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The Urban Density Premium across Establishments

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Abstract
We use longitudinal micro data to estimate the urban density premium for U.S. establishments, controlling for observed establishment characteristics and dynamic establishment behavior. We find that a doubling of urban density increases the average earnings of establishments by between 6 and 10 percent. The result holds after controlling for endogeneity issues and with the use of alternative measures of density. We find strong evidence against accumulated knowledge spillovers over time at the establishment level—that is, the density premium is realized at birth and is constant over the life of establishments. We find little evidence that the endogenous entry or exit of establishments can account for any of the estimated density premium.

Keywords: urban density premium, dynamic agglomeration economies, establishment entry and exit
JEL Codes: D22, R12, R30

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1. Introduction

For years, urban economists have studied why observationally similar workers earn more in more densely populated locations. Studies have consistently found an elasticity of earnings with respect to urban density of between 3 and 10 percent. This elasticity is generally robust to controlling for a variety of factors, including the migration of skilled workers across cities, the returns to worker experience at a particular location, and labor search and matching frictions.[1] Urban economists have also examined the returns to urban density for firms.[2] Only recent studies, however, examine the relationship between urban density and firm productivity at the micro level.[3] Consequently, there is little evidence on the role firm characteristics, behavior, or composition play in generating the empirical estimate of an urban density premium for employers.

In this paper, we estimate the density premium for U.S. establishments, controlling for a variety of observable establishment characteristics and dynamic establishment behavior that may be endogenously related to urban density. We use micro data from the Census Bureau's Longitudinal Business Database (LBD) to relate the average earnings per worker of an establishment to the population density of its metropolitan area. We interpret our average earnings measure as a proxy for labor productivity, though our results do not rest on this interpretation. In this regard, we build on earlier studies that relate firm productivity to urban agglomeration (e.g., Syverson, 2004; Combes et al., 2012; Lehmer and Möeller, 2010).

After controlling for observed establishment characteristics and the share of the local population with a college degree, we find that a doubling of urban density is associated with an increase in average establishment earnings between 7 and 10 percent. This estimate is robust to alternate

1 See Glaeser (1999), Glaeser and Mare (2001), Freedman (2008), Bacolod, Blum, and Strange (2009), Glaeser and Resseger (2010), Baum-Snow and Pavan (2012, 2013), and de la Roca and Puga (2010), among others.
2 These include Glaeser et al. (1992), Henderson, Kuncoro, and Turner (1995), Ciccone and Hall (1996), and Henderson (1997).
3 Examples include Henderson (2003), Moretti (2004), and Combes et al. (2012).

measures of urban density and an instrumental variables specification that controls for the simultaneous location choices of workers and firms.

Our data allow us to also examine the behavior of the density premium over the life cycle of establishments. This is important for two reasons. First, knowledge spillovers are thought to be a key driver of the urban agglomeration economies that generate a density premium. The notion that these spillovers affect the innovation, growth and productivity of firms is pervasive throughout the urban literature (see Audretsch and Feldman, 2004, Rosenthal and Strange, 2004; and Henderson, 2007 for reviews). Theoretical treatments of such spillovers in an urban context (e.g. Black and Henderson, 1999) are often based on seminal models of endogenous growth such as Romer (1986) and Lucas (1988). In such models, these spillovers generate increasing returns for the firm and accumulate over time. Theory dictates that firms in denser areas should have faster productivity growth, all else equal, because of the greater accumulation of knowledge spillovers. Second, several studies have found evidence of accumulated returns to agglomeration for workers (Glaeser and Mare, 2001; de la Roca and Puga, 2010; Baum-Snow and Pavan, 2012). That is, workers exhibit a greater density premium in their wages the longer they reside in a denser location. These studies attribute the resulting steeper wage-city tenure profile to faster human capital accumulation in denser areas, an interpretation that is consistent with accumulated returns from knowledge spillovers over time. We examine whether establishments reap similar accumulated returns because much of the underlying theory regarding knowledge spillovers implies a direct effect on firm productivity, which workers indirectly benefit from through their wage.

Surprisingly, we find no evidence of an increasing density premium as establishments age. We show that establishments rarely relocate, so that their age and their city tenure are identical in most cases. We estimate that establishments realize the density premium almost entirely at entry, and that it remains relatively constant over their lives. Again, this finding is robust to controls for a variety of establishment characteristics and to the use of alternate measures of population density, and it holds within an instrumental variables specification. It also holds within nearly all establishment categories, including size class, ownership status, broad industry group, and quintile of an establishment's within-city earnings distribution.

We consider this finding to be at odds with standard models of accumulated knowledge spillovers where incumbent firms reap the benefit of some external return from the localized stock of knowledge. These include many models of urban growth as well as models of innovation through a "knowledge production function" (e.g., Griliches, 1979; Jaffe, 1989). Note, though, that our evidence does not rule out knowledge spillovers as a key driver of urban growth. It simply rules out a mechanism where these spillovers directly affect the productivity of a city's incumbent firms. Our evidence is instead consistent with a story where knowledge moves across firms within a city through the entry margin. In this sense, we find a strong role for entrepreneurs as the mechanism for innovation and knowledge transmission within a metropolitan area. It is similarly consistent with the story of spillovers and entrepreneurship put forth by Audretsch and Feldman (2004, pp. 2728-29), and the model of innovation through entrepreneurial spinoffs by Chatterjee and Rossi-Hansberg (2012). Their model is particularly compelling because recent work by Klepper (2010) finds a strong role for spinoffs in forming the Detroit automobile and Silicon Valley high-tech industrial clusters, while work by Wenting (2008) finds a role for localized spinoffs for innovation within the fashion industry. The key insight from our finding is that knowledge diffusion within a city depends more on a reallocation process than a process where firms reap increasing returns from the general knowledge stock within the city. In other words, the returns to agglomeration are not "in the air" as Marshall (1890) put it, but are instead embodied within innovating entrepreneurs.

Finally, we examine the extent to which changes in the composition of establishments across metropolitan areas account for our main findings. We focus on the potential roles of selection (through the exit of relatively low-productivity establishments) and sorting (through the relocation or entry choices of relatively high-productivity establishments). Syverson (2004) shows that, within the concrete industry, a higher density of product demand leads to greater competition, which in turn leads to more exits among low-productivity concrete plants and higher mean productivity through a greater lower-truncation of the productivity distribution. The same mechanism may affect a broader range of establishments and depend on the density of their metropolitan area. For example, Combes et al. (2010) find that the endogenous sorting of high-skilled workers into larger cities accounts for about 35 percent of their estimated earnings density premium.

We find that a firm selection effect likely does not account for any of our estimated density premium. The findings are consistent with conclusions reached by Combes et al. (2012). Unlike their study, however, we are able to explicitly examine establishment exit rates as a function of productivity. We do find evidence of firm selection—establishment exit is concentrated at the low end of the establishment earnings distribution. There is little variation, however, in the degree of this concentration across metropolitan areas. Similarly, we find weak evidence at best in support of an establishment sorting mechanism. We examine differences in the characteristics of establishments at entry and establishments that relocate across metropolitan areas. Evidence on relocating establishments suggests a limited role of sorting. We find that the highest-earnings establishments are most likely to relocate, but that all movers tend to move to *lower-density* metropolitan areas, on average, when compared to a baseline of completely random relocation. We perform a counterfactual exercise where we shut down non-random relocation and it only slightly reduces our density premium estimate. We also use relocations to test whether the returns realized at entry occur at birth or at entry into the city at any point in the establishment's life cycle. When we differentiate between establishment age and city tenure, we find no additional effect of tenure, and conclude that any returns to agglomeration occur at birth. Finally, we test for at least suggestive evidence of establishment sorting at birth by comparing the relative earnings differences of new, single-unit firms to the relative earnings differences of the new establishments of multi-unit firms on the premise that existing firms should be more likely to endogenously choose the location of their new establishments. Our evidence does not suggest a role for sorting—entrants of multi-unit firms have relatively *lower* earnings in high-density metropolitan areas.

Thus, we conclude that there exists a substantial urban density premium for establishments, even after controlling for a variety of establishment characteristics and endogenous movements into and out of metropolitan areas. Furthermore, this premium is almost entirely realized at the time of establishment birth, and does not change over time. This suggests a much different view of how knowledge spillovers accumulate within cities than what current urban theory suggests. It is also in contrast to previous research on workers, which finds steeper wage-city tenure profiles in larger cities. For firms, we find that the entry margin is the most important source of knowledge spillover accumulation within a city.

The next section describes the data and discusses our approach to measuring key outcomes. Section 3 presents our evidence on the urban density premium across establishments, which we show is robust to controlling for a variety of establishment and CBSA characteristics as well as to alternative approaches to addressing measurement and endogeneity concerns. In Section 4, we present evidence on the density premium over the establishment life-cycle. Section 5 examines to what extent establishment exit, entry, and relocation account for our results. Section 6 concludes.

