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Abstract

This paper shows that local labor markets in the U.S. differ substantially and persistently in rates of population turnover. This fact cannot be easily explained by demographics, sectoral composition, or network centrality. Repeat migration accounts for a small fraction of the heterogeneity, and natives are more likely to exit mobile locations than immobile locations. Hence, there is a strong place component to migration propensity. The paper explores local labor market attributes that might account for higher mobility rates. There is evidence that mobile locations have more disperse and volatile income processes, but offer superior rates of human capital accumulation.

JEL codes: R23, J61
Keywords: internal migration; gross migration; regional labor markets; local labor markets

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1 Introduction

The typical economic intuition on population migration is households leaving undesirable regions for more desirable ones. This neatly fits into models of utility maximization and spatial equilibrium (e.g. Roback (1982)), as the mobility of agents (or the potential thereof) arbitrages away spatial differences in utility. This is a notion of net migration–the desirable location gaining population at the expense of the undesirable, until congestion effects or other prices make the marginal mover indifferent. The dominant empirical feature of population migration, however, is that gross flows dominate net flows by an order of magnitude. Hence, gross or "excess" migration is the very means by which population reallocation occurs.[1] Though the importance of gross migration was recognized as early as Ravenstein (1885) in U.K. data and discussed in the U.S. context by Sjaastad (1962), it has received less attention in the literature than one might expect given that population reallocation is a core topic of spatial economics and regional science.[2]

Perhaps the mere existence of excess turnover may not be of compelling research interest by itself, since there are always plenty of idiosyncrasies among households.[3] Potentially more consequential for regional economic analysis is that local labor markets exhibit persistent heterogeneity in their degrees of population turnover. That is, some locations are characterized by high mobility, both in- and out, and others have persistently low mobility. Even studies incorporating gross migration flows typically abstract from spatial heterogeneity.[4]

Determining what differentiates mobile and immobile labor markets, and whether the

[1]Excess turnover was termed "migration efficiency" in an earlier literature in sociology (Galle and Williams (1972)).

[2]Notable exceptions include empirical analyses in Miller (1973) and Tabuchi (1985) and regional population models of gross flows in Schachter and Althaus (1989), Kaplan and Schulhofer-Wohl (2012), Davis et al. (2013), Mangum (2015), and Monras (2015).

[3]Many other forms of labor market transitions are characterized by gross flows in large excess of net flows. Examples include employment states (Blanchard et al. (1990)), jobs among firms (Davis and Haltiwanger (1992), Davis et al. (2006)), and workers between firms (Fallick and Fleischman (2004), Davis et al. (2006)).

[4]Coen-Pirani (2010) documented the correlation of inflow and outflow rates across U.S. states, and this paper expands the analysis in several dimensions. Notably, this paper shows that the mechanism suggested in Coen-Pirani (2010), while relevant, is not quantitatively sufficient to explain the wide degree of heterogeneity between labor markets, as elaborated below.

factors are causal or incidental, is important for our understanding of local labor market dynamics. Local labor markets can provide laboratories for studying the labor market at large, as differences between places impose variation on worker outcomes. Examples of technique include studies of the labor market implications of location size (Glaeser and Maré (2001), Baum-Snow and Pavan (2012), Baum-Snow and Pavan (2013), Baum-Snow et al. (2014)), density (Bleakley and Lin (2012)), or sectoral composition (Beaudry et al. (2012)). More directly, knowing how population reallocates between places–and whether and how this differs across space–will inform our understanding of adjustment to local labor market shocks, in the spirt of Blanchard and Katz (1992).

This paper makes three empirical contributions in documenting a set of facts on local labor market mobility. First, it confirms a large degree of correlation between inflows to and outflows from local labor markets and establishes that some labor markets are persistently more mobile than others over long horizons.[5] The pattern is documented in several data sources. Second, the paper shows that compositional differences in population attributes (for example, in age and education) or in distance from other markets (in physical and in sectoral space) explain relatively little of the spatial heterogeneity in turnover rates. Moreover, the incidence of "repeat mobility," or households who have moved in the past being more likely to move again,[6] accounts for only a fraction of the spatial heterogeneity, and natives to mobile locations are more likely to migrate away than natives in less mobile places.

Thus, there is a place component to mobility. These descriptive exercises present the literature with a puzzle, and the paper's third contribution is to begin offering an explanation. This is not the sort of question for which there are obvious natural experiments, but some hypotheses can be tested more heuristically through cuts of the data. The paper offers several tests, focusing on differences in income distributions. First, mobility is correlated with income inequality in both raw and residual (i.e. controlling for individual characteristics)

[5]In most cases herein, local labor markets are defined as metropolitan areas.

[6]For the purposes here, it only matters that repeat migration can occur, and it is not important whether the repeat mobility is "return" (back to a previous location) or "onward" (to a new one), or whether repeat mobility is caused by an initial move or simply due to selection of households types.

measurements. This feature is not imposed by the migrants, but is also present when comparing the earnings distribution of natives and non-movers as well. Furthermore, migrants to and from mobile locations have more volatile income processes pre- and post-move than do migrants to and from less mobile locations. These facts suggest mobile labor markets have more uncertain distributions of income match quality, which could plausibly cause higher rates of inflow and outflows simultaneously.

Secondly, mobility is not obviously related to local mean incomes in the spatial cross section. However, mobile locations do show evidence of superior human capital accumulation. Earnings accelerate over the life cycle more quickly for workers in mobile places (not just among the migrants), an effect present even when controlling for market size. Additionally, migrants' incomes show a pattern consistent with human capital accumulation, earning at relative penalties when moving from immobile place to mobile, and retaining wage premia when migrating from mobile to immobile. Human capital accumulation is also plausibly related to simultaneous inflow and outflows, making for a more attractive destination while also allowing incumbent workers to leave without sacrificing all income premia.

This paper intends to spur more research center around spatial heterogeneity in worker mobility. Mobile locations appear to be fundamentally different labor markets, which offers an opportunity for studying worker outcomes within markets and population adjustments between them.

The paper proceeds as follows. Section 2 describes the data and lays out the basic empirical facts. Robustness across samples is considered. Section 3 accounts for the role of repeat mobility. Section 4 then describes the attributes of mobile and immobile places, from which a few hypotheses emerge. Sections 5 and 6 test for differences in income dynamics and rates of human capital accumulation. Section 7 concludes. Appendices contain exhibits with auxiliary results underlying the main analyses.

2 Empirical Patterns

This paper uses data from a variety of sources, and I briefly describe them before reviewing the evidence.

2.1 Data

The first source of migration flow data is the Internal Revenue Service's (IRS) Statistics of Income division summary files on county-to-county flows in the U.S. (IRS (2015)). Migration is inferred by the IRS from year-over-year address changes on a tax filer's return, and the IRS makes available a summary of the gross county-to-county flows.[7] The data report, for each place-to-place cell, the number of tax returns (the number of households, to a close approximation) and the number of exemptions (approximately, the number of persons), and for each origin and destination county, the total inflows and outflows. I use the household-level data for 1990-2013, aggregating county-to-county flows to consistent-definition metropolitan statistical areas (MSAs, year 2000).[8]

The dataset affords several advantages. First, the data contain actual gross flows between location pairs–i.e., the migration network–for a wide swath of U.S. geography. Second, the data are reported annually, a high frequency for studies of migration, and reveal migration patterns over time. Third, the dataset is nearly a census of migration flows, an advantage over even large microdata samples. However, it is a census of taxpayers only, so those who earn little income or otherwise do not file taxes are not represented.

The major disadvantage of the data is that it is an aggregation, so there is no information on the individual households composing the flows. Therefore, I also employ three workhorse microdata sources provided by the IPUMS project (Ruggles et al. (2015)). I use the five

[7]The IRS suppresses cells with fewer the 10 households, although the data also include a summary of total county-level inflows and outflows which include migrants on censored county pairs. For the few of my analyses that use the full place-to-place flow matrix, the data preparation includes an imputation procedure for censored observations based on known county inflows and outflows, past and future observed flows for the county pair, and proximity. The censoring is a more severe problem for flows between rural counties than among the urban areas that are the focus here.

[8]For exposition, I exclude cities with a high share of workers in military occupations.

percent sample of the 2000 decennial census and the 2006-2011 American Community Survey (ACS), and some ancillary analyses rely on the March Current Population Survey (CPS, Flood et al. (2015)). The census samples include retrospective questions on MSA and state of residence five years ago (one year ago in the ACS), which allow observation of one migration event.[9] The Census and ACS data also provide the main sources of information on cross sectional differences in populations composition and income between locations. Finally, for some longitudinal analyses, I turn to the Panel Study of Income Dynamics (PSID (2014)). The major advantage is its longitudinal structure, reporting the dynamic path of location decisions jointly with income. The major disadvantage is its relatively small sample. The geography available in the PSID is state.

