation is an MSA-person-year, with 8,963 person-years and 50 MSAs resulting in 448,150 total observations.

Column 1 provides the results of a baseline specification where the job creation rate (Table 2) or the establishment entry rate (Table 3) is the only MSA-specific covariate included in the model. These pooled estimates indicate that levels of business dynamism have small and imprecisely estimated effects on residential location choice, so I estimate the models with interactions between the business dynamism variables and the education group indicators added to test whether these pooled estimates are masking differential impacts by educational attainment. These results are in column 2 of both tables. I add the moving cost variable, distance in miles between MSAs, to the model in column 3, and I add both the MSA-year-specific average wage and HPI to the model in column 4, which allow me to control for variation in wage levels and housing prices across MSAs and over the years. This is intended to address the fact

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[6] While individual fixed effects net out the effects of time-invariant, individual-level unobservable confounders, they do not net out the effects of time-*varying*, individual-level characteristics correlated with both business dynamism and residential location choice. To address the possibility that individuals may live in multi-member households, that the location decision may be made jointly with other household members, and that household structure may change over time, I estimate the model with time-varying measures of household structure included. Specifically, I add an indicator equal to 1 if the sample member is married, an indicator equal to 1 if the sample member is cohabitating with a partner, and a variable with the number of children in the sample member's household, and the results presented in this section are unchanged. The results are similarly robust to the inclusion of an indicator equal to 1 if the sample member changed jobs in the last year.

that individuals may choose not to locate in MSAs where business dynamism is high if the average wage level is too low or if housing prices are too high. I add the Bartik-style industry mix control variable to the model in column 5, and I add interactions between the moving cost variable and the education groups to the model in column 6, with the idea that distance-based moving costs could affect the probability of choosing an MSA differently for individuals with different levels of education.[7] The results in column 6 of Tables 2 and 3 indicate that heterogeneity exists across education groups with respect to the effect of moving costs on residential location choice, supporting the inclusion of these interaction terms in the model. Therefore, my preferred specifications are those whose results are reported in column 6 of Tables 2 and 3, and I will discuss these findings in the paragraphs to follow.

Since high school graduates with no college experience are the omitted group, the main effects in the first row of Tables 2 and 3 give the effects of an increase in the job creation rate or establishment entry rate on the likelihood that a high school graduate with no college chooses to reside in any given MSA in any given year. The estimates in column 6 indicate that one standard deviation increase in job creation and establishment entry rates are associated with 8 and 15 percent decreases, respectively, in the odds a high school graduate with no college chooses an MSA.

Since odds ratios are multiplicative rather than additive, the estimates on the interactions between the business dynamism variables and the remaining educational groups give the boosts to the odds implied by the main effect for individuals in the remaining educational groups. These estimates indicate that increasing the job creation rate or the establishment entry rate has no statistically significant effect on choice of MSA for high school dropouts but boosts the odds

[7] In an alternate version of the model, I interacted the educational attainment variables with both the average wage and the HPI and found no significant differences in the effects of these variables across education groups.

individuals with some college and college graduates choose an MSA by 9 to 13 percent respectively (job creation rate) or by 15 to 20 percent respectively (establishment entry rate), relative to a high school graduate with no college.

Therefore, in total, a one standard deviation increase in the job creation rate is associated with a 4 percent increase in the odds college graduates choose an MSA but with 2 and 8 percent *decreases* in the odds high school dropouts and high school graduates with no college, respectively, choose an MSA, although the estimate for high school dropouts is not statistically significant at conventional levels. Similarly, a one standard deviation increase in the establishment entry rate is associated with a 2 percent increase in the overall odds a college graduate chooses an MSA but 2, 4, and 15 percent decreases, respectively, for high school graduates with some college, high school dropouts, and high school graduates who do not attend college. Although, like the job creation rate estimate, the establishment entry rate estimate for high school dropouts is imprecisely estimated.