2. Data and Measurement

We use establishment data from the Longitudinal Business Database (LBD) of the Census Bureau for our analysis.[4] The data include payroll and employment information for nearly every establishment in the U.S. on an annual basis, in addition to a variety of information on the establishment (e.g.,

[4] For additional details about the LBD, see the web appendix and Jarmin and Miranda (2002).

industry, location, whether it is part of a multi-establishment firm). Thus, the data provide us with a rich level of detail both within and across metropolitan areas, and allow us to circumvent sampling, scope, and measurement issues that usually plague survey data. We focus on establishments in 1992 and 1997, though we use data from all available years to best identify measures such as entry, exit, and establishment age. We focus on these two years because they are Economic Census years, meaning that the U.S. Census Bureau conducted an extensive census of all businesses, so these years tend to have the most reliable measures of establishment entry and exit. These years are also the last two Census years available that have consistent measures of industry across years; the U.S. changed its classification system from the older Standard Industrial Classification (SIC) system to the North American Industrial Classification System (NAICS) in 1997. We restrict our analysis to private, non-agricultural establishments, giving us 4.9 million observations in 1992 and 5.3 million observations in 1997.

We use the Consolidated Business Statistical Area (CBSA) definition of metropolitan areas as our city-level unit of analysis, focusing only on the Metropolitan Area locations (i.e., we ignore the smaller locations classified as Micropolitan Areas under the CBSA system). This provides us with 363 CBSAs in our study.[5] Our main measure of urban density is 1990 population per square mile, which we calculate for each CBSA by aggregating population and land area data up from the county level. We use the same approach to calculate the share of the 1990 CBSA population with a college degree. We use the college share as a proxy for the average worker skill in a CBSA, but note that it is a crude proxy since it will not capture variations in other skills, both observable and unobservable, that are not related to education. We also check the robustness of our results using alternative measures of population density. These include the 1990 population level (i.e., CBSA size), CBSA employment per square mile (measured using the current year), and an area-weighted measure of population density that weights the density of

[5] These CBSAs roughly correspond to the older definitions of Metropolitan Statistical Areas and Primary Metropolitan Statistical Areas.

subunits of a CBSA's land area by the population within that subunit. The measure has been used previously by Glaeser and Kahn (2004) and Rappaport (2008).[6]

We measure entry and exit at the annual frequency. This ensures that all exits measured in 1992 occurred during that year and all entrants measured in 1997 occurred during that year (rather than during the intervening five-year period). We define an entry (exit) as the first (last) time an establishment appears with positive employment in the available sample of the LBD, which spans 1975 through 2005. We also measure establishment age using the full LBD sample. An establishment is assigned an initial age of zero years at entry. Since we can only identify age by observing the establishment in the LBD, we topcode age at 16 years (the maximum observed age in 1992) for both years in our sample.

We use payroll per employee as our measure of average earnings at each establishment. Doing so presents us with several measurement issues. First, payroll in the LBD covers all individuals paid during the year but employment is reported for a particular point in time (March of the year). Thus, a standard measure of payroll per employee will tend to overstate the average earnings of establishments that had high worker turnover or were rapidly contracting during the year, and tend to understate the average earnings of establishments that were rapidly expanding during the year. Second, there is the timing of the payroll and employment data. Payroll in the LBD covers all employees paid during the calendar year (January to December). However, employment is measured during the year (in March). Finally, measurement error in either payroll or employment could lead to extreme outliers in the average earnings measure, though since the data are administrative, such measurement error is limited to reporting or input errors on the part of those collecting the data.

[6] We thank Jordan Rappaport for providing us with the area-weighted data.

To obtain a more accurate measure of earnings, we define the average earnings for an establishment in year t as the total annual payroll in year $t - 1$ divided by the average of employment in years $t - 1$ and t, or

(1)
$$w_{et} = \frac{P_{e,t-1}}{\frac{1}{2}\left(N_{et} + N_{e,t-1}\right)}$$

where $P_{e,t-1}$ is the total annual payroll of establishment e in year $t - 1$ and N_{et} is the reported employment of establishment e in year t. We define the average earnings of entrants as P_{et}/N_{et} and the average earnings of exits as $P_{e,t-1}/N_{e,t-1}$. We then evaluate these measures for outliers and impute an average earnings measure where necessary. We detail our evaluation and imputation algorithm in the appendix. Finally, we deflate our earnings measures using the Consumer Price Index to 1997 dollars.

Throughout our analysis, we consider the average earnings of an establishment as a proxy for its productivity. There are several issues with this. Earnings are a cost to the firm as much as they are a rent paid to productive labor. In addition, average earnings represent an average across a distribution of workers while productivity is usually thought of as a uniform measure within an establishment. Our key findings do not rest on whether one can interpret average establishment earnings as a measure of productivity. Nevertheless, the ability to interpret the measure as such allows a cleaner comparison of our findings with previous empirical work and the existing theory on agglomeration and firm productivity.

The LBD does not allow a direct measure of productivity, but we check and reaffirm the validity of earnings as a proxy in several ways. First, we note that our results below on the density premium across the earnings distribution parallel the findings of Combes et al. (2012), who perform a similar exercise with TFP. Namely, we find an urban density premium that increases with average earnings while Combes et al. find a city size premium that increases with TFP. Second, our results below on establishment exit show that establishments' exit rates decline sharply with average establishment earnings. This runs counter the concern that high-earnings establishments are predominantly high-cost rather than high-productivity establishments, since we expect that the least efficient establishments would be the most likely to exit. Finally, we replicate the results of Syverson (2004) using our average earnings measure in lieu of total factor productivity (TFP). The Syverson study is a particularly useful because it focuses on the relationship between establishment-level dynamics and local density. Syverson suggests that locations with a greater density of demand will have greater competition among local firms, and consequently, greater exit rates among their low-productivity firms . He tests and affirms the main implications of his model by looking at differences in the TFP distributions of plants in the ready-mix concrete industry across areas with different construction employment densities (the construction industry is the primary consumer of ready-mix concrete). He focuses on several key moments of the TFP distribution within each geographic area, and regresses each separately on (log) density. He finds that areas with greater demand density have a less disperse TFP distribution that exhibits greater lower truncation. These areas also have higher average TFP, larger plants, and a lower producer demand ratio. Table 1 shows our replication of the Syverson study, using average establishment earnings on a subsample that is identical to the one he uses.[7] As one can see, we find qualitatively similar results for all moments used in the Syverson study. Thus, we conclude that there is in fact a strong correlation between our measure of average earnings and establishment productivity.

Before proceeding to the main analysis, it is worth noting how basic establishment characteristics and behavior vary with urban density, since differences in these characteristics across metropolitan areas can affect the relationship between earnings and density through a composition effect. Table 2 presents basic sample statistics as well as the simple estimated relationships between the average (log) number of employees and age of establishments, the average annual entry rate, and the average annual exit rate on (log) density. The mean of log establishment employment is 1.50 (which

[7] We provide additional details on how we conduct this analysis in the appendix.

corresponds to mean employment, in levels, of about 16 workers), and the average establishment is 8 years old. About 10 percent of all establishments in each year are new entrants, and another 9 percent in each year exit. There is wide variation in these statistics across establishments, but much lower variation in their mean values across CBSAs. We estimate the relationship between these characteristics and urban density using OLS regressions that controls for the share of the CBSA population that is college educated and establishment characteristics (size, age, industry, and multi-unit firm status, excluding the characteristic used as the dependent variable).[8] Denser CBSAs tend to have smaller but older establishments, on average, though the differences in size are not statistically significant. Establishment entry rates decline with density, while exit rates are essentially unrelated with density, especially when controls for the CBSA college share and the remaining establishment characteristics are added.

3. Baseline Estimates of the Urban Density Premium

If we regress the log of average earnings on the log of density at the CBSA level, which is what one would do if one were to use published statistics for metropolitan areas, we obtain an elasticity estimate (density premium) of 8.1 percent. Controlling for college share reduces this estimate to 7.8 percent. These estimates are roughly in line with previous estimates obtained using data on individuals rather than establishments.[9]

Our goal is to estimate this elasticity at the establishment level, so that we can control for the CBSA college share as well as a variety of observable establishment characteristics, since it is well known

[8] All regressions include a dummy variable for year. In these and all subsequent establishment-level regressions in the paper, we report standard errors that are clustered at the CBSA level.
[9] See, for example, Ciccone and Hall (1996) and Sveikauskas (1975).

that earnings vary strongly with establishment characteristics like industry, size, and age.[10] To some extent, these characteristics also vary with density (Table 2). Therefore, differences in the composition of establishments along one or more of these dimensions can potentially affect our elasticity estimate. Our baseline specification regresses the log of average earnings on our density measure at the establishment level, with and without the above controls. We use both years of our panel and cluster standard errors by CBSA. Formally, for establishment e in CBSA j at year t, our baseline specification is

$$\ln w_{ejt} = \alpha_t + \beta \ln D_j + \gamma C_j + \delta Z_{et} + \varepsilon_{ejt}, \quad (2)$$

where $\ln w_{ejt}$ is the log of average establishment earnings, $\ln D_j$ is our density measure, C_j is the CBSA college share, Z_{et} is the set of establishment controls (the log of employment, fixed effects for age, fixed effects for four-digit SIC industry, and an indicator for membership in a multi-unit firm), and α_t is a year dummy.