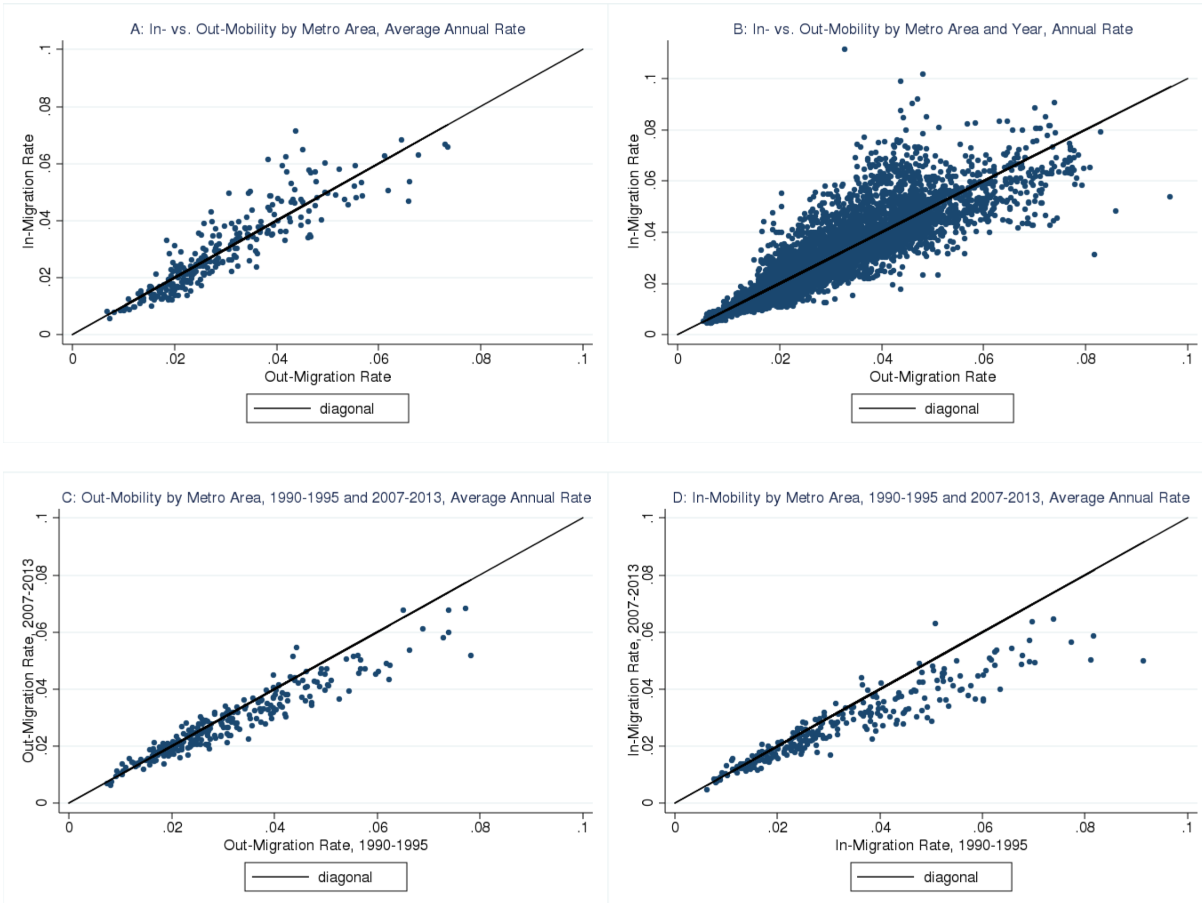
2.2 Correlation in Population Flows

I now turn to the primary descriptives. Figure 1, plot A, displays the initial empirical fact, the relationship between population inflows and outflows, at the metropolitan level using the IRS data. The inflow and outflow rates are calculated as a proportion of the start-of-year population. Clearly, there is a strong correlation between inflows and outflows: cities that receive migrants send away a remarkably similar magnitude. If the empirical pattern of migration were one of spatial arbitrage–population leaving bad locations and entering good locations–this line would have negative slope. With the strong positive correlation, net migration rates average less than half of a percent, meaning gross flows are an order of magnitude larger. The most mobile labor markets have three to four times the population turnover of the least mobile markets.

In a long enough horizon, this pattern could arise if local cycling caused cities to gain population in some years and lose it in others. Plots B, C, and D shows this is not the case. Plot B shows the contemporaneous metro-by-year rates of inflow and outlaw, which

[9] It is possible that a person leaves a state/MSA and returns before five years; this would be coded as non-migration. Census responses for location may not be the person's tax address reported to the IRS. This distinction is apparent in cities with a relatively large share of student population ("college towns").

Figure 1: Correlations In Gross Population Flows, 1990-2013



NOTES: Each dot represents a metro area, except in plot B, where a dot is a metro area-year. Source: IRS migration flow raw data.

are nearly as correlated as the averages in plot A. Plots C and D show the persistence in flows. Plot C shows the average gross outflow from the metro area for the early years of data (1990-1995) plotted agains the end of the data (2007-2013), and plot D does the same for inflows. While there is a general decline in mobility over this horizon (see Molloy et al. (2011) and Kaplan and Schulhofer-Wohl (2012)), the persistence in spatial heterogeneity is strong. Rank correlations are about 0.95.

2.3 Robustness

The rest of the paper is devoted to unpacking why some locations are persistently more mobile than others. But before proceeding, some initial robustness checks are in order.

Table 1 reports on mobility measures from across samples and compares raw mobility rates with indices that control for some potential explanations for the spatial heterogeneity in mobility.

2.3.1 Network Distance

One explanation is that certain locations are more centrally placed in space and might be more accessible than remote areas. Network centrality could apply to physical space as well as "similarities," broadly defined, including sectoral composition of the labor market. An easy way to test for this is through the well-known gravity model of migration.[10] The regression model is

$$m_{jkt} = \theta_0 + \theta_1 s_j + \theta_2 s_k + f(D_{jk}) + \alpha_j X_{jt} + \beta_k X_{kt} + d_t + d_j + d_k + \varepsilon_{jkt} \tag{1}$$

where m_{jkt} is the log flow between origin i and destination j in year t, θ_1, θ_2 account for market size, $f(D_{ij})$ is a pairwise (origin-destination) function of distance, X_j, X_k are origin and destination attributes, and d_j, d_k are original and estimation fixed effects. d_t is a time dummy to account for trends in migration nationally.

The IRS migration data provide the full matrix of gross place-to-place flows and are therefore best suited for a gravity model using pairwise measures of distance. The objects of interest here are the origin and destination fixed effects, as these recover the average out- and in-mobility unexplained by network distance. Table 1 reports the correlations between several specifications, with panels read as a matrix. The diagonal of a panel contains the correlations between origin and destination index for each specification. The lower triangle is the correlation between specifications in the origin mobility index; for example, between the raw outflow and a gravity adjusted origin fixed effect. The upper triangle does the same for the destination side.

[10]The gravity equation is a common tool for measuring migration elasticities; see Greenwood (1975). Its microfoundations from utility theory are developed by Niedercorn and Bechdolt (1969).

Table 1: Correlation Within and Between Alternate Mobility Indices

Legend	Correlation Reported: Index 1	Index 2
Index 1	Orig 1, Dest 1	Dest 1, Dest 2
Index 2	Orig 2, Orig 1	Orig 2, Dest 2

Index No.	**IRS**					
	Index/Index	Raw	Gravity	Gravity+LM	Log Rate	I.H.S.
1	Raw	0.907	0.592	0.618	0.592	0.484
2	Gravity	0.723	0.842	0.994	1.000	0.870
3	Gravity+LM	0.665	0.978	0.848	0.994	0.847
4	Log Rate	0.695	0.920	0.857	0.637	0.870
5	I.H.S.	0.427	0.689	0.733	0.370	0.983
	Census 2000					
		Raw	Demographics	Demo.+Moved In	Non-college	College
6	Raw	0.766	0.325		0.331	0.276
7	Demographics	0.818	0.622		0.983	0.909
8	Demo.+Moved In	0.834	0.931			
9	Non-college	0.766	0.973	0.880	0.626	0.826
10	College	0.807	0.869	0.884	0.796	0.466
	ACS					
		Raw	Demographics	Demo.+Moved In	Non-college	College
11	Raw	0.487	0.990		0.973	0.855
12	Demographics	0.954	0.740		0.980	0.878
13	Demo.+Moved In	0.932	0.965			
14	Non-college	0.908	0.970	0.912	0.742	0.773
15	College	0.793	0.873	0.881	0.757	0.515

Correlations Between Indices, Origin Side

Index/Index	1	3	7	8	12
1	1.000				
3	0.728	1.000			
7	0.730	0.594	1.000		
8	0.618	0.408	0.930	1.000	
12	0.812	0.472	0.777	0.739	1.000

NOTES: Indices are specifications of models (1) and (2). Select indices are reported in Table B1. Additional results from the models are reported in Table A1 and A2. Origin indices are in rows and destination indices in columns; see the legend for the structure of reporting correlation coefficients between index type. There are 272 metro areas in the IRS data, 239 in the 2000 Census, and 263 in the ACS. Source: Author's calculations using IRS, Census, and ACS data as described in main text.

The table focuses on the relationships between indices, but the underlying regression results are in Appendix Table A1, and I also briefly discuss these. Index 2 introduces a linear-in-parameters distance function of $f(D_{ij})$ including the physical distance between metro areas in log miles, and three measures of labor market similarity, the difference in college attainment rates, the difference in market population sizes, and a sum of differences in the employment share by industry (by NAICS category). All of these enter negatively, meaning differences between metro areas are associated with less migration flow (in either direction) between the pair. Empirically, the log miles term is most important. This is because most migration is regional, with 60 percent of between-metro migrants staying within census division and 70 percent within census region. But the distance function does not reduce the variance across the location fixed effects, and the correlation of the origin fixed effect with the raw out rate is 0.72, meaning the gravity adjustment does little to change the rank correlations–mobile locations are still mobile controlling for distance, broadly defined, so some other forces are at work.[11] (Index 2 is reported for the full set of metro areas in Appendix Table B1.)

Index 3 accounts for cyclical and long term labor market trends by including measures of the local unemployment rate, wages, and residential costs. Each of these has the expected sign as "attractor" or "repellant" to population. Finally, indices 4 and 5 are specification checks, the former fixing $\theta_i = 1$, so that outflows is measured as a rate, and the latter using the inverse hyperbolic sine instead of the log so that pairwise flows of zero can be included in the regression. But throughout the IRS panel of Table 1, correlations are positive and large. Reading down the diagonal, it is clear that distance and local labor market controls do little to break the correlation between inflows and outflows. Comparing indices with the raw rates and each other shows that various specifications of a gravity model do not change the rank pattern of spatial heterogeneity. Hence, a basic gravity explanation is unsatisfying.

[11] In many cases, actually, gravity fails to explain why so many coastal markets (especially west coast), which are remote by construction, are highly mobile. See Table B1.

2.3.2 Compositional Differences

A second explanation is demographic. Mobile locations might simply have more population share in typically mobile groups–the young, the college educated, the single, etc. Such an "explanation" only pivots the question, in a sense, from understanding spatial heterogeneity in mobility to heterogeneity in attractiveness or production of certain types of groups, and moreover, why these places might be "layover" cities, attracting disproportionate share of migrants that are soon to leave. Regardless, I actually find a limited role for demographic explanations, meaning there is a large degree of residual spatial heterogeneity.

To address questions of individual characteristics, I turn to the census microdata sources. To form indices of out and in-mobility from microdata, I run regressions of

$$I(move_{ij}) = \beta X_i + d_j + \varepsilon_i \tag{2}$$

where $I(move_{ij})$ is an indicator variable for whether the individual migrated from origin j according to the retrospective question, X_i is a vector of individual attributes and d_j is the location fixed effect of interest. I control for age-by-education categories, race, immigrant status, and household composition, limiting the sample to working age adults not enrolled in school.[12] I do this for the origin and destination side since the census offers information on last (origin) and current (destination) location of residence. The coefficients for the attributes are reported in Appendix Table A2, but there is nothing surprising, so I do not discuss.

Index 7 of Table 1 uses the demographic controls on 2000 census data (five year migration rate) and index 12 on ACS data (one year rate). Each of these indices are still highly correlated with the raw outflow rate. The destination side is also correlated, though to a lower extent. Monras (2015) shows that population inflows are more sensitive to local

[12]The respondents may have been enrolled in school in the year or five years prior, at their previous location. Inspection of the data reveals that several well-known "college towns" (e.g. Bloomington, IN, Athens, GA, College Station, TX) have inordinate amounts of migration in the census data. I account for college towns by including a measure of the share of adults enrolled in college or in the education profession.

labor market conditions than are outflows; for example, bad labor markets do not send more migrants than usual, but they attract many fewer in-migrants. Thus, in general, we should expect origin indices to be more persistent and more similar across specifications. Hence, I use origin indices as my preferred measures of local migration rates, especially when the full matrix of flows is not available.

Indices 8 and 13 add one more important modification–a control for whether the respondent was "at home," that is, residing in their state of birth, in the origin location. Thus, if a location appears to be mobile because it has a lot of transplant residents who are likely to move on again, this index would account for the non-natives living there. (By definition, there is no destination equivalent of this specification.) The correlation with the raw index remains, and the correlation between it and the demographics-only index is very high. Thus, spatial heterogeneity in mobility rates is apparent even after controlling for a location's history of in-migrants. This is a key result, and I will return to the repeat mobility issue in more depth in the next section.