Interestingly, the odds ratios in Tables 2 and 3 suggest that the MSA-specific average wage and HPI have little to no effect on the odds an individual chooses an MSA, as indicated by the odds ratios equal to 1 in columns 4 through 6 of both tables. On one hand, this may indicate that the frequency of wage offers is more important than the level of the wage or average housing prices for individuals when choosing where to live. On the other hand, there may not be enough variation in average wages or average housing prices within MSAs over time to identify the true effects of these variables when MSA fixed effects are included in the model.[8]

The interactions with the distance-based moving cost variable and the educational groups indicate heterogeneity with respect to the effect of moving costs on residential location choice

[8] To test whether the dispersion of wages matters more than the average, I estimated the model using the difference between the 90th percentile and 10th percentile values instead of the average, and the results do not change.

among individuals of different educational groups. The odds ratios for the main effect of distance for the main effect multiplied by the odds ratios for the interactions with the remaining educational groups in column 6 of Tables 2 and 3 indicate that a one standard deviation increase in the distance between an individual's MSA of residence and an alternative MSA is associated with a 5 percent reduction in the probability a high school dropout chooses the alternative MSA, a 3 percent reduction for high school graduates with and without college experience, and a 1 percent reduction for college graduates. These findings are consistent with previous studies suggesting that moving costs may decrease with education (Molloy, Smith, and Wozniak 2011; Balgova 2020).

Instead of choosing areas where business dynamism is high, the results presented thus far indicate that high school graduates and GED recipients with no college experience are choosing to reside in more stagnant areas. The statistics in Table 1 show that less educated movers move to MSAs with higher job creation rates than their origin MSAs on average, and the gap between origin and destination job creation rates is larger for them than for individuals with more education. Therefore, the finding that less educated workers are avoiding more dynamic business environments is likely not driven by less educated movers disproportionately choosing to move to MSAs with lower business dynamism. The statistics in Table 1 also show that the magnitudes of the declines business dynamism where non-movers reside are similar for all educational groups on average, suggesting that this finding is not driven by less educated non-movers choosing to stay in places that experience disproportionately large declines in dynamism. Finally, Table 1 also shows that less educated individuals are much less likely to move on average than people with college experience. Taken together, these facts suggest that the finding that less educated individuals are choosing to reside in more stagnant areas is simply driven by the fact they are much less likely to move, which, coupled with declining dynamism everywhere over the observation period, results in them choosing MSAs with lower dynamism on average than those chosen by more educated individuals.

There are a number of reasons why less educated workers may be less likely to move than more educated workers: prohibitively high costs, family ties, or a relative lack of job opportunities elsewhere that align with their skillsets despite higher overall dynamism. The latter coupled with the positive effects for college graduates indicate that the wage offer arrival rate may not necessarily be increasing in business dynamism for all individuals as the conceptual framework presented in this paper implies. Further research using more granular data on the types of jobs that are being created and destroyed and the skill level required to complete them is needed to understand which of these mechanisms is most salient. Finally, these findings suggest that efforts to reverse the trend of declining business dynamism by implementing policies that incentive new job and establishment creation in local labor markets may only increase internal migration among college-educated labor force participants and, as such, will likely not completely reverse the aggregate trend of declining internal migration in the United States. Moreover, they may contribute to the persistence of inequality across space with respect to educational attainment.

It is important to note is the relatively small magnitude of the odds ratios reported in Table 2. Wozniak (2010) finds that a one standard deviation increase in the labor market conditions, measure by a Bartik-type employment growth variable, leads to an 11 to 14 percent increase in the probability a college graduate chooses a state, which is larger than the 2 to 4 percent increases implied by my estimates in Tables 2 and 3. She finds no effect for high school graduates and a negative effect (10 to 22 percent) for high school dropouts. In contrast, I find that a standard deviation increase in the job creation rate decreases the odds of a high school graduate choosing a given MSA by 15 percent, but I find a smaller, imprecisely estimated effect for high school dropouts.

The inclusion of individual fixed effects in my specifications may be one explanation for the difference in magnitude between my estimates and Wozniak (2010)'s findings. If individual preferences for residing in an MSA are corelated with local labor market conditions, the odds ratios implied by the estimated coefficients on the measures of local labor market conditions could overstate their effect on residential location choice when individual fixed effects are not included. A second explanation could be differences in the time period over which the data were collected. Wozniak (2010) used the 5 percent Integrated Public Use Micro Sample of the U.S. Census for the Census years 1980, 1990, and 2000 and examined the choice of local labor market of residence at the time of the Census. Therefore, the most recent data used in her analysis describe residential location choices in the year 2000. In contrast, my data describe residential location choices made between 1998 and 2011. All individuals in my sample, no matter the education group, appear to be less sensitive to business dynamism and local labor market conditions than those in Wozniak's sample, which is consistent with studies that have documented a decreasing responsiveness of the population to local labor market conditions since the year 2000 using aggregate data (Partridge et al. 2012; Dao, Furceri, and Loungani 2017).