The results for the full sample of establishment-years appear in Table 3. Unconditionally, we find a somewhat higher density premium at the establishment level (10.2 percent) relative to using aggregate data. Controlling for the CBSA college share reduces this estimate to 8.0 percent. Controlling for both college share and establishment characteristics reduces the estimate further, to 7.4 percent.[11] In each case, the estimated elasticity is highly significant. Thus, even at the micro level, and even after controlling for establishment characteristics that are known to exhibit strong correlations with earnings, we still find a large and significant density premium for establishments.

It is plausible that the above estimates mask wide heterogeneity in the density premium across different subgroups of the data. In Table 4, we re-estimate (2) separately for entrants and exits, multi-unit and single-unit firms, establishment size categories, and major industry groups. Entrants and exits each exhibit a slightly higher elasticity of earnings with respect to density relative to all establishments,

[10] For example, see Brown and Medoff (1989, 2003).

[11] This is consistent with recent work by Lehmer and Möeller (2010), who find an urban density premium that persists after controlling for firm size.

but neither of their coefficients is significantly different from our baseline estimate of 7.4 percent.[12] Of all the different cuts of the data, single-unit versus multi-unit firms is the only grouping where we find a significant difference in the estimated elasticity. Single-unit firms exhibit the higher density premium, 8.0 percent versus 5.8 percent for multi-unit firms.[13] We also estimate the density premium for five establishment size classes and for five broad industry groups (construction, manufacturing, retail trade, finance and professional services, and local services). Across size classes, we find no significant differences in the density premium across groups. Across industries, finance and professional services have the highest estimated density premium, while retail trade and local services have the lowest estimates.[14]

Estimates of an urban density premium face an endogeneity issue: urban density may be a consequence rather than a cause of local productivity advantages. This is what Combes et al. (2010) refer to as the "endogenous quality of labor." Furthermore, it is not clear that population density, measured as total population per CBSA square mile, is the most accurate measure of the density of economic activity.

To deal with potential endogeneity biases, we re-estimate equation (2) using a two-stage least squares approach used by Combes et al. (2010). We instrument the density and college share variables with a variety of geological and climate data for each CBSA. The geology variables include data on the fraction of the CBSA that is water-covered, the mean elevation and the fraction of the CBSA above 1000m, an index of terrain ruggedness, the average annual temperature and moisture, the number of

[12] We exclude age as a control for establishment characteristics in the entry regressions since, by definition, all entrants are zero years old.

[13] It is worth noting that this finding is consistent with research by Henderson (2003), who found that measures of localization and urbanization economies generated higher estimated returns for single-plant manufacturing firms.

[14] We also estimated the density premium across quintiles of the earnings distribution within each CBSA. Consistent with the findings of Combes et al. (2012), we find a premium that increases with establishment earnings. Our findings are in the appendix.

potential growing days, and the fraction of the soil represented by a vector of soil types. The results are in Table 5.[15] We only have such data for 283 of our 363 CBSAs, so we report both the OLS and IV results for this restricted sample. The restricted sample produces a somewhat higher estimate of the density premium (9.8 percent, compared to 7.4 percent in Table 3). Instrumenting density and college share in our 2SLS approach, however, only changes the estimated density premium from 9.8 percent to 10.4 percent, a statistically insignificant change. Thus, we conclude that the simultaneity issue does not account for our estimated density premium.

Population density is only one of several measures used in the literature to estimate the returns to urban agglomeration. Some (e.g., Baum-Snow and Pavan, 2012) use city size, measured as total population. Others use employment density rather than population density (e.g., Ciccone and Hall, 1996). Some recent studies (Glaeser and Kahn, 2004; Rappaport, 2008) have used an area-weighted population density measure on the premise that the municipal boundaries of a metropolitan area (which are used to define CBSAs) do not adequately reflect the area of economic activity. These measures aggregate up a population density measure from subsections of the metropolitan area and weight each subsection by its population. This gives more weight to, say, downtown areas, and less weight to outlying rural areas that happen to be within the municipal boundaries of a metropolitan area.

We reestimate equation (2) using OLS and four different measures of population density. The first uses population density, but weights the regression by establishment employment. This specification tests whether a worker-weighted regression produces a different result than an establishment-weighted regression. The second uses the log of the CBSA population. The third uses (log) employment density, measured using the current employment level (in 1992 or 1997) of the CBSA. The

[15] We present diagnostic statistics from the first stage regressions in the appendix, as well as estimates from CBSA-level regressions of (log) density on our instruments. The *F*-value on the first stage regression is 15.30 (*p*-value = 0.000), while the CBSA-level regression has an R-squared of 0.28 and a regression *F*-value of 6.90 (*p*-value = 0.000).

last uses the area-weighted population density from Rappaport (2008). The results are in the last four columns of Table 6. The estimated density premiums range from 5.6 to 9.5 percent, with the area-weighted measure producing the highest estimate. In all cases, however, the density premium is positive and significant, and qualitatively similar to our baseline estimate in Table 3. Thus, we conclude that our results our robust to the measure of urban agglomeration used.

4. The Density Premium over the Establishment Life Cycle

Knowledge spillovers are thought to be a key driver of an urban density premium. This line of thinking is driven partly by seminal models of endogenous growth through knowledge spillovers (Romer, 1986; Lucas, 1988) where spillovers are the outcome of localized human capital accumulation, by models of spillovers and innovation, where the free flow of localized information fosters greater innovation (e.g., Jaffe, 1989). There is evidence that worker tenure profiles are steeper in denser cities (Glaeser and Mare, 2001; de la Roca and Puga, 2010; Baum-Snow and Pavan, 2012). This finding is attributed to faster "learning" due to greater human capital accumulation, consistent with the endogenous growth models. These models, however, characterize their impact through productivity-growth at the firm level. Therefore, we examine whether firms experience accumulated returns similar to workers.

Specifically, we examine whether the estimated density premium for establishments increases as they age. We show below that establishment relocations are relatively rare, so an establishment's city tenure is equal to its age in most cases. Thus, a rising density premium with respect to establishment age would be evidence of a direct effect of localized knowledge spillovers on firm productivity.

We extend the regression specification in equation (2) to include an interaction between the fixed effects for establishment age and urban density,

(3) $$\ln w_{ejt}(a) = \alpha_t^1 + \varphi(a) + \beta^1 \ln D_j + \zeta(a) \ln D_j + \gamma^1 C_j + \delta^1 \tilde{Z}_{et} + \varepsilon_{ejt}^1(a),$$

Above, a denotes age and $\tilde{Z}_{et}$ represents the same establishment characteristics as before except for age (industry, size, and multi-unit firm status). The coefficient of interest in this exercise is $\hat{\zeta}(a)$, since $\partial\hat{\zeta}(a)/\partial a > 0$ signifies a density premium that rises with establishment age.

In Figure 1, we present results for three specifications of equation (3), analogous to the specifications in the first, second, and fourth columns of Table 3. The figure plots $\hat{\beta}^1 + \hat{\zeta}(a)$ as a function of age for each specification. Regardless of the specification used, the density premium for establishments is essentially flat over their lifespan. In the baseline specification, the estimated elasticity varies within a relatively tight range of 9.3 to 11.1 percent. When we include all controls, the range is even tighter, between 6.9 and 7.8 percent. In comparison, each of these ranges are smaller than the reduction in the density estimate from controlling for the CBSA college share, and these differences are all well within the standard error bands for their respective specification. Figure 2 replicates the exercise for different subgroups of the data. The six panels of the figure report the coefficients $\hat{\beta}^1 + \hat{\zeta}(a)$ from the estimation of the full specification of (3) separately by (i) continuing versus exiting establishments, (ii) establishments in multi-unit and single-unit firms, (iii) establishment size class, (iv) major industry group, (v) within-CBSA earnings quintile, and (vi) using the alternative density measures from Table 4.[16] In nearly every case, the estimated density premium does not vary with age. There are even some cases where the estimates fall somewhat with age (multi-unit firms, establishments in the lowest CBSA earnings quintile), and only the Construction industry shows any evidence of a notable and significant rise in the density premium with age, from 7.1 to 11.1 percent over an establishment's first

[16] We also estimated a version of (3) using the instrumental variables approach reported in Table 4. The IV estimates of the age-density interactions are almost identical to the OLS estimates. Both show that the density premium is essentially constant with respect to age.