Finally, indices 9 and 10 (14 and 15 for ACS) split the sample into non-college educated and college educated workers, who may face different labor market opportunities. Mobile locations are similarly mobile for both sets of workers, especially on the origin side. One interesting aside, however, is the relatively low correlation for in- and outflow rates among the college educated, which could be due to the ongoing concentration of educated workers in certain locations (Moretti (2013), Ganong and Shoag (2013), Broxterman and Yezer (2015), Diamond (2016)).

The bottom panel of the table reports the correlations in the origin side indices across specifications. Cities are measured to be similarly mobile across datasets with different structures, timelines, and forms of reporting.[13] The patterns are robust to controls for network distance or demographic explanations. So then, what makes a mobile location?

[13] The lowest across-index correlations involve the gravity adjusted IRS index, which assigns slightly higher values to coastal locations.

3 Repeat Mobility

As alluded to earlier, one possible mechanism is that a location is mobile because it was mobile before. That is, if "repeat mobility" is common, locations with a larger share of non-native residents will exhibit more turnover as a consequence of their transient composition.[14] The literature has long recognized that movers are likely to move again, whether "return" (to a previous location) or "onward" (to a never-visited location) (Herzog and Schlottmann (1982), DaVanzo (1983), Kennan and Walker (2011)).

Repeat mobility is the chief mechanism by which Coen-Pirani (2010) generates correlation in gross inflows and outflows. In that paper's model, new arrivals to a location are more likely to find themselves mismatched, and therefore more likely to move away. Long time residents, on the other hand, are a selected sample of those positively matched. When paired with persistent productivity shocks, growing locations will have more in- and out-mobility than the average location. Indeed, the mobile locations tend to be growing in population. For example, the correlation in population growth and the gravity adjusted index is 0.49. Perhaps mobile places are simply attractive to in-migrants, many of whom turn around and leave again, and that is sufficient explanation.

The data indicate there is more to the story than repeat mobility alone. While I concur with the existing literature that one-time migrants are more likely to move again, this is insufficient explanation for the marked spatial heterogeneity between local labor markets. I investigate this empirically by estimating versions of the following equation.

$$Pr(move) = \beta X + \alpha_1 orig\_mobility + \alpha_2 I(not\_at\_home) + \alpha_3 orig\_mobility \times I(not\_at\_home) + \epsilon \tag{3}$$

where $orig\_mobility$ is an origin's mobility index and $I(not\_at\_home)$ is an indicator for whether the individual had migrated in to that origin from elsewhere. If repeat mobility

[14] I use "native" to refer to region of birth domestically, not status as an immigrant from a foreign country.

explains spatial heterogeneity, including this term will drive the mobility index coefficient toward zero. The interaction then measures whether in-migrants are more or less likely to move out of mobile places than immobile.

In the census data, "not at home" is indicated by whether the person was in a location other than his birth state. For example, a California-born resident of Los Angeles is "at home," but those born outside of California are not.[15] Unfortunately, the data do not indicate when an out-of-state born person moved in (whether as a child or working age adult) or how many moves occurred prior, but this forms the best available measure relevant for the fundamental idea–that transplants are more likely to leave. The longitudinal structure of the PSID allows me to separately control for whether the origin is "home" (the place of residence in childhood) and whether the respondent moved in from elsewhere, though the spatial detail is limited to states.

Notice that by controlling generically for transplant status, specification (3) accounts for many factors that might underlie repeat mobility and focuses on the effect of it on spatial heterogeneity in mobility rates. It is agnostic as to whether subsequent moves for transplants are more likely because of a causal force–e.g. people are more likely to dislike a new place than a familiar one–or mere selection of people with idiosyncratically low moving costs. The point of emphasis is what happens to the origin mobility index coefficient.

Table 2 reports the results for several samples. In all cases, I use indices of origin mobility from out of sample. Columns 1 and 2 report results for census data, using the IRS-based gravity adjusted index and the ACS index, respectively. Columns 3 and 4 use the ACS index, but separately for the non-college and college educated sample. Column 5 is ACS data using a census index, and Column 6 is PSID using an IRS index.

Model 1 controls for individual attributes besides transplant status. In all cases, the mobility index is positively associated with an individual's migration probability. At these coefficient sizes, a standard deviation increase in the origin's mobility rate leads to an increase

[15] For metros crossing state lines, any state of birth in the metro area is considered at home (e.g. New Jersey-born New York MSA residents are natives).

Table 2: Regressions of Mobility Controlling for Transplant Status

Spec:	1	2	3	4	5	6
Dataset	Census	Census	Census	Census	ACS	PSID
Index Source	IRS	ACS	ACS	ACS	Census	IRS
Sample	All	All	Non-college	College	All	All
Model 1						
Mobility Index	0.0307	0.0332	0.0315	0.0448	0.0068	0.00012
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0003)***	(0.0000)***	(0.00001)***
Model 2						
Mobility Index	0.0263	0.0246	0.0227	0.0364	0.0060	0.00007
	(0.0002)***	(0.0002)***	(0.0003)***	(0.0005)***	(0.0001)***	(0.00001)***
Not at home	0.0816	0.0868	0.0764	0.1092	0.0206	0.14656
	(0.0003)***	(0.0003)***	(0.0004)***	(0.0007)***	(0.0001)***	(0.00222)***
Moved in						0.10936
						(0.00200)***
Moved In X Mobility Index	-0.009	0.0065	0.0069	0.0083	-0.000	0.00007
	(0.0004)***	(0.0004)***	(0.0004)***	(0.0007)***	(0.0001)***	(0.00002)***
Mean Mobility Rate						
All	0.0995	0.0995	0.0809	0.1467	0.0244	0.0467
At Home	0.0655	0.0655	0.0545	0.0998	0.0169	0.0206
Not at home	0.1368	0.1368	0.1117	0.1842	0.0319	0.1425
N	4,201,166	4,149,912	3,022,319	1,192,093	5,787,886	96,333

NOTES: The table reports regression results in form of model (3). "At home" is defined as residing in metro area in the state of one's birth; this can be distinguished from a recent move in the PSID only. All models include controls for age by education, household structure, race and nativity. Census and ACS data control for the metro area's share of college students. ACS includes year dummies. Source: Author's calculations using IRS, Census, ACS, and PSID data as described in main text.

of 30% in the individual's migration probability. Model 2 introduces the control for transplant status, but this only reduces the index coefficients to a 24-26 percent effect. Thus, even controlling for incumbency, mobile places are still substantially more likely to send away migrants. Moreover, a positive interaction term indicates that transplants are actually even more likely to re-migrate out of mobile places than immobile, although the sign of the interaction is not robust across samples and index choices.

A simple back-of-the-envelope exercise helps to quantify the role of repeat mobility in explaining spatial heterogeneity. From column 1 of Table 2, transplants are 8.1 percentage points more likely to move than those already residing in their place of birth. If mobility rates were the same everywhere, and locations varied only in the share of transplants, then the difference between two locations k, j in mobility rates would be $0.081 \cdot (s_k - s_j)$ where s is the share of natives/non-transplants. In the data, the 90-10 percentile gap in mobility rates between cities is 13 percentage points, meaning the transplant shares would have to differ by an impossible 160 percentage points. Besides, such a projection would assume a perfect rank correlation between observed mobility rate and transplant share, which is not the case. Using demographics and transplant share to predict migration rates by city via the regressions of (3), the 90-10 difference in predicted rate is just 6 percentage points, less than half the actual gap. In an average across cities, observed demographics and transplant status can explain only one-third of the local deviation from mean migration rate. Clearly, there remains a significant place-based component to migration rates even after controlling for the tendencies and attributes of repeat migrants.

4 Local Labor Market Characteristics

If there is a place component to migration probability, what are the attributes of mobile places? There could, of course, be many and varied reasons across cities. This paper is intended, in part, to stimulate work on this pattern, and cannot itself find every explanation. However, local labor market characteristics, subject of a long and useful tradition of research in regional studies, are a good place to start. In particular, I will describe the relationship between local income distributions and mobility rates. There are three reasons for focusing on income distributions. First, income distributions are the most prominent features of local labor markets besides sectoral composition, and differences in local sectoral composition are not obviously driving heterogeneity in mobility, which persisted even after controlling for sectoral isolation (in the gravity models) and composition of worker types (in the census microdata).[16] Second, an important strand of literature in local labor markets concerns the relationship between city size and average earnings or dispersion in earnings ((Glaeser and Maré (2001), Baum-Snow and Pavan (2012), Baum-Snow and Pavan (2013), Baum-Snow et al. (2014)), so it seems natural to extend these questions to another feature of persistent heterogeneity in local labor markets. In essence, this is another way to use local labor markets as a "laboratory" for studying the aggregate labor market. Finally, there are

[16] Also, Coen-Pirani (2010) found previously that inflows and outflows from local labor markets contained observationally similar workers, further suggesting that compositional changes are not driving the turnover.

plausible reasons to believe that the differences in income distributions could actually be causing the in- and out-mobility and are not merely coincidental, though the particulars of this conjecture will be elaborated in more detail after observing patterns in the data.

As an initial exploration, Table 3 examines whether mobility is correlated with features of local income distributions. The columns report the correlation of the various metro level mobility indices with the rows of local income statistics. The top panel focuses on means and the bottom panels on dispersion. Measures of earnings come from the 2000 decennial census, although results using the 1990 census and the ACS are quite similar. In each panel, there is a calculation using the raw data as well as the residuals from Mincer-style regressions that control for education, experience, work hours, demographics like race and family status, and industry and occupational classifications (at the two digit level, with about two dozen categories each). Using the residuals allows for the study of peculiar place-based components after accounting for obvious compositional differences.

I being with mean earnings. The top row shows that more mobile locations have on average slightly lower earnings. However, the row using residual incomes (i.e. the city fixed effect) shows that this might be compositional, since mobile places offer higher residual incomes in at least some measures of income mobility. The next six rows split out the calculation of raw and residual means by migrant-type subsamples: workers at home (their birth location, regardless of whether they have ever moved), non-migrants (workers who were in the same labor market five years prior), and migrants (new entrants in the last five years). The correlations among incumbent residents are very similar to the full sample, suggesting the patterns are inherent in the locations themselves and are not driven by having disparate shares of transplants.

How might higher incomes be associated with more in- and out-mobility? If a local labor market offered higher incomes because of locally-specific productivity, it would be plausible that this would attract in-migrants, though there is no obvious reason why it would also propel out-migrants. Besides, income differentials of this nature should be arbitraged away in steady-state equilibrium through net migration and the adjustment of other local prices. Thus, there need be no pattern between and mobility and average earnings stemming from locally-specific productivity. However, there is an alternative theory relating average earnings to mobility: if a local labor market offered more substantial human capital accumulation, this could at once attract in-migrants and allow out-migration by permitting individuals to carry some of their income premium along with them upon moving. Human capital accumulation could also fail to show up as a persistent income premium in the cross section, with different people coming and going from the local market at different points of human capital stock, which would be consistent with the weak to negative correlations in Table 3. Thus, human capital augmentation seems a viable candidate for causing higher turnover. Section 6 below will look for evidence of faster human capital accumulation among higher mobility cities.