Along with the key findings, it is important to discuss the limitations of the analysis presented in this paper. There are two main limitations of the conditional logit approach that are relevant to the choice problem described in this paper. The first is the assumption of independence of irrelevant alternatives (IIA). The IIA assumption within the context of this problem implies that the odds of choosing MSA k over MSA j in this situation where there are many MSAs from which to choose is the same as the odds of choosing MSA k over MSA j in a situation where j and k are the only two MSAs from which to choose. As McFadden (1974) acknowledges, this assumption is likely invalid in cases where the choice set contains many close substitutes, and it is reasonable to expect that out of 50 local labor markets, some may be close substitutes. Therefore, to indirectly test the IIA assumption, I estimated the model after expanding the choice set to include all MSAs ever observed in the NLSY97. The estimates generated using the restricted choice set are similar to those generated using the full choice set although slightly smaller in magnitude (see Table A.3), and the key findings remain unchanged, which suggests the IIA assumption is not unreasonable in this context.

The second limitation of the conditional approach is the computational burden associated with estimating choice behavior for 1,906 individuals who choose from 50 alternatives in as many as 13 time periods. Because of this, my empirical specifications are sparse, relevant, time-varying, individual- or MSA-specific attributes correlated with business dynamism and an individual's choice of location are likely omitted, and I am unable to interpret the estimates discussed in section 5 as causal. An example of a relevant omitted variable is one that captures whether the individual changes jobs from one year to the next. Whether an individual changes jobs during the year is likely correlated with both her choice of location in that year and levels of business dynamism in the local labor market.

A final limitation of the paper and the primary threat to identifying the effects of job creation rates on residential location choice comes from the fact that the job creation rate is correlated with both the likelihood an individual chooses to reside in a given MSA and with another time-varying MSA characteristic: changes in local labor supply. The job creation rate is correlated with changes in local labor supply by definition because the DHS denominator is the

MSA's average employment for the current and previous year. So, the effect of the job creation rate on residential location choice will be confounded by employment changes resulting from labor supply shifts. To address this issue, I use the establishment entry rate, whose denominator is the average number establishments in the current and previous years as, an alternative measure of business dynamism. I also lag the job creation and establishment entry rate variables to address concerns about reverse causality.

6. Conclusion

In this paper, I use a conditional logit approach to estimate a model describing a recent labor market entrant's choice of local labor markets. Using individual-level data from the NLSY97 and the BDS, I investigate the extent to which business dynamism at the local labor market level, where a local labor market is defined as an MSA, affects an individual's choice of MSA. Additionally, I examine the differential effect of business dynamism on choice of MSA for individuals with varying levels of education.

I find that increasing business dynamism, defined as the rate of job creation or establishment entry, increases the probability a recent labor market entrant with a college degree chooses an MSA by 2 to 4 percent but reduces the probability a high school graduate with no college education does so by 8 to 15 percent. While the effects are relatively small in magnitude compared to findings in the literature, they suggest that policies aimed at incentivizing job creation in metropolitan areas in the United States could play a small role in attracting college graduates to local labor markets but could act as an even larger deterrent for less educated labor force participants. As such, efforts to reverse the trend of declining business dynamism will not completely reverse the aggregate trend of declining internal migration in the United States and may contribute to the persistence of inequality across space with respect to educational attainment of the labor force. The relatively small effects for all groups support previous evidence of a decrease in the responsiveness of the population to changes in local labor demand since 2000 and further suggests that policies aimed that incentivizing business dynamism may not do much to offset the declining trend in internal migration in the United States.

Future research should compare the effects of multiple measures of local labor market conditions on residential location choice to better understand which local labor market characteristics matter in the location decisions of less educated individuals and why/how they differ from characteristics sought by highly educated labor force participants. After characterizing the extent to which skill disparities across regions arise because of differences in business dynamism and other measures of local labor market conditions, future research should seek to understand why less educated labor force participants choose to remain in more stagnant labor markets with the goal of offering suggestions to policymakers seeking to improve labor market outcomes for less educated residents.