15 years. Among the alternative density measures, only the area-weighted population density measure shows a rise in the density premium, from 8.4 to 9.7 percent, but the increase is not significant.

We thus conclude that, while there is clearly a premium associated with locating in a dense metropolitan area, it is almost entirely realized at entry. Establishments do not grow relatively more productive at denser locations through a returns realized through a greater accumulation of knowledge spillovers, in contrast to models of urban growth such as Black and Henderson (1999). This does not imply that accumulated knowledge spillovers do not exist for firms, or that they do not contribute to faster productivity growth in denser cities, but it does imply that these spillovers yield a fixed return at entry. While the difference appears subtle, the theoretical implication is that knowledge diffusion within the city occurs primarily through a reallocation channel rather than through a production spillover.

The evidence is consistent with a model where innovation diffuses across firms through spinoffs, as in Chatterjee and Rossi-Hansberg (2012). In their model, workers are tasked with generating innovations for a firm. Innovations vary in their quality, and those of sufficiently high quality induce their innovator to quit her existing firm and use the innovation to form a startup. Recent work on the Detroit automobile industry and Silicon Valley's high-tech industry by Klepper (2010), and on the fashion industry by Wenting (2008), show that a similar evolution of spinoffs played a key role in generating industrial clustering and growth within these industries. Our results thus far, however, do not distinguish between entry via new firm creation and entry through relocation. Without this distinction, models where the concentration of many firms generates a (static) benefit to density are also consistent with our results. These would include models where density itself generates an externality (Fujita and Ogawa, 1982), where firms benefit from shared access to specialized inputs (Abdel-Rahman and Fujita, 1990), and where a concentrated skilled labor pool reduces search frictions (Helsey and Strange, 1990). Later, we show that birth rather than relocation accounts for most of our result.

Before moving on, it is worth noting that there is a tension between our finding of a density premium that is independent of an establishment's age and a density premium that others have found to increase with a worker's city tenure (e.g., Glaeser and Mare, 2001; de la Roca and Puga, 2010; Baum-Snow and Pavan, 2012). It is important to keep in mind, though, that our estimates represent a combination of a fixed establishment return to agglomeration and the average return to agglomeration of its workers. In addition, the average return to workers can change over time through compositional changes in an establishment's workforce or through changes in the individual-level returns. In the extreme case where an establishment's workforce remains the same over time, earlier research suggests that our estimated density premium should rise over time. To reconcile the evidence, the establishment-specific component of the density premium would need to *decline* with age. If there were worker turnover, however, the interpretation becomes more complicated. For example, if lower-tenure workers consistently replace higher-tenure workers at a pace that keeps the average city tenure of workers roughly constant over an establishment's life, then we return to the interpretation that establishment-specific returns to urban agglomeration are unrelated to establishment age. For our results to mask an underlying increase in the establishment-specific returns over time, the average city tenure of workers would need to be decreasing over an establishment's life. How worker tenure evolves over an establishment's life cycle, however, is an open empirical question that requires access to matched employer-employee data, and therefore outside the scope of this paper. We nevertheless feel that understanding the link between worker and firm returns to density is an important part understanding urban agglomeration economies, and hope to explore this relationship further in future work.

5. The Roles of Selection and Sorting

We conclude our analysis by examining how much establishment dynamics, via entry and exit, account for the fact that we find a sizable, positive density premium for establishments that does not change over their life cycle. Recent models of urban agglomeration allow for a role for these dynamics (e.g., Behrens, Duranton, Robert-Nicoud, 2010). There are two ways that establishment turnover can affect our estimates. The first is through a selection effect. Specifically, if the least productive establishments are most likely to exit, and dense cities have greater competition that leads to higher exit rates, then we should see a stronger selection effect in denser cities. The selection effect inflates the estimated density premium through a greater lower-truncation of the establishment earnings distribution in denser cities. The second channel is a sorting effect. High-earnings firms may self-select into high-density cities, leading to an endogeneity issue in the estimation of the density premium. The can do so either at entry, which is difficult to identify, or through relocation to another city.

5.A. Selection through Exit

Recent research has tried to quantify how much of the estimated returns to agglomeration in previous studies are due to selection through firm exit. Syverson (2004) finds that higher local demand density for ready-mix concrete leads to a greater selection effect. Combes et al. (2012) examine whether selection matters more broadly using establishment TFP distributions across French metropolitan areas. They observe a strong selection effect, but find that it does not vary with city size, and therefore does not have an effect on their estimated returns to agglomeration. Their data, however, do not allow them to explicitly account for exit, which is a crucial part of models of firm selection (see Jovanovic, 1982; Hopenhayn, 1992; and Ericson and Pakes, 1995).

Our data suffer no such issues. We proceed by explicitly examining establishment exit rates as a function of their within-CBSA earnings distribution. We then compare the exit-earnings relationship in high-density versus low-density CBSAs to test for differences between the two. If there is a greater selection effect within high-density CBSAs, we should observe higher exit rates among low-earnings establishments within these CBSAs.

We group all establishments into one-percentile bins based on their ranking within their CBSA-specific earnings distribution (similar to how we grouped establishments by earnings quintile, but at a finer detail). We then pool all establishments within each percentile bin based on whether they reside in a CBSA within either the top or bottom quartile of the CBSA density distribution. Exit rates are calculated as the fraction of establishments that exit within each percentile bin. We calculate these exit rates for all establishments and for establishments aged 5 years or less. The latter group is of interest because exit rates are highest early in an establishment's life cycle. We report results that use an exit probability and average earnings measure that control for establishment characteristics (industry, size, age, multi-unit firm status). This eliminates differences in exit rates and earnings distributions that are due to observable differences in establishment composition across cities.[17]

Our estimates are in Figure 3. The top panels report exit rates a function of the earnings distribution, while the bottom panels report the difference between exit rates in high-density versus low-density CBSAs. In general, we find results consistent with the conclusions of Combes et al. (2012). There is clearly a strong selection effect for all establishments, as exit rates decline with average establishment earnings, and the highest exit rates are for establishments in the bottom 20 percent of the earnings distribution. At the same time, there is little difference in exit rates between high-density and low-density CBSAs. For all establishments, exit rates are somewhat higher in high-density CBSAs, but this difference is only marginally significant for the middle of the earnings distribution (between the 30th and 55th percentiles). For younger establishments, the differences are noisier but smaller, on average, and not significant anywhere along the earnings distribution.

[17] We also performed the exercise using the raw earnings and exit probabilities and obtain very similar results.

Table 6 presents further evidence against a role for selection. In this exercise, we explicitly follow cohorts of entrants within the top and bottom quartile of the CBSA density distribution for their first 5 years and compare the relative difference in the evolution of earnings distributions among the surviving establishments. The estimates again show a clear selection effect with each CBSA group—mean earnings are higher and there is much less dispersion for surviving establishments, with much of the reduction in dispersion occurring in the bottom half of the earnings distribution. The difference in the selection effect between the high-density and low-density CBSAs, however, is small. If anything, high-density CBSAs have a relatively smaller increase in mean earnings and less truncation of their earnings distribution. Thus, we conclude that firm selection does not account for the density premiums estimated in the previous sections.

5.B. Sorting through Relocation

The estimated density premium for establishments can also be affected by sorting. That is, the premium may be overstated because productive establishments sort into dense areas. Studies that focus on the density premium for workers can control for such sorting by estimating the within-worker density premium for individuals who migrate across cities. Examining sorting for establishments is more complex because establishments can sort along two margins: relocation or entry. The longitudinal information on the establishment's location allows us to examine establishment relocations, but it can suffer from miscoding issues. We have an accurate measure of entry, but one cannot separately identify whether the location at entry was endogenously chosen or whether it happened to be the residence of the entrepreneur. Because of these limitations, little empirical research has been done on the sorting of firms into cities (an exception is Duranton and Puga, 2001, using French data). We conclude our analysis by examining whether high-earnings establishments sort into high-density CBSAs, either by relocation or by entry.

We start with relocating establishments. Because of the potential for the miscoding of location, we identify relocations in the data as establishments whose county code changes no more than once during our sample period.[18] We focus primarily on continuing establishments over the 1991-92 and 1996-97 periods. Restricting the analysis to moves between CBSAs identifies just over 81,000 moves, which represents 1.03 percent of all continuous establishments.[19] In comparison, entrants compose 10.3 percent of all establishments.