The lower panel of Table 3 displays the correlations between local income dispersion and the mobility indices. Income dispersion is strongly correlated with mobility, and high turnover locations tend to have wider (i.e. more unequal) income distributions. This is evident in several typical measures of dispersion. The pattern holds above the median (90-50 percentile), but stronger still below it (50-10 percentile), though it is not driven by points farther out to the tails (99-01, 99-50 and 50-01). This suggests the mobile locations have dispersion throughout the mass of the working population, and not excessively high or low earners.

The bottommost panel shows the pattern is largely unchanged when using residual incomes. That is, mobile places tend to have a wide dispersion of income for unobserved reasons, not because of, say, a wide diversity of occupations or worker education. This is consistent with the notion that there is a place component to turnover not due to sectoral composition.

Why might income dispersion be relevant for turnover? It is a reasonable candidate for driving both in and out-mobility to the extent it comes from "match quality." If earnings outcomes are subject to idiosyncratic match quality, workers of similar observable type would be passing each other in and out of the city, good matches flowing in and bad matches flowing out. This is similar intuition to Coen-Pirani (2010), but not limited to new entrants. Furthermore, uncertainty about a match could also incentivize experimental migration by offering a higher option value–a worker would want to try the high variance market, and if it does not work out, he can try again elsewhere or go home again. Thus, places with high variance in incomes for any host of reasons might exhibit more mobility in and out, even driving out incumbents.

The evidence is consistent with dispersion in match distribution. Importantly, the correlation of mobility with income dispersion remains when splitting the income data by subsamples of non-migrants and workers born in the location, indicating that the dispersion comes from a local data generating process and is not imposed by having a large share of transplants. This is especially important point for considering income dispersion, since migrants could otherwise cause local income dispersion simply by having fewer income draws to "settle in" to the location. When the mobile places exhibit higher variance even among incumbents, it suggests they have a more disperse, uncertain primitive income match distribution.

In summary, mobile places do not necessarily offer higher or lower earnings on average, though the distribution of incomes is more disperse, even when controlling for a wide array of worker characteristics. Next, I investigate whether disperse match quality means more individual earnings uncertainty. Then I test the conjecture that mobile places offer superior human capital accumulation.

5 Income Uncertainty

Conceptually, a wide dispersion of match quality could obtain without individual uncertainty. That is, mobile locations may consistently offer the individuals incomes that are disperse in the cross section. This could generate out mobility as suggested above. However, mobility could be more greatly affected if the dispersion was also associated with greater temporal

Table 3: Correlation Between Local Income Distribution Characteristics and Mobility Indices

Income Data	Stat	Sample	1 IRS Raw	2 IRS Gravity Adj.	3 Census Raw	4 Census Demog. Adj.
Raw	Mean	All	-0.273	-0.154	-0.133	-0.354
Residual	Mean	All	0.175	0.184	-0.105	-0.089
Raw	Mean	At-home	-0.398	-0.311	-0.262	-0.471
	Mean	Non-Migrants	-0.223	-0.135	-0.046	-0.308
	Mean	Migrants	-0.418	-0.169	-0.449	-0.429
Residual	Mean	At-home	0.266	0.243	-0.019	0.003
	Mean	Non-Migrants	0.215	0.201	-0.055	-0.046
	Mean	Migrants	0.252	0.212	0.038	0.001
Raw	StdDev	All	0.568	0.487	0.510	0.482
	90-10	All	0.562	0.509	0.480	0.460
	99-01	All	0.375	0.287	0.427	0.388
	90-50	All	0.423	0.392	0.278	0.266
	99-50	All	0.178	0.158	0.168	0.266
	50-10	All	0.606	0.500	0.539	0.515
	50-01	All	0.372	0.258	0.429	0.311
	StdDev	At-home	0.542	0.522	0.457	0.466
	StdDev	Non-Migrants	0.532	0.485	0.406	0.448
	StdDev	Migrants	0.288	0.210	0.508	0.237
Residual	StdDev	All	0.467	0.530	0.276	0.342
	90-10	All	0.467	0.523	0.274	0.366
	99-01	All	0.439	0.491	0.253	0.269
	90-50	All	0.400	0.486	0.243	0.291
	99-50	All	0.406	0.461	0.253	0.285
	50-10	All	0.415	0.422	0.233	0.348
	50-01	All	0.274	0.299	0.141	0.135
	StdDev	At-home	0.369	0.433	0.240	0.318
	StdDev	Non-Migrants	0.426	0.531	0.212	0.313
	StdDev	Migrants	0.280	0.242	0.245	0.174

NOTES: The table reports correlation coefficients between in the metro area cross section the income distribution statistic (rows) and the mobility index (columns). Metro area index values are reported in Table B1. There are 240 metro areas with mobility indices and income data available. Source: Author's calculations using IRS, Census, and ACS data as described in main text.

shocks to an individual's earnings. One way to test for this second layer is to measure whether migration events in and out of mobile places are associated with larger income shocks than those in to or out of immobile places.

To look at earnings dynamics, I turn to the longitudinal PSID. As before, I want to condition on observable characteristics (which may themselves be subject to trends and shocks) and focus on an otherwise unexplained place component. For each person-year observation, I use the annual March CPS to predict that person's income given their experience, education, race, occupation, industry, and location in the year of observation t. Then I look at residuals from this prediction over time, $y^e_{it} \equiv y_{it} - \hat{y}_{it}$, in a regression of the following form:

$$y^e_{it} = \sum_{s=1}^{T} I(move)[\delta^{origin\_mobility}_{t-s} + \delta^{destination\_mobility}_{t+s}] + \nu_{it} \tag{4}$$

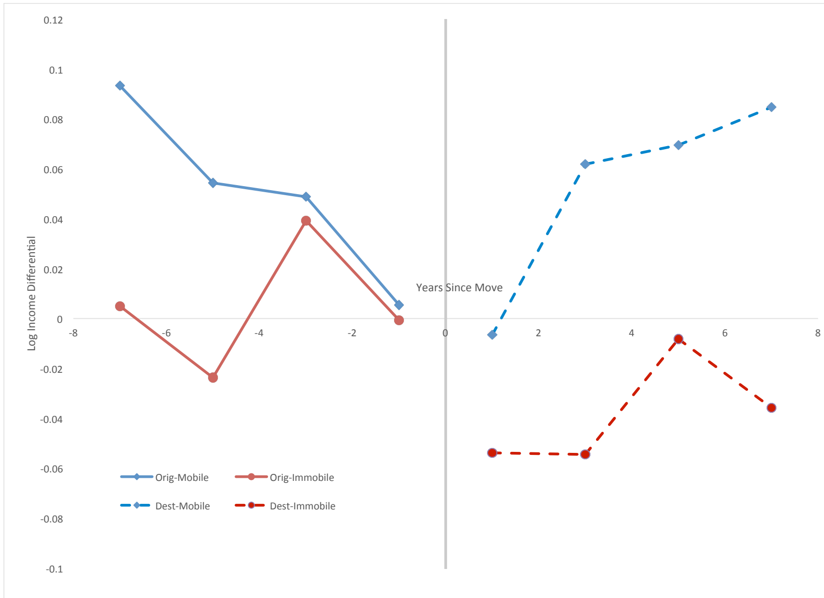
where $I(move)$ is an indicator for a migration event and the δ's are parameters of interest measuring the mean residual income s periods before and after the move event (at $s = 0$). These are measured relative to a non-migrating individual, and I am mainly interested in dynamics over δ_s.[17] To maintain consistency over time in the PSID, the periods are two-year intervals, and I use four observations on each side of the move (so, eight years before and after). For exposition, I split the locations into the more mobile and less mobile halves.

The coefficients are displayed in Figure 2 and reported with standard errors in Appendix Table A3. On the origin side of the migration event, workers out of mobile places are experiencing relative declines in income (from a statistically significant ten log point premium to zero). Workers out of immobile places exhibit much flatter profiles, not significant from zero. On the destination side, incomes for movers improve over time, but much more quickly for those arriving in mobile destinations.[18] Taken together, it appears that mobile locations are not only more disperse in the cross-section, but also produce more volatile individual income dynamics. Both of these are centered around a move event, so the patterns suggest

[17] If migrants on average have higher or lower earnings, this would be swept out by the constant.

[18] The dynamic pattern remains when splitting the destination into return and new (to the individual) locations.

Figure 2: Earnings Dynamics Pre- and Post-Move, by Location Mobility



NOTES: The figure plots residual log income over time for migrants moving at a normalized time zero, indicated by the vertical line. The model is (4). Point estimates and standard errors are reported in Table A3. Source: Author's calculations using PSID, IRS, and CPS data as described in main text.

that migration from mobile places is more driven by income than migration to or from immobile places.

6 Human Capital Accumulation

Table 3 showed that city level mobility, in some cases, was correlated with residual income premia, though never with average incomes. I conjectured that human capital formulation could be associated with gross in- and out-mobility and fail to show up in a cross sectional correlation of mobility to incomes. I explore this conjecture further in this section. My approach to testing for superior human capital formation is similar to Glaeser and Maré (2001). First, I test whether the income-experience profile varies with mobility rates. Second, I test whether the earnings outcomes of movers (recent entrants to the local labor market) are consistent with human capital formation in their origin and destination cities.

6.1 The Income-Experience Profile

The first test is to measure the income-experience profile in more versus less mobile locations to look for differences in how earnings grow as the worker gains experience. I use variants of the regression:

$$y_{ij} = \beta X_i + (1+\gamma_1 college) \times (\gamma_2 exper_i + \gamma_3 exper_i^2) + \sum_{a \in \{0:5:25\}} \gamma_a exper_i^{a,a+4} \cdot mobility_j + \varepsilon_{ij} \quad (5)$$

where *exper* is implied experience and X is a vector of worker attributes. The first terms (in parentheses) measure the typical income profile over the life cycle, interacted with college degree attainment, while controlling for the observed characteristics in X. The terms $\gamma_a exper^{a,a+4} \cdot mobility_j$ are an interaction of five-year experience categories with the location's mobility index. These measure the income profile in higher turnover locations compared to low turnover.

The results on 2000 Census data are presented in Table 4. All regressions control for available demographic characteristics, education categories, hours and weeks worked, and occupational and industry dummies. Column 1 is the basic specification, which includes dummies for the city's population size category. The experience-mobility interaction terms show that more mobile places do not offer higher incomes to young workers, but a substantial premium emerges at five years and continues through mid-career. For example, a worker with ten years experience in a city with a one standard deviation higher mobility rate earns about three percent more than the same worker in an average mobility place. For comparison, a standard deviation in mobility is worth about one and one-half years experience for a worker of this age. The premium declines into the late career, though not completely. This profile is consistent with a worker ascending the experience-earnings profile more rapidly in more mobile locations, evidence for higher human capital accumulation.