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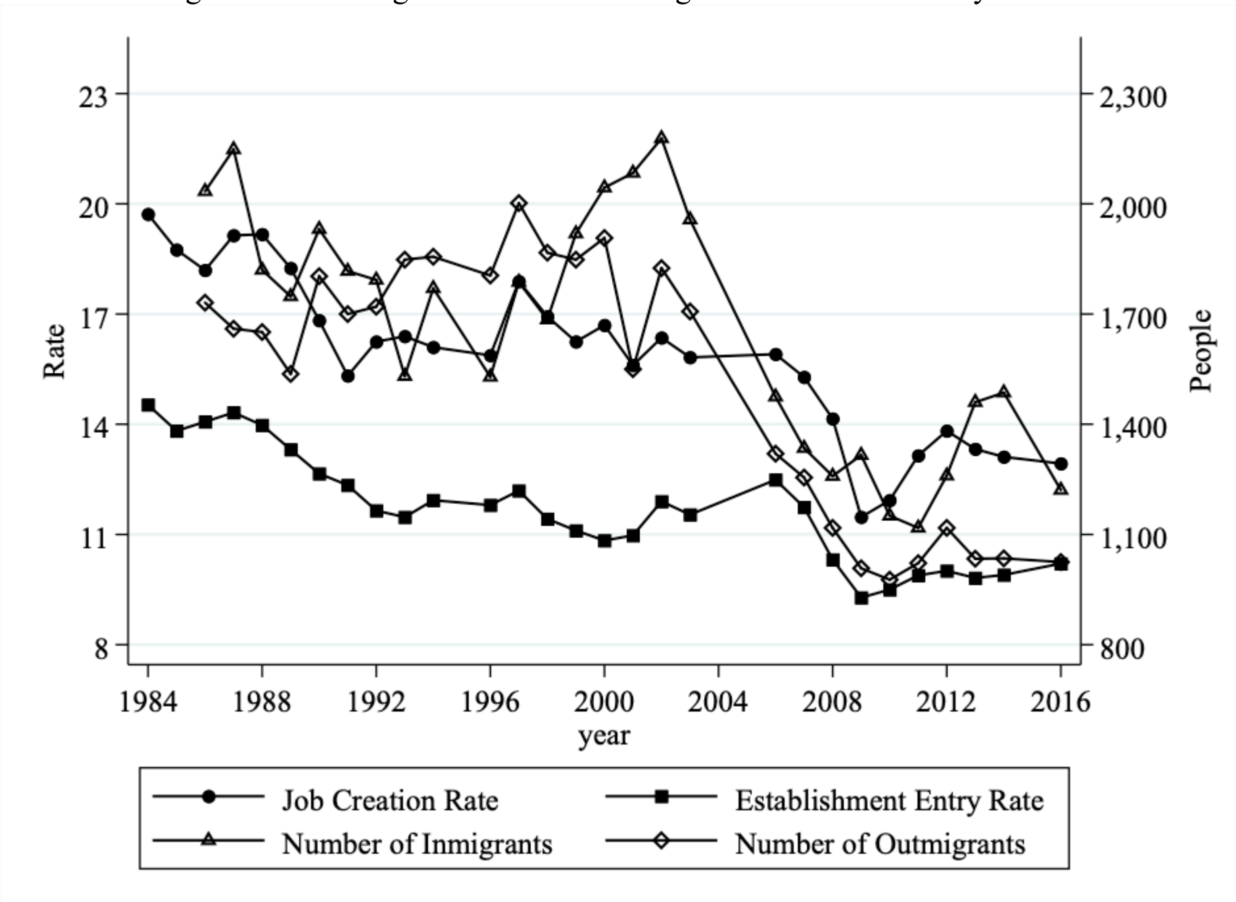
Figure 1. Declining Rates of Internal Migration and Business Dynamism



Notes: The figure shows estimates of the number of inmigrants to and outmigrants from U.S. metropolitan areas by year from the U.S. Census Bureau's Current Population Survey Annual Social and Economic Supplement and the national job creation and establishment entry rates by year from the BDS.