Table 7 reports the differences in the basic characteristics of continuous establishments who move versus those that remain in the same CBSA. Relocating establishments tend to be younger, slightly larger, and less likely to be part of a multi-unit firm, on average. They also have earnings that are 10.7 percent higher than stayers, on average, implying that higher-earnings establishments are in fact more likely to sort. Relocating establishments come from CBSAs that are slightly denser (1.1 percent) and have a somewhat higher share of individuals with at least a college degree (0.4 percentage points). At the same time, they tend to move to CBSAs that are considerably less dense (21.7 percent) and have lower shares of their population with a college degree (0.7 percentage points). Thus, while establishments with higher earnings are more likely to move, the average relocation goes in the opposite direction of what a sorting story would suggest.

Figure 4 examines the behavior of relocating establishments across the full earnings distribution to see whether the simple means in Table 7 mask a richer pattern of relocation across metropolitan areas. As with the selection exercise of the previous section, we allocate all continuous establishments

[18] Geographic miscoding generally occurs because of a reporting error in a particular year. When they are corrected, it appears as if the establishment relocated then relocated back to their original location. We have to reason to believe that the propensity of miscoding is correlated with either establishment earnings or CBSA density.

[19] Inter-CBSA moves represent 35 percent of all inter-county moves. In addition, 79 percent of all moves out of a CBSA are to another CBSA (the remainder are to non-metropolitan areas). We reject about 26 percent of potential relocations because of multiple changes in an establishment's county code.

into one-percentile bins based on the earnings distribution of their CBSA of origin.[20] We then calculate the fraction of establishments that relocate within each percentile bin. These estimates are presented in the first panel of the figure. Next, we calculate the change in (log) CBSA density for the subset of establishments that relocate. We plot the average change within each percentile in the bottom panel of the figure.

The thick blue lines in each panel represent the estimates derived directly from the data. The top panel shows that relocations are disproportionately concentrated in the top 20 percent of the within-CBSA earnings distribution. Relocation rates are essentially constant at just under 1 percent for establishments in the bottom 60 percent of the earnings distribution. Those in the top 5 percent of the distribution are 64 percent more likely to move than those in the bottom 60 percent. The bottom panel shows that establishments move to lower-density CBSAs, on average, across almost the entire earnings distribution. Establishments in the bottom 60 percent of the distribution move to a CBSA with a population density that is about 21 percent lower than the density of their original CBSA, on average. The decline is smaller as one moves further up the earnings distribution. Only the top 5 percent of establishments experience a small but statistically insignificant increase in CBSA density, on average.

CBSAs vary widely in their size (i.e., number of establishments) and in their earnings distributions. Consequently, the case where moves are purely random, in the sense that moves do not depend on establishment earnings and they are not directed towards a particular location, may generate spurious relations between earnings, move probabilities, and changes in CBSA density. To examine how much our estimates differ from a baseline of random relocations, we generate a simulated panel of establishments that inhabit the empirically observed distribution of CBSAs and allow them to

[20] As before, we use a residual measure of earnings the probability of moving that controls for establishment size, age, industry, and multi-unit firm status. Results using the unconditional earnings and move measures are very similar to those reported in the figure. In the appendix, we present additional results using the earnings distribution measured across the full sample of establishments (i.e., one that is not CBSA-specific). Again, the results are qualitatively similar to those in the figure.

move with equal probability to a randomly selected CBSA. We then calculate the probability of moving and the average change in density by the percentile of their origin CBSA's earnings distribution (as we do with the LBD data). We provide the details of this simulation in the appendix. Our generated baseline is very much in the spirit of Ellison and Glaeser (1997), who compare how much industrial concentration differs from the case where industries cluster completely randomly through a "dartboard" approach.

Our results are also in Figure 4. The thick red dashed lines present the difference between the estimates obtained from the data and our simulated estimates. The probability of moving is qualitatively unchanged by construction, since, in the simulated data, all establishments have an equal probability of moving. Thus, the difference just normalizes the empirically observed move probabilities by the sample mean. The change in CBSA density, relative to the simulated estimates, is actually more negative than what we observe in the data. Our simulation predicts that density should rise 39 percent, on average, when establishments move, regardless of where an establishment lies within its origin-CBSA's earnings distribution. Thus, relative to the case of random relocations, we find that relocating establishments in the bottom 60 percent of the distribution experience a 60 percent decline in the population density of their CBSA, while those in the top 5 percent experience a 32 percent decline, on average. Establishments at the high end of the earnings distribution tend to move to denser CBSAs in relative terms, but in absolute terms, all establishments move to less dense CBSAs.

We consider the effects of these relocations on our density premium estimates to be small, however, for several reasons. First, while high-earnings establishments are the most likely to move, the change in the density of their CBSAs relative to other movers (23 percent) is small relative to the standard deviation in CBSA density measured across establishments (105 percent) or CBSAs (94 percent). Second, relocation rates are fairly low on average. The highest-earnings establishments, which are the most mobile, only have a 1.6 percent chance of moving in a given year. Most establishments have less than a one percent chance. Finally, the density estimate derived from a regression using our simulated establishment data is only slightly different from the in the estimate using the LBD data. Specifically, if we estimate equation (2) on the sample of continuous LBD establishments, we obtain a density premium estimate of 0.072 (standard error of 0.008). If we estimate the same equation on our simulated establishments, we obtain an estimate of 0.067 (standard error of 0.003). This rough comparison suggests that establishment sorting accounts for only 7 percent of our estimated density premium.

We conclude this subsection by showing that relocations also have little effect on our finding that establishments realize a density premium almost entirely upon entry. One might worry that our earlier results do not distinguish between entry into a CBSA through birth and entry into a CBSA through relocation. The distinction has theoretical implications because a density premium realized primarily at birth is consistent with a model of spillovers through spinoffs, while a premium realized primarily at entry into a new city (regardless of age) would be consistent with models where firms gain returns to agglomeration through local comparative advantage, localized access to shared inputs, or other factors that benefit all firms at a given location.

We use our data on relocations between 1991 and 1997 to distinguish between establishment age and city tenure. We focus on the single cross-section of establishments active in 1997, which allows us calculate city tenure with accuracy up to its first 6 years. We then run a version of equation (3) that also allows the density premium to vary with city tenure, conditional on the establishment having moved at least once since 1991. The estimated equation is

$$\text{(4)} \qquad \ln w_{ejt}(a,\tau) = \alpha^2 + \varphi^2(a) + \beta^2 \ln D_{jt} + \zeta^2(a) \ln D_{jt} + \gamma^2 C_{jt} + \delta^2 \tilde{Z}_{et}$$
$$+\theta(\tau) + \eta I(m_t) + \mu(\tau) \ln D_{jt} + \nu(\tau)[\ln D_{jt} \cdot I(m_t)] + \varepsilon^2_{ejt}(a,\tau).$$

The equation is the same as before, except that it now includes dummies for whether the establishment has moved to its current CBSA since 1991, $I(m_t)$, city tenure, $\theta(\tau)$, with tenure τ top-coded at 6 years, and interaction of the city tenure dummies with (log) density, both unconditionally, and conditional on relocating from somewhere else. Figure 5 presents the estimates of the evolution of the density premium with respect to age ($\hat{\beta}^2 + \hat{\zeta}(a)$) and with respect to city tenure ($\hat{\beta}^2 + \hat{\mu}(\tau) + \hat{\nu}(\tau)$). We estimate that the density premium is about 6.0 percent at birth, independent of city tenure, and is again roughly constant over the life of the establishment. Conditional on age, we find that entry into a new city increases the density premium by 0.9 percent the first year, but the increase is not significant. The additional effect of density on relocating establishments varies between -0.6 percent and 1.6 percent in subsequent years, but these differences are also not statistically significant. As with age, we find no significant rise in the estimated premium with city tenure. Thus, we conclude that entry into a city at birth, rather than at any point in the life-cycle, is when establishments reap the greatest return to density.

5.C. Sorting through Entry

As a final exercise, we document differences in the earnings distribution of entrants between high-density and low-density CBSAs. Direct identification of establishment sorting through entry is virtually impossible because one cannot distinguish whether a birth occurred in a particular metropolitan area because the location was endogenously chosen over other locations or because the entrepreneur lives there. Figueiredo, Guimarães, and Woodward (2002) and Michelacci and Silva (2007) both find a strong "home bias" in the startup location choices of entrepreneurs. Using data from Italy, Michelacci and Silva find that the fraction of entrepreneurs operating where they were born was significantly larger than the fraction of dependent workers working where they were born. Since we cannot identify this distinction in our data, we only examine whether there is at least suggestive evidence of sorting in the earnings differences among entrants.