The remaining columns offer robustness checks and measurements of heterogeneity. Column 2 adds interactions of experience dummies with log population. This reduces the experience-mobility interactions by about half, but the profile shape is qualitatively similar. Thus, some of the evidence for human capital accumulation is confounded with population size effects, but still the conjecture is not rejected. Column 3 adds MSA fixed effects to soak up average differences between cities. This requires a dropping of one experience category and a concomitant change in coefficient interpretation, but does not change the profile.

Columns 4 to 6 confirm that the observed profile is not caused by the migrants themselves, but appears to be a feature of the data generating process in mobile locations. Column 4, following Dahl (2002), adds a control function for the likelihood that a worker born in some location j would reside in their observed location. There is evidence of selection (unlikely locations are associated with higher earnings), but this does not change the experience-mobility profile. Column 5 limits the sample to non-migrants, and column 6 to non-migrants in their birth location. The results are very similar to column 2, strongly suggesting that the difference in profiles comes has a place component. Finally, columns 7 and 8 split the sample among the non-college and college educated. The profiles are similar, though slightly larger for the college educated.

In summary, mobile locations exhibit a steeper income-experience profile, with early to mid-career workers earning the largest premium relative to similar workers in less mobile locations.

6.2 Movers Compared to Non-Movers

Continuing to follow the logic of Glaeser and Maré (2001), I next use migrants to look for evidence of superior human capital in mobile locations. Here, I leverage the current and retrospective locations available in census data, comparing the difference in the two locations' mobility rates (though income is only observed in the current place). The logic is that if mobile locations offer more human capital accumulation, then workers have to gain experience in the mobile place to obtain a premium. Thus, recent migrants into mobile

Table 4: Income-Experience Profile by Labor Market Mobility Rate

	1	2	3	4	5	6	7	8
Experience	0.0335	0.0330	0.0326	0.0326	0.0332	0.0332	0.0314	0.0448
	(0.0001)***	(0.0003)***	(0.0003)***	(0.0003)***	(0.0003)***	(0.0004)***	(0.0004)***	(0.0007)***
Experience sq.	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
College X Experience	0.0091	0.0082	0.0086	0.0086	0.0076	0.0074		
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***	(0.0003)***	(0.0004)***		
College X Experience sq.	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000		
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		
Mobility Index X Exper.								
0-4 yrs	-0.003	0.0066			0.0054	0.0011	0.0063	0.0098
	(0.0009)***	(0.0010)***			(0.0011)***	(0.0013)	(0.0011)***	(0.0019)***
5-9 yrs	0.0233	0.0109	0.0040	0.0040	0.0109	0.0091	0.0076	0.0158
	(0.0008)***	(0.0008)***	(0.0013)***	(0.0013)***	(0.0009)***	(0.0012)***	(0.0010)***	(0.0015)***
10-14 yrs	0.0308	0.0160	0.0093	0.0093	0.0165	0.0207	0.0136	0.0201
	(0.0007)***	(0.0008)***	(0.0013)***	(0.0013)***	(0.0009)***	(0.0012)***	(0.0009)***	(0.0015)***
15-19 yrs	0.0251	0.0187	0.0122	0.0122	0.0204	0.0273	0.0194	0.0173
	(0.0007)***	(0.0008)***	(0.0012)***	(0.0012)***	(0.0008)***	(0.0011)***	(0.0009)***	(0.0015)***
20-24 yrs	0.0145	0.0175	0.0109	0.0108	0.0184	0.0263	0.0171	0.0197
	(0.0007)***	(0.0007)***	(0.0012)***	(0.0012)***	(0.0008)***	(0.0011)***	(0.0009)***	(0.0015)***
25-29 yrs	0.0064	0.0112	0.0042	0.0040	0.0128	0.0212	0.0126	0.0104
	(0.0007)***	(0.0008)***	(0.0013)***	(0.0013)***	(0.0008)***	(0.0011)***	(0.0009)***	(0.0015)***
30+ yrs	0.0114	0.0043	-0.002	-0.002	0.0058	0.0203	0.0049	0.0040
	(0.0007)***	(0.0007)***	(0.0012)*	(0.0012)*	(0.0007)***	(0.0011)***	(0.0008)***	(0.0016)**
Log Pop. X Exper.								
0-4 yrs		0.0754			0.0755	0.0822	0.0656	0.0895
		(0.0007)***			(0.0008)***	(0.0010)***	(0.0009)***	(0.0014)***
5-9 yrs		0.0848	0.0094	0.0094	0.0860	0.0930	0.0771	0.0959
		(0.0007)***	(0.0003)***	(0.0003)***	(0.0007)***	(0.0009)***	(0.0008)***	(0.0012)***
10-14 yrs		0.0859	0.0104	0.0104	0.0866	0.0937	0.0779	0.0969
		(0.0006)***	(0.0004)***	(0.0004)***	(0.0006)***	(0.0009)***	(0.0007)***	(0.0012)***
15-19 yrs		0.0825	0.0071	0.0070	0.0830	0.0901	0.0749	0.0934
		(0.0006)***	(0.0005)***	(0.0005)***	(0.0006)***	(0.0008)***	(0.0007)***	(0.0011)***
20-24 yrs		0.0781	0.0027	0.0027	0.0784	0.0858	0.0718	0.0872
		(0.0006)***	(0.0006)***	(0.0006)***	(0.0006)***	(0.0009)***	(0.0007)***	(0.0012)***
25-29 yrs		0.0765	0.0012	0.0011	0.0766	0.0840	0.0701	0.0864
		(0.0006)***	(0.0006)*	(0.0006)*	(0.0007)***	(0.0009)***	(0.0007)***	(0.0012)***
30+ yrs		0.0799	0.0045	0.0044	0.0796	0.0868	0.0728	0.0913
		(0.0007)***	(0.0007)***	(0.0007)***	(0.0007)***	(0.0009)***	(0.0008)***	(0.0013)***
Pop.: 250k-500k	0.0526	-0.023			-0.024	-0.032	-0.019	-0.030
	(0.0013)***	(0.0014)***			(0.0015)***	(0.0019)***	(0.0016)***	(0.0028)***
Pop.: 500k-1mil	0.0817	-0.053			-0.054	-0.076	-0.044	-0.066
	(0.0011)***	(0.0015)***			(0.0016)***	(0.0020)***	(0.0018)***	(0.0029)***
Pop.: 1 mil+	0.1615	-0.077			-0.077	-0.102	-0.059	-0.106
	(0.0010)***	(0.0021)***			(0.0022)***	(0.0029)***	(0.0025)***	(0.0040)***
Selection Term				-0.046				
				(0.0036)***				
Cons	6.7381	6.3382	6.8066	6.8159	6.3143	6.2164	6.4173	6.9649
	(0.0101)***	(0.0111)***	(0.0100)***	(0.0100)***	(0.0118)***	(0.0162)***	(0.0130)***	(0.0207)***
MSA FEs			y	y				
Sample	all	all	all	all	Non-migrants	Non-migrants, & at home	Non-college	College
N	2,317,556	2,317,556	2,317,556	2,317,556	2,144,614	1,239,252	1,623,223	694,333

NOTES: The table reports the results from log earnings regression of model (5). “Experience” is implied experience: age minus years of schooling, less 5, censored at zero. Source: Author’s calculations using 2000 Census and IRS data as described in main text.

places should earn less if they came from immobile places, since they did not acquire human capital as quickly in their previous work location. On the other hand, recent migrants to less mobile locations should earn more if they came from more mobile places. Of course, an empirical test of this should account for the possible selection of workers to migrant status. I use versions of the regression:

$$y_{ij} = \beta X_i + f(exper_i, college_i) + I(moved) \cdot \Delta mobility_{jk} + I(moved) \cdot I(j = home) + \varepsilon_{ij} \quad (6)$$

where X is a vector of attributes, $f(\cdot)$ is a experience function as in (5), $I(moved)$ indicates a migrant and $\Delta mobility_{jk}$ indicates the difference in mobility rate between the past and current location. For simplicity, I will split migrants into those moving "up" (to a higher mobility place from lower) and "down" (to lower mobility). I also include controls for whether the current location is a move back to one's home (birthplace).

Table 5 reports the results. As a first check, column 1 simply includes a dummy for a migrant and another for a move home. The average migrant exhibits a very slight earnings disadvantage to an observationally equivalent worker, and moves home–possibly more likely to be occurring for non-labor market reasons–come at a income cost of about four percent. Column 2 splits the migrant dummy into moves up and down. Movers up (going from a less mobile to a more mobile place) exhibit about one percent lower incomes than observationally equivalent workers, and movers down (from more to less mobile places) earn at just under a one percent premium. These migrant patterns are consistent with a story of superior human capital accumulation in mobile cities. Workers entering mobile places earn at a penalty relative to incumbent workers, though workers exiting mobile places retain a premium in their new markets.

Column 3 interacts the move up and down dummies with the five-year experience categories. This is an important test of the conjecture because workers with less than five years experience typically were not working in their previous locations, their place of residence five years ago. Young workers did not accumulate local labor market experience in past locations, though older workers did. The result shows that young workers in either direction exhibit premia relative to non-migrating young workers, which could be purely a selection story. Older workers, in contrast, having accumulated experience in their past location, exhibit penalties and premia consistent with superior human capital accumulation in mobile places: movers up earn at a penalty, and movers down at a premium, especially around 10-20 years experience. Columns 4 and 5 split the sample by college education to reveal some heterogeneity. Non-college educated workers seem most susceptible to the move-up penalty, while college educated workers reap most of the move-down premium. Perhaps the college educated are more able to control the circumstances under which they move.

In summary, there is evidence that mobile cities offer opportunity for superior human capital accumulation, and this could be one reason they are at once attractive to in-migrants and allow higher rates of out-mobility. This result is robust to and coincident with the well-established relationship between city size.

7 Conclusion

This paper has highlighted a robust but understudied feature of local labor markets, the persistent spatial heterogeneity in population turnover. This heterogeneity cannot be easily explained by demographic or compositional differences, location remoteness (in physical or sectoral space), or even by the perpetuation of turnover through repeat mobility. The paper aims to push future lines of research in regional studies, and local labor markets in particular, by documenting these patterns.