Table 1. Descriptive Statistics

	High School Dropouts		No College		Some College		College Graduates		Full Sample	
Movers										
N movers	3		30		53		134		220	
Percent movers	4.8		7.1		9.6		15.4		11.5	
N moves	3		51		69		176		299	
Moves/mover	1.00		1.70		1.30		1.31		1.36	
Years observed	5.32		6.28		4.60		3.96		4.70	
Norm. moves/ mover	0.88		1.27		1.33		1.56		1.36	
Mean origin JCR	15.1		16.4		15.1		15.0		15.3	
Mean destination JCR	16.4		16.7		15.3		15.0		15.4	
JCR difference	1.3		0.3		0.2		0		0.1	
JCR percent change	8.6		1.8		1.3		0		0.8	
Non-Movers										
N non-movers	60		393		498		735		1,686	
Percent non-movers	95.2		92.9		90.4		84.6		88.5	
Mean JCR start ob. pd.	17.5		16.8		15.9		15.4		15.9	
Mean JCR end ob. pd.	14.9		14.2		13.5		13.1		13.5	
JCR difference	-2.6		-2.7		-2.4		-2.3		-2.4	
JCR percent change	-14.8		-15.9		-14.9		-14.8		-15.1	
Full Sample	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Age at LM entry	19.6	2.3	19.5	2.1	23.0	2.8	24.4	2.2	22.8	3.1
Female	0.24	0.43	0.35	0.48	0.44	0.50	0.56	0.50	0.46	0.50
Black	0.27	0.45	0.25	0.44	0.26	0.44	0.18	0.38	0.22	0.42
Hispanic	0.52	0.50	0.30	0.46	0.32	0.47	0.16	0.37	0.25	0.43
Start ob. period	2002	2.7	2002	2.4	2005	2.9	2006	2.3	2005	3.1
End ob. period	2007	4.2	2008	3.8	2010	2.6	2010	1.6	2010	2.8
Years observed	5.3	3.6	6.3	3.8	4.6	2.8	4.0	2.2	4.7	3.0
N	63		423		551		869		1,906	

Notes: Full sample includes all recent labor market entrants who live in one of the 50 most frequently observed MSAs in the NLSY97 data during the first year in which they enter the labor market. JCR = job creation rate. A mover is someone who moves at all during the observation period. N moves is the total number of moves made by all movers. Years observed is the average length of the observation period in years. Norm. moves/mover gives the expected number of moves per mover if every individual were observed for 4.70 years. Data are from the NLSY97 and the BDS.

Table 2. Conditional Logit Results, Job Creation Rate as Measure of Business Dynamism

Variables	(1)	(2)	(3)	(4)	(5)	(6)
JCR main effect	0.99	0.95***	0.93***	0.94***	0.94***	0.92***
	(0.011)	(0.012)	(0.021)	(0.021)	(0.021)	(0.024)
JCR X Dropout		1.13***	1.05	1.04	1.04	1.06
		(0.026)	(0.048)	(0.047)	(0.047)	(0.094)
JCR X Some college		1.06***	1.10***	1.09***	1.09***	1.09***
		(0.012)	(0.024)	(0.024)	(0.024)	(0.028)
JCR X College grad		1.06***	1.13***	1.12***	1.12***	1.13***
		(0.011)	(0.024)	(0.024)	(0.024)	(0.025)
Distance main effect			0.97***	0.97***	0.97***	0.97***
			(0.0003)	(0.0003)	(0.0003)	(0.001)
Distance X Dropout						0.98***
						(0.004)
Distance X Some college						1.00***
						(0.001)
Distance X College grad						1.02***
						(0.001)
Wage				1.00***	1.00***	1.00***
				(0.001)	(0.001)	(0.001)
HPI				1.00	1.00	1.00
				(0.0003)	(0.0003)	(0.0003)
Observations	448,150	448,150	448,150	448,150	448,150	448,150
Pseudo R^2	0.042	0.043	0.804	0.804	0.804	0.815
Log likelihood	-39,183	-39,157	-8,027	-8,017	-8,017	-7,561
Bartik industry mix	N	N	N	N	Y	Y

Notes: JCR = MSA-specific job creation rate. Distance = distance between MSAs in miles. Wage = MSA-specific average weekly wage. HPI = MSA-specific house price index. Bartik industry mix = Bartik shift-share industry mix variable described in section 5. Each specification includes individual, MSA and year fixed effects. The top number in each cell is the odds ratio, and standard errors are in parentheses. Data are from the NLSY97, BDS, QCEW, and FHFA. * p<0.1, ** p<0.05, *** p<0.01.