We examine differences in the earnings distribution across high-density and low-density metropolitan areas for entrants in absolute terms and relative to incumbent establishments. We focus on the earnings differences of entrants that are new firms relative to the differences of new establishments of multi-unit firms. The working hypothesis is that a multi-unit firm is more likely to endogenously choose the location of its new establishment, whereas a new, single-establishment firm is more likely to start up where its entrepreneur is resides. Therefore, a sorting mechanism should be stronger for the entrants of multi-unit firms.

Table 8 presents the statistics for the earnings distribution of entrants into CBSAs of the highest quartile and lowest quartile of the CBSA density distribution, using an earnings measure that conditions out establishment characteristics. Entrants in high-density CBSAs have earnings that are 21.2 percent higher, on average, than the earnings of entrants in low-density CBSAs. The difference in median earnings is nearly as large (18.0 percent).[21] Relative to the earnings of incumbent establishments in their respective CBSA categories, entrants in high-density CBSAs have earnings that are only 1.3 percent higher, on average, and relative median earnings are essentially equal. Entrants of multi-unit firms exhibit similar earnings differences between high-density and low-density CBSAs. In absolute terms, their mean earnings are 16.3 percent higher and their median earnings are 13.9 percent higher in high-density CBSAs. Relative to incumbents, multi-unit firm entrants in high-density CBSAs have mean earnings that are 3.6 percent *lower*, and median earnings that are 4.1 percent lower, in high-density CBSAs. More importantly, relative to all entrants, multi-unit entrants have mean earnings that are 4.9 percent lower, and median earnings that are 4.1 percent lower, in high-density CBSAs. These results are not a clear rejection of a role for sorting, but do not present any first-order evidence for the sorting of high-earnings entrants into high-density CBSAs.

[21] Without controlling for establishment characteristics, the difference in mean earnings is 26.0 percent and the difference in median earnings is 24.2 percent.

6. Conclusions

The density premium is a key feature of urban agglomerations. A large body of research has examined the premium afforded to individual workers, but few studies have explored the premium afforded to individual firms. Using longitudinal micro data on U.S. establishments, we estimate a density premium of about 7.4 percent after controlling for the college share of a metropolitan area and observable establishment characteristics. The estimate varies little across various subgroups of the data and is robust to instrumenting for the simultaneous determination of density and productivity as well as the use of alternative measures of density.

Our most striking finding is that the urban density premium does not rise with establishment age (or city tenure), implying that any potential returns to agglomeration are realized at birth and fixed over time. The result is in contrast to previous research on workers that find a steeper wage-city tenure profile in larger cities. We interpret the result as evidence that knowledge spillovers occur within a city through a reallocation channel rather than through a production spillover that affects incumbent firms. Our findings do not, however, preclude a role for knowledge spillovers as a source of urban growth. Models of innovation through firm spinoffs (e.g., Chatterjee and Rossi-Hansberg, 2012) are consistent with our interpretation, as are any models that stress a prominent role for firm entry in the transmission of returns to urban agglomeration. The key insight is that the diffusion of local knowledge and firm productivity are linked through the creation of new businesses and not necessarily through the exchange of knowledge between existing businesses.

Finally, we examine how much firm selection (through exit) and firm sorting (through relocation or entry) drive our results. While we find evidence of a selection effect in general, exit rates follow a similar pattern across the earnings distribution for both high-density and low-density metropolitan areas, suggesting that selection is not a main driver of observed urban density premia. We find weak evidence of sorting among establishments that relocate—high-earnings establishments are the most likely to relocate, and they move to relatively denser metropolitan areas, on average. At the same time, we find that all relocating establishments tend to move to *lower-density* metropolitan areas in absolute terms. We hypothesize that new establishments of multi-unit firms should be the most likely to have their location endogenously chosen, yet we find that they have weaker evidence of sorting, relative to new single-unit firms.

We conclude by identifying three avenues for future research. The first is advancing urban theory to include a more prominent role for firm entry, for the reasons we note above. The second is a deeper examination of the location choices and characteristics of new businesses. Our data allow us to provide only cursory evidence on firm sorting, though we provide robust evidence that much of the returns to urban agglomeration occur at entry. Understanding firm behavior at entry is therefore critical to understanding the nature of agglomeration economies. The third is an exploration of the relationship between a firm's return to city tenure and a worker's return to city tenure. There is a tension between our results and earlier research on workers. Geographic differences in the composition and turnover of an establishment's workforce no doubt play a role. Documenting and quantifying this role would provide a better understanding of how urban agglomeration affects both workers and firms.

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Table 1. Comparison of Results for Firm Selection in the Concrete Industry

Moment	Estimate from Syverson (2004), using TFP for y_{et}	Estimate from the LBD, using avg. earnings for y_{et}
Interquartile range of distribution of $\ln y_{et}$	-0.015 (0.004)	-0.028 (0.013)
Median value of $\ln y_{et}$	0.018 (0.003)	0.095 (0.015)
Size-weighted mean of $\ln y_{et}$[1]	0.024 (0.004)	0.081 (0.015)
Tenth percentile of distribution of $\ln y_{et}$	0.056 (0.010)	0.080 (0.027)
Mean plant size[1]	0.211 (0.012)	0.065 (0.016)
Producer-demand ratio[2]	-0.363 (0.015)	-0.680 (0.033)
Number of Observations	665	410

Notes: Table reports the estimates from the regression of the listed moment on a measure of demand density (the log of construction employment) and a year dummy across geographic locations (BEA Census Economic Areas for Syverson, and our sample of CBSAs for the LBD.) Estimates in the first column come from Syverson (2004, "Model 2" on p. 1206.), and estimates in the second column are authors' estimates from the LBD. See text for more details. Standard errors are in parentheses.

1. Size is measured as the log of total sales in Syverson (2004) and as the log of employment in the LBD.
2. The producer-demand ratio is the number of plants per 1,000 construction employees.

Table 2. Basic Statistics on Relationships between CBSA Establishment Characteristics and Density

	ln *Size* (employees)	Age (years)	Entry Rate (share of estabs.)	Exit Rate (share of estabs.)
Sample Mean	1.50	8.01	0.103	0.092
Std. Deviation across Establishments	1.37	6.80	0.304	0.289
Std. Deviation across CBSAs	0.10	0.86	0.009	0.015
OLS regression on ln(Density) and College Share				
$\ln D_j$	-0.007 (0.012)	0.189 (0.052)	-0.004 (0.001)	0.000 (0.002)
College Share, C_j	-0.186 (0.090)	-2.139 (0.672)	0.034 (0.015)	0.020 (0.012)
Establishment Controls	Yes	Yes	Yes	Yes
R^2	0.332	0.195	0.087	0.131
Number of Observations	10,256,604			

Notes: Table reports summary statistics for the listed variables in each column, as well as the results of regressions of the listed variables on the log of 1990 population density and the share of the 1990 population with a college degree. All regressions include a year dummy. Establishment characteristics, where listed, include the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC. Standard errors, clustered by CBSA, are in parentheses.

Table 3. Establishment-Level Relations between Earnings and Density

	All Establishments			
	(1)	(2)	(3)	(4)
$\ln D_j$	0.102 (0.007)	0.080 (0.010)	0.092 (0.010)	0.074 (0.010)
College Share, C_j		1.024 (0.102)		0.883 (0.093)
Year effects?	Yes	Yes	Yes	Yes
Controls for establishment characteristics?	No	No	Yes	Yes
R^2	0.014	0.017	0.310	0.313
Number of Observations	10,256,604			

Notes: Table reports estimates from the regression of the log of average establishment earnings on the listed variables for our sample of establishment-year observations from the LBD. Establishment characteristics include the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC. Standard errors, clustered by CBSA, are in parentheses.