The paper then starts this agenda by suggesting that mobile locations are materially different local labor markets. In particular, mobile places have more income dispersion, income volatility, and steeper income-experience profiles. The patterns apply generally to

Table 5: Earnings Outcomes for Movers

	1	2	3	4	5
Sample	All	All	All	Non-College	College
Migrate - any	-0.002				
	(0.0011)**				
Migrate - up mobility		-0.011			
		(0.0015)***			
x 0-4 yrs. exp.			0.0170	0.0375	-0.003
			(0.0035)***	(0.0051)***	(0.0050)
x 5-9 yrs. exp.			-0.024	-0.009	-0.037
			(0.0030)***	(0.0045)**	(0.0044)***
x 10-14 yrs. exp.			-0.006	-0.019	0.0043
			(0.0035)*	(0.0047)***	(0.0054)
x 15-19 yrs. exp.			-0.011	-0.027	0.0069
			(0.0039)***	(0.0050)***	(0.0064)
x 20-24 yrs. exp.			-0.002	-0.029	0.0344
			(0.0044)	(0.0054)***	(0.0074)***
x 25-29 yrs. exp.			-0.031	-0.049	-0.006
			(0.0051)***	(0.0063)***	(0.0085)
x 30+ yrs. exp.			-0.032	-0.053	0.0128
			(0.0049)***	(0.0056)***	(0.0093)
Migrate - down mobility		0.0083			
		(0.0016)***			
x 0-4 yrs. exp.			0.0377	0.0614	0.0125
			(0.0042)***	(0.0058)***	(0.0063)**
x 5-9 yrs. exp.			-0.007	0.0046	-0.018
			(0.0034)**	(0.0047)	(0.0051)***
x 10-14 yrs. exp.			0.0115	0.0039	0.0191
			(0.0037)***	(0.0049)	(0.0059)***
x 15-19 yrs. exp.			0.0128	-0.004	0.0346
			(0.0041)***	(0.0051)	(0.0069)***
x 20-24 yrs. exp.			0.0002	-0.009	0.0155
			(0.0046)	(0.0056)*	(0.0080)*
x 25-29 yrs. exp.			0.0117	-0.008	0.0430
			(0.0054)**	(0.0067)	(0.0092)***
x 30+ yrs. exp.			-0.000	-0.020	0.0452
			(0.0053)	(0.0059)***	(0.0104)***
Moved Home	-0.040	-0.042			
	(0.0032)***	(0.0032)***			
x 0-4 yrs. exp.			-0.018	-0.011	-0.020
			(0.0083)**	(0.0125)	(0.0115)*
x 5-9 yrs. exp.			-0.032	-0.042	-0.023
			(0.0063)***	(0.0088)***	(0.0093)**
x 10-14 yrs. exp.			-0.052	-0.053	-0.048
			(0.0074)***	(0.0098)***	(0.0115)***
x 15-19 yrs. exp.			-0.036	-0.041	-0.032
			(0.0085)***	(0.0105)***	(0.0141)**
x 20-24 yrs. exp.			-0.059	-0.054	-0.062
			(0.0100)***	(0.0121)***	(0.0172)***
x 25-29 yrs. exp.			-0.079	-0.082	-0.073
			(0.0117)***	(0.0141)***	(0.0206)***
x 30+ yrs. exp.			-0.046	-0.029	-0.083
			(0.0114)***	(0.0128)**	(0.0230)***
N	2,467,207	2,467,207	2,467,207	1,600,307	866,900
N Moved Up	146,983	146,983	146,983	68,119	78,864
N Moved Down	122,895	122,895	122,895	64,469	58,426
N Moved Home	29,756	29,756	29,756	15,329	14,427

NOTES: The table reports the results for the mover-interacted coefficients from a regression of log earnings in the model (6). The regressions include controls for education, experience, race, household structure, industry and occupation dummies (2-digit level). Source: Author's calculations using Census and IRS data as described in main text.

many types of workers. A possible story emerges to explain simultaneously high in- and out-mobility. More disperse income distributions and more volatile income processes generate a wider degree of good matches attracting migrants and poor matches pushing them away. At the same time, by offering superior human capital accumulation, higher mobility places allow, at the margin, greater rates of inflow and outflow. These results motivate the study of local labor markets according to their mobility status much like the literature has studied the relationship between incomes and size.

More generally, the paper shows that spatial features of gross mobility should not be ignored in the study of regional economies. The patterns documented here indicate that local labor market features have implications for the rates of regional adjustment. Models of local labor market adjustment typically focus on net migration, although empirically, such adjustment occurs through a substantial degree of gross migration. With heterogenous rates of excess mobility, the growth or decline of particular local labor markets would introduce different productivity or welfare costs in the aggregate.

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A Appendix: Auxiliary Results

Table A1: Mobility Index: Gravity Regression Results

Index #	2	3	4	5
	Gravity	Gravity+LM	Log Rate	I.H.S.
Origin Size	0.8011	0.7538		0.3490
	(0.0152)***	(0.0160)***		(0.0124)***
Dest. Size	0.5029	0.4999	0.5021	0.2179
	(0.0153)***	(0.0160)***	(0.0153)***	(0.0124)***
Move	-2.197	-2.189	-2.196	-1.733
	(0.0130)***	(0.0130)***	(0.0130)***	(0.0148)***
Log Mile Distance	-1.098	-1.098	-1.098	-1.256
	(0.0013)***	(0.0013)***	(0.0013)***	(0.0011)***
College Share Diff.	-1.850	-1.868	-1.850	-3.215
	(0.0244)***	(0.0244)***	(0.0244)***	(0.0172)***
Industry Dissimilarity	-0.007	-0.007	-0.007	-0.034
	(0.0008)***	(0.0008)***	(0.0008)***	(0.0006)***
Size Diff.	-0.313	-0.314	-0.313	-0.502
	(0.0014)***	(0.0014)***	(0.0014)***	(0.0010)***
Orig. Unempl. Rate		0.1983		
		(0.0065)***		
Dest. Unempl. Rate		-0.144		
		(0.0064)***		
Orig. Wage		-0.415		
		(0.0330)***		
Dest. Wage		0.4291		
		(0.0334)***		
Orig. Home Price		0.2591		
		(0.0110)***		
Dest. Home Price		-0.118		
		(0.0111)***		
Cons	-2.684	-2.022	-4.804	5.4607
	(0.2329)***	(0.2472)***	(0.1665)***	(0.1897)***
$K \times J \times T$	581,847	581,847	581,847	1,714,167

NOTES: The table reports additional coefficients from the gravity regression model (1). Source: Author's calculations using IRS data as described in main text.

Table A2: Mobility Index: Census Data Regression Results, Origin Side

Index #	7	8	12	13
	Census 2000		ACS 2006-11	
	Demographics	Demo. + Moved In	Demographics	Demo. + Moved In
Aged 30-39	-0.033	-0.037	-0.011	-0.012
	(0.0006)***	(0.0006)***	(0.0003)***	(0.0003)***
Aged 40-49	-0.067	-0.073	-0.022	-0.024
	(0.0006)***	(0.0006)***	(0.0003)***	(0.0003)***
Aged 50-59	-0.085	-0.095	-0.028	-0.030
	(0.0006)***	(0.0006)***	(0.0003)***	(0.0003)***
Aged 20-29 x College	0.1252	0.1204	0.0400	0.0384
	(0.0029)***	(0.0029)***	(0.0009)***	(0.0009)***
Aged 30-39 x College	0.0639	0.0598	0.0037	0.0021
	(0.0015)***	(0.0015)***	(0.0007)***	(0.0007)***
Aged 40-49 x College	-0.000	-0.004	-0.006	-0.007
	(0.0014)	(0.0014)***	(0.0007)***	(0.0007)***
Aged 50-59 x College	-0.017	-0.020	-0.008	-0.009
	(0.0014)***	(0.0014)***	(0.0007)***	(0.0007)***
Children, 1	-0.022	-0.021	-0.008	-0.007
	(0.0004)***	(0.0004)***	(0.0002)***	(0.0002)***
Children, 2	-0.032	-0.031	-0.009	-0.009
	(0.0004)***	(0.0004)***	(0.0002)***	(0.0002)***
Children, 3+	-0.031	-0.030	-0.009	-0.009
	(0.0005)***	(0.0005)***	(0.0003)***	(0.0003)***
Race/Eth., Black	-0.016	-0.015	-0.001	0.0001
	(0.0004)***	(0.0004)***	(0.0003)***	(0.0003)
Race/Eth., Hisp.	-0.020	-0.013	-0.005	-0.004
	(0.0006)***	(0.0006)***	(0.0003)***	(0.0003)***
Race/Eth., Asian	0.0141	0.0197	0.0043	0.0054
	(0.0010)***	(0.0010)***	(0.0004)***	(0.0004)***
Race/Eth., Other	0.0448	0.0433	0.0046	0.0039
	(0.0013)***	(0.0013)***	(0.0008)***	(0.0008)***
Married	0.0000	-0.001	-0.005	-0.006
	(0.0003)	(0.0003)***	(0.0002)***	(0.0002)***
Immigrant	-0.001	-0.060	-0.001	-0.018
	(0.0006)***	(0.0007)***	(0.0003)***	(0.0003)***
Citizen	-0.017	-0.014	-0.004	-0.003
	(0.0007)***	(0.0007)***	(0.0003)***	(0.0003)***
College Town	0.2205	0.1830	0.0712	0.0643
	(0.0081)***	(0.0080)***	(0.0040)***	(0.0040)***
Not at Home		0.0888		0.0256
		(0.0004)***		(0.0002)***
Cons	0.2375	0.2142	0.0904	0.0835
	(0.0083)***	(0.0082)***	(0.0058)***	(0.0058)***
N	4,104,864	4,104,864	5,827,478	5,827,478

NOTES: The table reports additional coefficients from the census data mobility index model (2). Source: Author's calculations using Census data as described in main text.

Table A3: Incomes Dynamics for Movers in PSID, by Origin and Destination Mobility

Years to Move	Origin		Destination	
	Mobile	Immobile	Mobile	Immobile
-8	0.0966	-0.001		
	(0.0350)***	(0.0384)		
-6	0.0591	-0.029		
	(0.0299)**	(0.0414)		
-4	0.0498	0.0368		
	(0.0256)*	(0.0339)		
-2	0.0072	-0.003		
	(0.0202)	(0.0253)		
2			-0.006	-0.053
			(0.0221)	(0.0268)**
4			0.0618	-0.054
			(0.0248)**	(0.0280)*
6			0.0695	-0.008
			(0.0255)***	(0.0330)
8			0.0847	-0.035
			(0.0277)***	(0.0319)

NOTES: The table reports coefficients and standard errors from the move event model (6); coefficients are plotted in Figure 2. $N = 63,564$.
Source: Author's calculations using Census and IRS data as described in main text.