Table 3. Conditional Logit Results, Establishment Entry Rate as Measure of Business Dynamism

Variables	(1)	(2)	(3)	(4)	(5)	(6)
EER main effect	1.03	0.95**	0.89***	0.88***	0.88***	0.85***
	(0.020)	(0.021)	(0.037)	(0.037)	(0.037)	(0.039)
EER X Dropout		1.20***	1.10	1.09	1.09	1.13
		(0.036)	(0.071)	(0.070)	(0.070)	(0.144)
EER X Some college		1.13***	1.16***	1.15***	1.15***	1.15***
		(0.017)	(0.035)	(0.035)	(0.035)	(0.041)
EER X College grad		1.12***	1.20***	1.19***	1.19***	1.20***
		(0.016)	(0.034)	(0.034)	(0.034)	(0.037)
Distance main effect			0.97***	0.97***	0.97***	0.97***
			(0.0003)	(0.0003)	(0.0003)	(0.001)
Distance X Dropout						0.98***
						(0.004)
Distance X Some college						1.00***
						(0.001)
Distance X College grad						1.02***
						(0.001)
Wage				1.00***	1.00***	1.00***
				(0.001)	(0.001)	(0.001)
HPI				1.00	1.00	1.00
				(0.0003)	(0.0003)	(0.0003)
Observations	448,150	448,150	448,150	448,150	448,150	448,150
Pseudo R^2	0.041	0.043	0.804	0.804	0.804	0.815
Log likelihood	-39,183	-39,133	-8,024	-8,013	-8,013	-7,558
Bartik industry mix	N	N	N	N	Y	Y

Notes: EER = MSA-specific establishment entry rate. Distance = distance between MSAs in miles. Wage = MSA-specific average weekly wage. HPI = MSA-specific house price index. Bartik industry mix = Bartik shift-share industry mix variable described in section 5. Each specification includes individual, MSA and year fixed effects. The top number in each cell is the odds ratio, and standard errors are in parentheses. Data are from the NLSY97, BDS, QCEW, and FHFA. * p<0.1, ** p<0.05, *** p<0.01.

Table A.1 Metropolitan Statistical Areas in Choice Set

Metropolitan Statistical Area Name	Times Chosen	2010 Population	2010 JCR	2010 EER
Miami-Fort Lauderdale-Pompano Beach, FL	205	5,564,635	15.5	13.6
Austin-Round Rock-San Marcos, TX	167	1,716,289	15.0	12.0
Phoenix-Mesa-Glendale, AZ	234	4,192,887	14.9	11.3
Dallas-Fort Worth-Arlington, TX	318	6,366,542	14.7	10.8
Charlotte-Gastonia-Rock Hill, NC-SC	124	2,243,960	14.6	10.8
San Antonio-New Braunfels, TX	105	2,142,508	14.3	9.8
Denver-Aurora-Broomfield, CO	194	2,543,482	14.2	11.4
Brownsville-Harlingen, TX	110	406,220	14.1	10.0
Orlando-Kissimmee-Sanford, FL	124	2,134,411	14.0	12.2
Atlanta-Sandy Springs-Marietta, GA	301	5,286,728	13.7	10.9
Portland-Vancouver-Hillsboro, OR-WA	118	2,226,009	13.4	10.4
Houston-Sugar Land-Baytown, TX	176	5,920,416	13.3	10.7
Washington-Arlington-Alexandria, DC-VA-MD-WV	476	5,649,540	13.3	10.1
Eau Claire, WI	379	161,151	13.3	9.0
Detroit-Warren-Livonia, MI	239	4,296,250	13.1	8.7
San Diego-Carlsbad-San Marcos, CA	254	3,095,313	13.1	10.6
Tucson, AZ	251	980,263	12.9	9.3
New York-Northern New Jersey-Long Island, NY-NJ-PA	111	18,897,109	12.6	10.8
Riverside-San Bernardino-Ontario, CA	175	4,224,851	12.6	11.0
Nashville-Davidson-Murfreesboro-Franklin, TN	1152	1,646,200	12.6	9.4
Lansing-East Lansing, MI	217	534,684	12.6	6.9
Los Angeles-Long Beach-Santa Ana, CA	755	12,828,837	12.5	10.4
Minneapolis-St. Paul-Bloomington, MN-WI	292	3,333,633	12.4	9.1
Pueblo, CO	111	159,063	12.4	8.1
San Francisco-Oakland-Fremont, CA	309	4,335,391	12.3	9.5
Santa Barbara-Santa Maria-Goleta, CA	164	423,895	12.2	8.8
Indianapolis-Carmel, IN	178	1,887,877	12.1	8.8
Oklahoma City, OK	219	1,252,987	12.1	9.5
Richmond, VA	246	1,186,501	12.1	8.4
Boston-Cambridge-Quincy, MA-NH	164	4,552,402	11.9	8.7
Baltimore-Towson, MD	170	2,710,489	11.9	8.9
Memphis, TN-MS-AR	203	1,316,100	11.9	8.1
Springfield, MO	162	436,712	11.9	9.0
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	342	5,965,343	11.8	8.9
Virginia Beach-Norfolk-Newport News, VA-NC	287	1,713,954	11.8	8.6
New Orleans-Metairie-Kenner, LA	112	1,189,866	11.7	8.8
Seattle-Tacoma-Bellevue, WA	237	3,439,809	11.6	10.1
Chicago-Joliet-Naperville, IL-IN-WI	481	9,461,105	11.3	9.5
St. Louis, MO-IL	141	2,787,701	11.2	8.9
Modesto, CA	145	514,453	11.1	8.2
Kansas City, MO-KS	219	2,009,342	11.0	8.8
Hickory-Lenoir-Morganton, NC	119	365,497	10.9	7.3
Birmingham-Hoover, AL	182	1,061,024	10.4	7.9
Jackson, MS	133	586,320	10.4	8.8
Buffalo-Niagara Falls, NY	146	1,135,509	10.2	7.7
Fort Wayne, IN	124	388,621	10.2	7.4
Lynchburg, VA	128	246,412	10.2	6.7
Allentown-Bethlehem-Easton, PA-NJ	138	821,173	10.0	7.6
Rochester, NY	168	1,079,671	9.6	8.0
York-Hanover, PA	123	434,972	9.6	7.3