Table 4. Establishment-Level Relations between Earnings and Density by Sub-Group

	Entrants and Exits		***Multi- & Single-Unit Firms***	
	Entrants	Exits	Single-Unit	Multi-Unit
$\ln D_j$	0.076 (0.011)	0.079 (0.013)	0.080 (0.010)	0.058 (0.009)
College Share, C_j	1.135 (0.129)	0.815 (0.100)	0.945 (0.108)	0.700 (0.088)
Year effects?	Yes	Yes	Yes	Yes
Controls for establishment characteristics?	Yes	Yes	Yes	Yes
R^2	0.257	0.271	0.279	0.460
Number of Observations	1,063,789	950,456	7,587,861	2,668,379

	By Establishment Size				
	1 to 9 Employees	10 to 99 Employees	100 to 249 Employees	250 to 999 Employees	1,000+ Employees
$\ln D_j$	0.079 (0.010)	0.064 (0.010)	0.067 (0.009)	0.075 (0.012)	0.071 (0.013)
College Share, C_j	0.926 (0.104)	0.769 (0.084)	0.862 (0.111)	0.749 (0.113)	0.703 (0.421)
Year effects?	Yes	Yes	Yes	Yes	Yes
Controls for establishment characteristics?	Yes	Yes	Yes	Yes	Yes
R^2	0.270	0.521	0.539	0.517	0.521
Number of Observations	7,578,426	2,437,528	171,787	58,707	10,156

	By Major Industry Group				
	Construction	Manufacturing	Retail Trade	Finance & Prof. Services	Local Services
$\ln D_j$	0.084 (0.019)	0.072 (0.016)	0.064 (0.016)	0.101 (0.012)	0.056 (0.005)
College Share, C_j	0.882 (0.214)	0.911 (0.135)	0.770 (0.099)	1.134 (0.124)	0.803 (0.099)
Year effects?	Yes	Yes	Yes	Yes	Yes
Controls for establishment characteristics?	Yes	Yes	Yes	Yes	Yes
R^2	0.154	0.279	0.254	0.219	0.280
Number of Observations	982,179	635,839	2,554,622	1,795,447	2,730,177

Notes: Table reports estimates from the regression of the log of average establishment earnings on the listed variables for our sample of establishment-year observations from the LBD. Establishment characteristics include the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC. Standard errors, clustered by CBSA, are in parentheses.

Table 5. Establishment-Level Relations between Earnings and Density, Alternative Specifications

Density Measure	Population Density	Population Density	Population Density	Population (Level)	Employment Density	Area-Wtd. Population Density
Estimation Method	OLS, Restricted Sample	IV, Restricted Sample	OLS, Emp.-Weighted	OLS	OLS	OLS
$\ln D_j$	0.098	0.104	0.067	0.056	0.073	0.095
	(0.007)	(0.009)	(0.010)	(0.006)	(0.010)	(0.006)
College Share, C_j	0.898	1.067	0.767	0.798	0.799	0.840
	(0.099)	(0.237)	(0.096)	(0.106)	(0.091)	(0.108)
Year effects?	Yes	Yes	Yes	Yes	Yes	Yes
Controls for establishment characteristics?	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.317	0.315	0.490	0.313	0.313	0.313
Number of Observations	7,761,264		10,256,604			

Notes: Table reports estimates from the regression of the log of average establishment earnings on the listed variables for our sample of establishment-year observations from the LBD. All regressions includes controls for year and observable establishment characteristics (the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC). The first two columns report the OLS and 2SLS estimates on a subsample of 283 CBSAs where we have the data on climate and geology that we use as instruments. These instruments include the fraction of the CBSA that is water-covered, the fraction above 1000m elevation, an index of the ruggedness of the land, the average annual temperature and moisture, the number of growing days, and the fraction of the land containing a set of 8 different soil types. The last four columns report OLS estimates where we use alternative specifications of urban density: the log of population density using an employment-weighted regression, the log of population, the log of employment density, and the log of population density generated by weighting each subunit of a metropolitan area by its total population. Standard errors, clustered by CBSA, are in parentheses.

Table 6. Statistics on the Earnings Distribution of Surviving Entrants in High- and Low-Density CBSAs

Statistic	*Change in Distributional Statistic: Five-Year Survivors - Entrants* Low-Density CBSAs	High-Density CBSAs	*Difference-in-Difference: High-Density – Low-Density*
Mean Earnings	0.268	0.252	-0.016
Median Earnings	0.208	0.200	-0.008
Standard Deviation	-0.224	-0.204	0.020
Interquartile Range	-0.269	-0.222	0.047
90-10 Ratio	-0.613	-0.545	0.068
50-10 Ratio	-0.435	-0.384	0.051
Entrant Survival Rate	0.485	0.479	
Observations	38,820	332,018	

Notes: Table reports distributional statistics of earnings of entering establishments that survived to their fifth year, pooled across the top quarter (high density) or bottom quarter (low density) of CBSAs, ranked by 1990 population density. Statistics are based on an estimate of average establishment earnings that controls for establishment characteristics (the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC).

Table 7. Summary Statistics of Relocating Establishments

Mean	Non-Relocating Establishments	Relocating Establishments	Difference
(log) Earnings	9.830 (0.812)	9.937 (0.903)	0.107 [0.003]
Size (employees)	19.08 (110.68)	19.67 (85.22)	0.59 [0.30]
Age (years)	8.59 (5.57)	6.34 (5.16)	-2.25 [0.02]
Percent in Multi-Unit Firms	27.3 (44.6)	23.5 (42.4)	-3.8 [0.1]
(log) Density at Origin	5.936 (1.048)	5.947 (1.068)	0.011 [0.002]
(log) Density at Destination	---	5.730 (1.049)	-0.217[1] [0.005]
College Share at Origin (Percent)	22.39 (5.46)	22.78 (6.09)	0.39 [0.02]
College Share at Destination (Percent)	---	22.07 (6.18)	-0.71[1] [0.03]
Observations	7,799,688	81,766	

Notes: Table reports summary statistics for establishments who relocated from one CBSA to another versus establishments that remained in place. Standard deviations of the statistics are in parentheses. Standard errors for the difference between statistics are in brackets.

1. Estimate represents the difference in log density (or college share) between the origin and destination CBSA.

Table 8. Statistics on the Earnings Distribution of Entrants in High- and Low-Density CBSAs

All Entrants

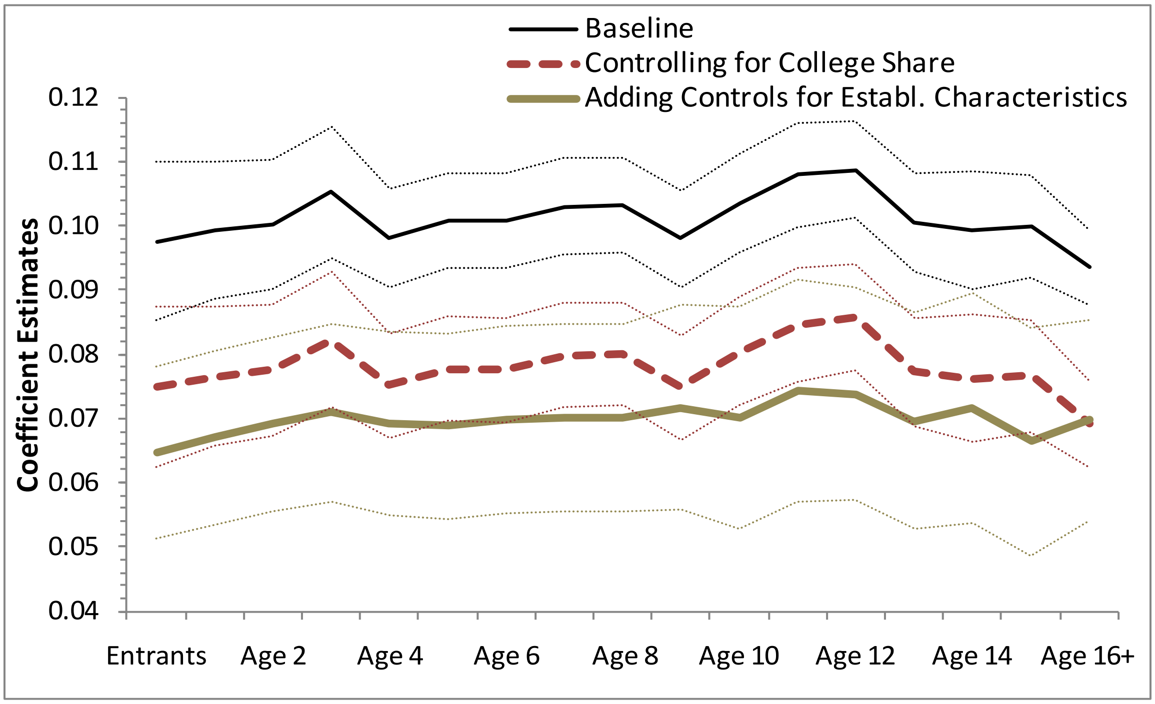
Statistic	Low-Density CBSAs	High-Density CBSAs	High – Low Density Difference: Absolute Difference	High – Low Density Difference: Relative to Incumbents
Mean Earnings	9.640	9.852	0.212	0.013
Median Earnings	9.756	9.936	0.180	0.000
Standard Deviation	0.883	0.910	0.026	-0.014
Observations	80,092	693,139		

Entrants of Multi-Unit Firms

Statistic	Low-Density CBSAs	High-Density CBSAs	High – Low Density Difference: Absolute Difference	High – Low Density Difference: Relative to Incumbents	High – Low Density Difference: Relative to All Entrants
Mean Earnings	9.860	10.023	0.163	-0.036	-0.049
Median Earnings	9.906	10.045	0.139	-0.041	-0.041
Standard Deviation	0.677	0.737	0.060	0.019	0.033
Observations	18,530	165,691			