B Appendix: Full List of MSAs by Mobility Index

Table B1: Reporting of Mobility Indices (Origin Side Only)

Rank	Metro Area	Out Migration	Indices			
(Gravity Index)	Index:	Ann. Rate	Gravity	Demo.	Demo.+Moved-in	Demo.
	Data:	IRS	IRS	Census 2000	Census 2000	ACS
	Average	2.87				
1	San Diego, CA	5.02	2.71	1.10	0.78	0.36
2	Lawton, OK	6.61	2.42			
3	Los Angeles-Long Beach, CA	3.48	2.37	0.16	-0.01	-0.30
4	Phoenix, AZ	3.50	2.31	-0.28	-1.32	-0.27
5	Seattle-Everett, WA	3.14	2.27	-0.47	-0.98	-0.79
6	Las Vegas, NV	4.39	2.24	0.44	-0.82	0.34
7	Riverside-San Bernardino, CA	4.96	1.98	1.20	1.13	0.28
8	Colorado Springs, CO	6.47	1.97			1.26
9	Salinas-Sea Side-Monterey, CA	6.21	1.87			
10	San Angelo, TX	4.89	1.86			
11	Vallejo-Fairfield-Napa, CA	3.96	1.80	0.14	0.02	-0.27
12	Grand Forks, ND	3.63	1.79			
13	Bremerton, WA	5.55	1.77	2.26	1.71	0.74
14	Miami-Hialeah, FL	3.15	1.75	-1.19	-1.93	-0.79
15	Great Falls, MT	2.87	1.70			
16	Yuma, AZ	4.31	1.70	1.68	1.17	0.21
17	Fayetteville, NC	7.32	1.64	4.15	4.03	2.50
18	Cheyenne, WY	3.85	1.59			
19	Wichita Falls, TX	4.62	1.57	1.90	1.90	1.37
20	Tucson, AZ	4.12	1.54	0.53	-0.26	-0.01
21	Tampa-St. Petersburg-Clearwater, FL	3.91	1.51	0.09	-0.90	0.00
22	San Jose, CA	5.58	1.49	1.71	1.73	0.33
23	Washington, DC	3.46	1.38	-0.15	-0.52	-0.60
24	Missoula, MT	3.23	1.37			
25	Panama City, FL	4.53	1.36	2.37	1.82	1.82
26	Clarksville-Hopkinsville, TN	5.34	1.35	2.96	2.49	1.73
27	Iowa City, IA	5.42	1.34	2.09	2.58	0.93
28	Rapid City, SD	2.51	1.33			
29	Bradenton, FL	4.21	1.31			1.00

Rank	Metro Area	Out Migration	Indices			
(Gravity Index)	Index:	Ann. Rate	Gravity	Demo.	Demo.+Moved-in	Demo.
	Data:	IRS	IRS	Census 2000	Census 2000	ACS
30	Denver-Boulder-Longmont, CO	2.81	1.30	-2.32	-3.27	-2.42
31	Naples, FL	4.20	1.30	0.76	-0.44	0.71
32	Lawrence, KS	7.36	1.29			
33	Santa Barbara-Santa Maria-Lompoc, CA	5.69	1.24	2.08	2.15	1.36
34	Gainesville, FL	6.79	1.24	2.59	2.55	3.45
35	Dallas-Fort Worth, TX	2.89	1.23	-0.58	-0.88	-0.80
36	Melbourne-Titusville-Cocoa-Palm Bay, FL	4.29	1.22	0.93	-0.11	0.76
37	Flagstaff, AZ	6.14	1.21	1.83	1.47	1.65
38	Orlando, FL	4.66	1.16	0.82	-0.04	1.00
39	Lakeland-Winterhaven, FL	4.77	1.08	0.40	-0.19	0.93
40	Casper, WY	2.08	1.07			
41	Bakersfield, CA	3.97	1.07	1.36	1.41	0.04
42	Ventura-Oxnard-Simi Valley, CA	5.16	1.06	1.66	1.62	0.69
43	Las Cruces, NM	3.64	1.05	1.23	1.16	0.13
44	Reno, NV	4.05	1.02	1.25	0.22	0.07
45	Pensacola, FL	4.81	1.01	1.17	0.46	1.35
46	Abilene, TX	4.49	0.99	1.69	1.94	2.13
47	Provo-Orem, UT	5.55	0.97	1.34	1.30	0.91
48	Santa Fe, NM	4.38	0.97	1.59	1.19	1.17
49	Austin, TX	4.53	0.95	0.49	0.40	-0.29
50	Myrtle Beach, SC	4.12	0.93	-0.05	-0.54	-0.10
51	Olympia, WA	4.69	0.88	1.03	0.63	0.61
52	Bryan-College Station, TX	6.61	0.88	2.76	3.25	3.27
53	McAllen-Edinburg-Pharr-Mission, TX	2.89	0.87	-0.08	-0.02	-0.52
54	State College, PA	4.19	0.84	-0.06	0.56	0.48
55	San Antonio, TX	3.21	0.83	0.37	0.41	-0.18
56	Spokane, WA	3.12	0.78	0.06	-0.33	-0.51
57	Houston-Brazoria, TX	2.58	0.78	-0.68	-0.90	-0.79
58	Portland-Vancouver, OR	2.54	0.77	-0.52	-1.13	-0.84
59	Sumter, SC	3.62	0.76	0.91	0.96	1.63
60	Sacramento, CA	3.42	0.76	0.05	-0.02	-0.03
61	Brownsville-Harlingen-San Benito, TX	3.51	0.75	0.75	0.92	0.14
62	Lubbock, TX	4.67	0.74	1.50	1.93	1.29
63	Columbia, MO	3.94	0.74	0.32	0.40	0.09
64	Ocala, FL	3.85	0.70	0.64	-0.13	0.75
65	Odessa, TX	3.21	0.69	1.18	1.36	-0.07
66	Albuquerque, NM	3.29	0.69	0.72	0.27	-0.26
67	New York-Northeastern NJ, NY	2.09	0.66	-1.16	-0.93	-1.04
68	Boston, MA	3.18	0.66	-1.27	-1.10	-0.77
69	Eugene-Springfield, OR	3.71	0.66	0.21	-0.36	0.16
70	Merced, CA	4.96	0.65	1.38	1.51	0.68
71	Bloomington, IN	4.64	0.63	1.64	2.08	2.24
72	Champaign-Urbana-Rantoul, IL	4.67	0.61	0.93	1.30	1.19
73	Jacksonville, FL	3.54	0.61			-0.12
74	San Luis Obispo-Atascad-P Robles, CA	5.25	0.59	2.13	2.43	1.68
75	Victoria, TX	2.82	0.58			
76	Bellingham, WA	3.85	0.55	0.45	0.25	-0.37
77	Atlanta, GA	2.59	0.55	-0.49	-1.05	-0.61
78	Chicago-Gary-Lake, IL	2.07	0.55	-1.00	-0.96	-1.12
79	Santa Cruz, CA	5.67	0.54	1.80	1.92	1.67
80	Fargo-Morehead, ND	2.57	0.54	0.03	-0.09	-1.17
81	Amarillo, TX	2.60	0.52	0.64	0.66	0.21
82	Billings, MT	1.94	0.51	-0.41	-0.71	-1.62
83	Pascagoula-Moss Point, MS	3.84	0.51	0.86	0.65	1.15
84	Redding, CA	3.28	0.50	0.40	0.53	-0.23
85	Norfolk-VA Beach-Portsmouth, VA	3.69	0.49	1.39	1.01	0.25
86	Bangor, ME	2.00	0.47			
87	Corpus Christi, TX	4.09	0.47			
88	New London-Norwich, CT	4.49	0.46			
89	Tallahassee, FL	4.77	0.46	1.11	1.01	1.47
90	Lafayette-W. Lafayette, IN	4.17	0.44	1.00	1.35	0.86
91	Burlington, VT	2.17	0.40			
92	Fresno, CA	3.21	0.39	0.36	0.45	-0.57
93	Laredo, TX	2.33	0.38	0.04	0.20	-0.58
94	Salt Lake City-Ogden, UT	2.59	0.37	-0.20	-0.36	-0.64
95	Bismarck, ND	1.68	0.37			
96	Savannah, GA	3.48	0.36	1.46	1.49	1.14
97	Charleston-N.Charleston, SC	3.94	0.35	0.66	0.46	0.36
98	Grand Junction, CO	2.77	0.35			

Rank	Metro Area	Out Migration		Indices		
(Gravity Index)	Index:	Ann. Rate	Gravity	Demo.	Demo.+Moved-in	Demo.
	Data:	IRS	IRS	Census 2000	Census 2000	ACS
99	Chico, CA	4.48	0.31	1.06	1.26	1.03
100	Stockton, CA	4.79	0.29	0.92	1.06	0.75
101	Sioux City, IA	1.85	0.29	-0.09	0.09	-0.49
102	Medford, OR	2.99	0.28	-0.20	-1.15	0.27
103	Goldsboro, NC	3.24	0.28	0.41	0.54	-0.70
104	Richland-Kennewick-Pasco, WA	2.88	0.25	0.88	0.36	-0.52
105	Lincoln, NE	3.13	0.25	-0.17	0.02	-1.03
106	Bridgeport, CT	4.63	0.23	0.15	-0.23	-0.28
107	Columbus, GA	4.29	0.23	0.99	0.76	0.96
108	Bloomington-Normal, IL	4.04	0.21	0.22	0.59	0.32
109	Visalia-Tulare-Porterville, CA	3.55	0.21	0.68	0.79	-0.31
110	Pine Bluff, AR	2.54	0.18			
111	Barnstable-Yarmouth, MA	3.88	0.17	-0.33	-0.26	0.07
112	Sioux Falls, SD	1.91	0.13			
113	Manchester, NH	4.37	0.11	-0.98	-1.25	0.37
114	Modesto, CA	4.34	0.11	0.68	0.82	0.80
115	Dubuque, IA	1.80	0.11			
116	Charlottesville, VA	3.21	0.11	1.07	1.02	1.41
117	Yakima, WA	2.96	0.11	0.50	0.36	-0.29
118	Santa Rosa-Petaluma, CA	3.87	0.09	0.49	0.56	0.47
119	Eau Claire, WI	1.98	0.08	-1.07	-0.83	-0.76
120	Portland, ME	2.83	0.04	-1.51	-1.65	-0.98
121	Athens, GA	4.27	0.01	1.68	1.90	1.83
122	Durham, NC	3.47	0.01	-0.06	-0.27	-0.40
123	Madison, WI	3.30	0.00	-0.43	-0.23	-0.45
124	Waco, TX	3.49	0.00	0.85	1.17	0.45
125	Dover, DE	2.74	0.00	0.53	0.07	0.26
126	LaCrosse, WI	1.97	-0.02	-0.56	-0.31	-0.55
127	Boise City, ID	2.02	-0.02	-0.69	-1.45	-0.50
128	Wausau, WI	1.65	-0.03	-1.22	-0.85	-1.58
129	Greenville, NC	3.24	-0.05	0.54	0.91	0.85
130	Steubenville-Weirton, WV	1.42	-0.09			
131	Minneapolis-St. Paul, MN	1.57	-0.10	-1.51	-1.54	-1.44
132	Fayetteville-Springdale, AR	2.49	-0.10	-0.02	-0.61	-0.61
133	Omaha, NE	2.36	-0.10	-0.65	-0.93	-0.86
134	Joplin, MO	1.90	-0.11	-0.55	-0.86	-0.47
135	Sherman-Denison, TX	3.41	-0.12			
136	Waterloo-Cedar Falls, IA	2.02	-0.13	-0.45	-0.03	-0.51
137	Decatur, IL	2.23	-0.14	-0.22	0.10	-0.56
138	Danville, VA	1.22	-0.18	-1.17	-0.84	0.06
139	Muncie, IN	3.25	-0.18	-0.12	0.23	0.55
140	Florence, AL	1.35	-0.19	-1.03	-0.86	-0.54
141	Tyler, TX	3.72	-0.20	0.08	0.25	0.02
142	New Orleans, LA	3.63	-0.20	-0.49	-0.21	2.00
143	Detroit, MI	1.95	-0.20	-1.39	-1.18	-0.88
144	Mobile, AL	2.58	-0.20	-0.51	-0.48	-0.45
145	Elkhart-Goshen, IN	2.83	-0.20	-0.46	-0.56	0.02
146	Monroe, LA	2.18	-0.22	0.21	0.61	-0.01
147	Texarkana, TX	1.84	-0.23			
148	Jackson, MI	2.63	-0.24	-0.06	0.45	0.74
149	Oklahoma City, OK	2.38	-0.24	0.41	0.23	
150	Salem, OR	3.40	-0.26	0.60	0.20	-0.17
151	Shreveport, LA	2.44	-0.27	0.08	0.17	-0.16
152	Erie, PA	1.96	-0.27	-0.86	-0.44	-1.06
153	Wichita, KS	2.32	-0.28	-0.39	-0.50	-0.87
154	Philadelphia, PA	2.18	-0.28	-1.06	-0.96	-0.97
155	Poughkeepsie, NY	3.65	-0.29			
156	Gadsden, AL	2.12	-0.30	-0.60	-0.20	-0.96
157	Lima, OH	1.56	-0.32	-0.86	-0.40	-0.29
158	Jackson, TN	1.74	-0.33	-0.46	-0.31	-0.62
159	Janesville-Beloit, WI	2.61	-0.34	-0.33	-0.19	-0.25
160	Kankakee, IL	2.63	-0.34	0.20	0.57	-0.09
161	Sheboygan, WI	2.09	-0.34	-1.33	-0.93	-0.75
162	Lewiston-Auburn, ME	2.60	-0.35			
163	Anniston, AL	2.65	-0.36	0.16	0.36	0.24
164	Memphis, TN	2.21	-0.37	-0.23	-0.55	-0.71
165	Cumberland, MD	0.83	-0.38			
166	Rochester, MN	2.41	-0.39	0.25	0.17	-0.40
167	Pittsfield, MA	2.34	-0.39			