Notes: Data are from the NLSY97, U.S. Census, and BDS.

Table A.2. Sample Selection

	Respondents		Person-Years	
1997 Cohort		8,984		134,760
Restrictions applied to respondents				
Ever in military	-653	8,331		
Unable to determine LM entry date	-107	8,224		
Not interviewed within 12 months of LM entry	-1,211	7,013		
Interview closest to and following LM entry is after 2011	-1,185	5,828		
Younger than age 18 at LM entry	-402	5,426		
MSA not reported at start of observation period	-2,538	2,888		
MSA observed only once	-562	2,326		
Not in LF for more than 1 year during ob. period	-420	1,906		
Subtotal	-7,078	1,906		28,590
Restrictions applied to periods				
Delete first year of the observation period			-1,906	
Delete periods after first gap in history			-17,721	
Final sample		**1,906**		**8,963**
Location observations per person (excluding initial location)				
1		304		304
2		282		564
3		211		633
4		211		844
5		194		970
6		173		1038
7		139		973
8		134		1072
9		142		1278
10		43		430
11		31		341
12		30		360
13		12		156
Total		**1,906**		**8,963**

Notes: MSA=metropolitan statistical area, LM=labor market, LF=labor force. Data are from the NLSY97.

Table A.3. Conditional Logit Results, Choice Set Includes All MSAs

Variables	(1)	(2)
JCR main effect	0.95***	
	(0.013)	
JCR X Dropout	1.01	
	(0.041)	
JCR X Some college	1.03**	
	(0.015)	
JCR X College grad	1.07***	
	(0.015)	
EER main effect		0.94**
		(0.025)
EER X Dropout		1.02
		(0.061)
EER X Some college		1.05**
		(0.021)
EER X College grad		1.13***
		(0.021)
Distance	0.97***	0.97***
	(0.0005)	(0.0005)
Distance X Dropout	0.99***	0.99***
	(0.002)	(0.002)
Distance X Some college	1.01***	1.01***
	(0.001)	(0.001)
Distance X College grad	1.02***	1.02***
	(0.001)	(0.001)
Wage	1.00***	1.00***
	(0.001)	(0.001)
HPI	1.00	1.00
	(0.0002)	(0.0002)
Observations	3,408,922	3,408,922
Pseudo R^2	0.751	0.751
Log Likelihood	-20,751	-20,742

Notes: JCR = MSA-specific job creation rate. EER = MSA-specific establishment entry rate. Distance = distance between MSAs in miles. Wage = MSA-specific average weekly wage. HPI = MSA-specific house price index. Each specification includes individual, MSA and year fixed effects along with the Bartik shift-share industry mix variable described in section 5. The top number in each cell is the odds ratio, and standard errors are in parentheses. Data are from the NLSY97, BDS, QCEW, and FHFA. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.