Rank	Metro Area	Out Migration		Indices		
(Gravity Index)	Index:	Ann. Rate	Gravity	Demo.	Demo.+Moved-in	Demo.
	Data:	IRS	IRS	Census 2000	Census 2000	ACS
168	Wilmington, NC	3.08	-0.39	0.63	0.47	0.21
169	Binghamton, NY	2.26	-0.41	0.47	0.89	-0.78
170	Lake Charles, LA	2.35	-0.42	-0.02	0.31	0.15
171	Des Moines, IA	2.07	-0.42	-0.27	-0.06	-0.95
172	Alexandria, LA	2.09	-0.43	-0.70	-0.39	-0.50
173	New Haven, CT	3.91	-0.43	-0.19	-0.10	0.20
174	Baltimore, MD	2.79	-0.45	-0.61	-0.68	-0.68
175	Kansas City, MO	2.11	-0.45	-0.84	-1.28	-0.85
176	Flint, MI	3.08	-0.45			
177	Pueblo, CO	2.54	-0.46			
178	Worcester, MA	3.70	-0.46	-0.25	0.08	-0.22
179	South Bend-Mishawaka, IN	3.14	-0.49	0.18	0.32	0.18
180	Lafayette, LA	2.50	-0.49	-0.30	0.15	-0.13
181	Racine, WI	3.44	-0.49	0.24	0.52	-0.13
182	Tulsa, OK	2.38	-0.49	0.55	0.30	
183	Hattiesburg, MS	2.45	-0.51	-0.18	-0.01	-0.05
184	Duluth-Superior, MN	1.86	-0.52	-0.77	-0.42	-0.48
185	Utica-Rome, NY	2.32	-0.52	-0.05	0.58	-0.70
186	Elmira, NY	1.36	-0.53			
187	Lexington-Fayette, KY	2.26	-0.53	0.33	0.42	-0.16
188	Charlotte-Gastonia-Rock Hill, NC	2.73	-0.53	-0.66	-0.92	-0.56
189	Longview-Marshall, TX	2.65	-0.54	0.47	0.57	-0.19
190	Columbus, OH	2.35	-0.54	-0.82	-0.71	-0.90
191	Mansfield, OH	1.82	-0.54	-0.89	-0.67	-0.56
192	Tuscaloosa, AL	2.72	-0.56	-0.47	-0.17	0.06
193	Hartford-Bristol-Middleton-New Britain, CT	2.95	-0.57	-0.92	-1.00	-0.96
194	Augusta-Aiken, GA	2.43	-0.58	0.42	0.08	0.11
195	Springfield, IL	2.26	-0.59			
196	Auburn-Opelika, AL	3.08	-0.62	0.02	0.11	-0.18
197	Springfield, MO	2.05	-0.62	-0.36	-0.55	-0.41
198	Nashville, TN	2.13	-0.63	-0.68	-0.97	-0.78
199	Columbia, SC	2.89	-0.63	0.06	-0.01	-0.24
200	Syracuse, NY	2.47	-0.65	-0.48	0.03	-0.56
201	Kokomo, IN	2.18	-0.65	-0.45	-0.21	0.53
202	Lansing-E. Lansing, MI	3.61	-0.67	0.21	0.67	0.89
203	Houma-Thibodoux, LA	1.62	-0.68	-0.97	-0.45	-0.75
204	Cedar Rapids, IA	2.36	-0.68	-0.18	0.06	-0.57
205	Johnstown, PA	1.61	-0.70	-0.97	-0.34	-0.54
206	Dothan, AL	1.35	-0.71	0.59	0.50	-0.86
207	Terre Haute, IN	2.02	-0.73	-0.59	-0.30	-0.36
208	Fort Wayne, IN	2.08	-0.75	-0.75	-0.67	-0.67
209	Macon-Warner Robins, GA	2.20	-0.76	0.08	0.16	-0.30
210	Rochester, NY	2.00	-0.77	-0.75	-0.37	-0.76
211	Owensboro, KY	0.96	-0.77			
212	St. Louis, MO	1.58	-0.78	-1.14	-1.10	-1.22
213	Little Rock-North Little Rock, AR	2.11	-0.79	-0.59	-0.66	-0.82
214	Vineland-Milville-Bridgetown, NJ	2.81	-0.80	0.47	0.70	0.08
215	Buffalo-Niagara Falls, NY	1.89	-0.80	-0.84	-0.29	-0.98
216	Decatur, AL	2.13	-0.81	-0.86	-1.02	-0.45
217	Rockford, IL	2.48	-0.82	-0.40	-0.43	-0.16
218	Davenport-Rock Island-Moline, IA	1.81	-0.83	-0.93	-1.07	-1.48
219	St. Joseph, MO	1.95	-0.88	-0.28	-0.05	-0.63
220	Baton Rouge, LA	2.23	-0.89	-0.69	-0.43	-0.66
221	Topeka, KS	2.25	-0.89	0.06	0.10	-0.54
222	Williamsport, PA	1.23	-0.89	-1.03	-0.48	-1.09
223	Milwaukee, WI	2.15	-0.90	-0.92	-0.73	-0.94
224	Battle Creek, MI	2.88	-0.90	-0.33	-0.07	-0.21
225	Atlantic City, NJ	3.45	-0.93	0.06	-0.20	0.13
226	Indianapolis, IN	2.03	-0.93	-0.94	-0.90	-0.75
227	Springfield, OH	2.52	-0.98	-0.29	-0.14	-0.37
228	Albany, GA	1.72	-1.00	0.53	0.75	0.24
229	Beaumont-Port Arthur-Orange, TX	2.75	-1.00	0.04	0.22	0.48
230	Albany-Schenectady-Troy, NY	1.69	-1.01	-0.91	-0.48	-0.99
231	Knoxville, TN	1.94	-1.01	-0.84	-0.85	-1.07
232	Cleveland, OH	2.16	-1.03	-0.97	-0.73	-0.79
233	York, PA	2.74	-1.04	-0.58	-0.39	-0.54
234	Pittsburgh-Beaver Valley, PA	1.56	-1.05	-1.51	-1.04	-1.33
235	Springfield-Holyoke-Chicopee, MA	2.59	-1.09	-1.20	-1.10	-1.02
236	Birmingham, AL	1.98	-1.14	-0.82	-0.59	-0.47

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	Index:	Ann. Rate	Gravity	Demo.	Demo.+Moved-in	Demo.
	Data:	IRS	IRS	Census 2000	Census 2000	ACS
237	Providence-Fall River-Pawtucket, RI	2.42	-1.17	-1.46	-1.33	-0.61
238	Altoona, PA	1.37	-1.17	-1.26	-0.66	-0.87
239	Toledo, OH	1.92	-1.18	-0.50	-0.20	-0.54
240	Green Bay, WI	1.91	-1.18	-0.76	-0.37	-0.40
241	Asheville, NC	1.91	-1.19	-0.53	-0.63	-0.11
242	Charleston, WV	1.34	-1.19			
243	Wheeling, WV	1.12	-1.20			
244	Lancaster, PA	2.61	-1.21	-0.54	-0.17	-0.40
245	Akron, OH	2.36	-1.22	-0.69	-0.34	-0.59
246	Appleton-Oskosh-Neenah, WI	1.95	-1.23	-1.17	-0.79	-0.77
247	Richmond-Petersburg, VA	1.98	-1.23	0.74	0.74	1.58
248	Grand Rapids, MI	1.90	-1.23	-1.26	-0.97	-0.82
249	Jackson, MS	1.55	-1.29	-0.95	-0.68	-0.41
250	Burlington, NC	2.10	-1.29	-0.82	-0.82	-0.72
251	Reading, PA	2.82	-1.29	-0.61	-0.18	-0.28
252	Fort Smith, AR	1.36	-1.30	-0.77	-1.15	-0.23
253	Cincinnati, OH	1.72	-1.31	-0.86	-0.76	-0.64
254	Saginaw-Bay City-Midland, MI	1.76	-1.33	-0.87	-0.41	-0.79
255	Peoria, IL	1.75	-1.42	-0.84	-0.55	-0.58
256	Parkersburg-Marietta, WV	0.75	-1.44			
257	Chattanooga, TN	1.55	-1.44	-2.74	-3.19	-2.02
258	Youngstown-Warren, OH	1.78	-1.48	-0.98	-0.73	-0.60
259	Louisville, KY	1.30	-1.50	-1.14	-1.11	-1.38
260	Evansville, IN	1.02	-1.52	-1.25	-1.19	-0.97
261	Harrisburg-Lebanon-Carlisle, PA	2.33	-1.54	-0.26	0.16	-0.40
262	Rocky Mount, NC	1.98	-1.58			
263	Greenville-Spartanburg-Anderson, SC	1.66	-1.63	-1.19	-1.29	-0.81
264	Florence, SC	1.75	-1.70			
265	Allentown-Bethlehem-Easton, PA	2.42	-1.78	-0.62	-0.40	-0.40
266	Scranton-Wilkes-Barre, PA	1.40	-1.81	-1.63	-1.20	-1.35
267	Hagerstown, MD	1.86	-1.86	-0.50	-0.62	-0.14
268	Huntington-Ashland, WV	1.05	-1.94			
269	Hickory-Morgantown, NC	1.10	-1.97	-1.46	-1.29	-0.85
270	Lynchburg, VA	1.53	-2.01	-0.73	-0.55	-0.29
271	Roanoke, VA	1.50	-2.02			
272	Johnson City-Kingsport-Bristol, TN	0.70	-2.44	-1.46	-1.65	-0.96