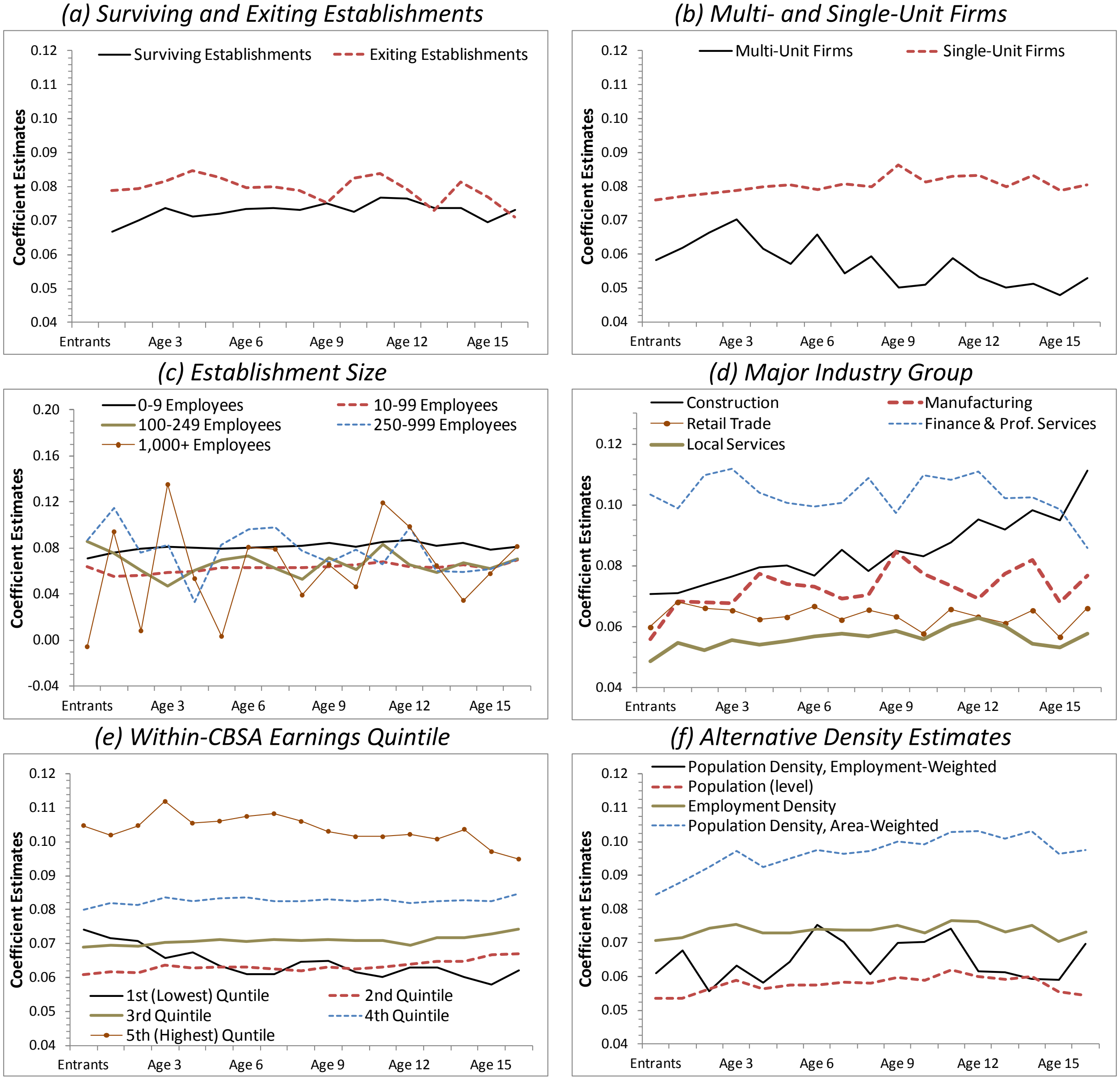
Notes: Table reports distributional statistics of earnings of entering establishments pooled across the top quarter (high density) or bottom quarter (low density) of CBSAs, ranked by 1990 population density. Statistics based on an estimate of average establishment earnings that controls for establishment characteristics (the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC).

Figure 1. Estimated Elasticity of Earnings with respect to Density by Establishment Age



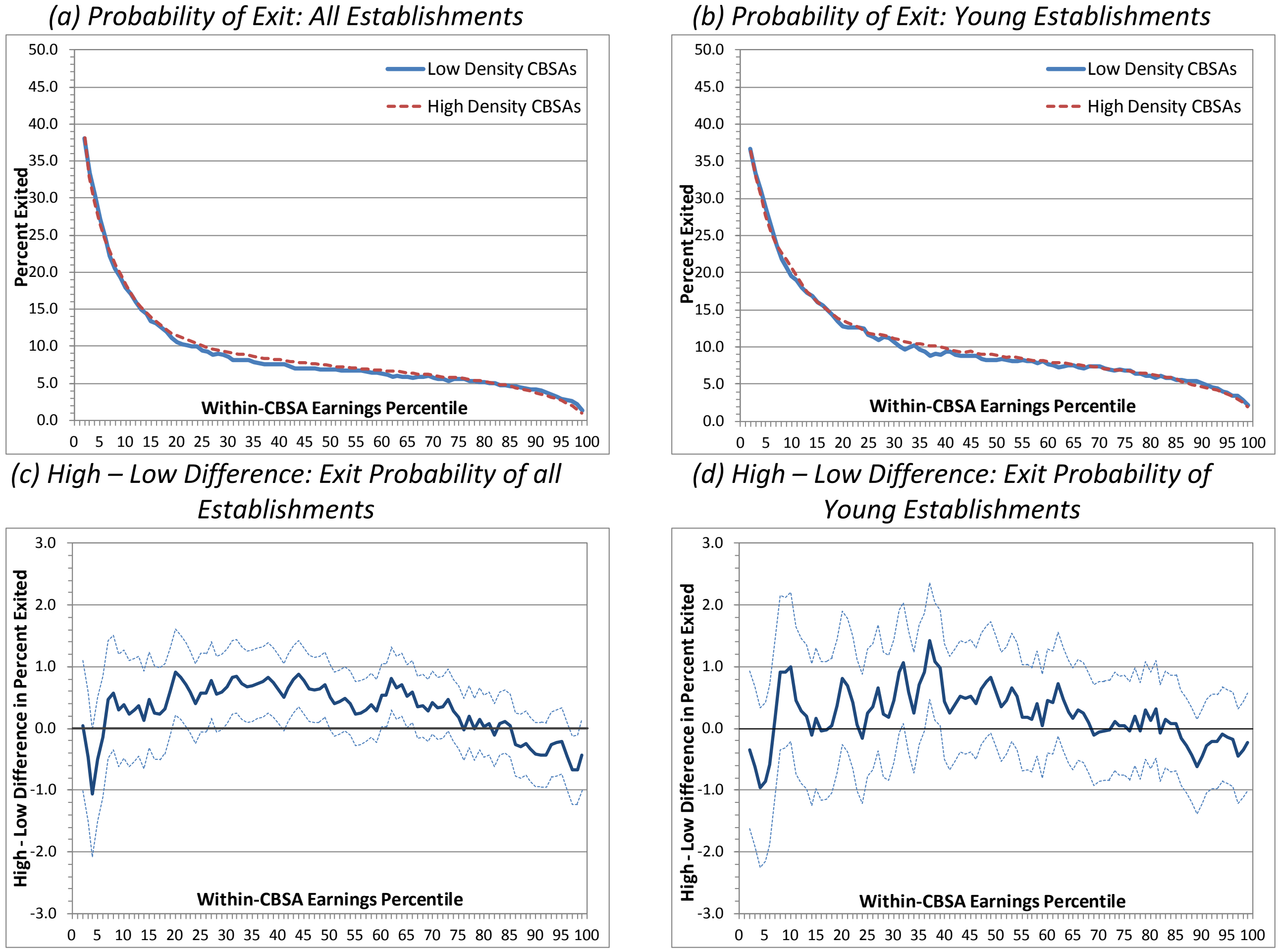
Note: The figure plots the predicted elasticity of earnings with respect to density as a function of age. Estimates come from equation (3) in the text. See text for details. Thin dashed lines represent standard error bands, with standard errors clustered by CBSA.

Figure 2. Elasticity of Earnings with respect to Density by Establishment Age and Sub-Group



Note: Each panel of the figure plots the predicted elasticity of earnings with respect to density as a function of age within each reported category. Estimates come from equation (3) in the text. See text for details. Thin dashed lines represent standard error bands, with standard errors clustered by CBSA.

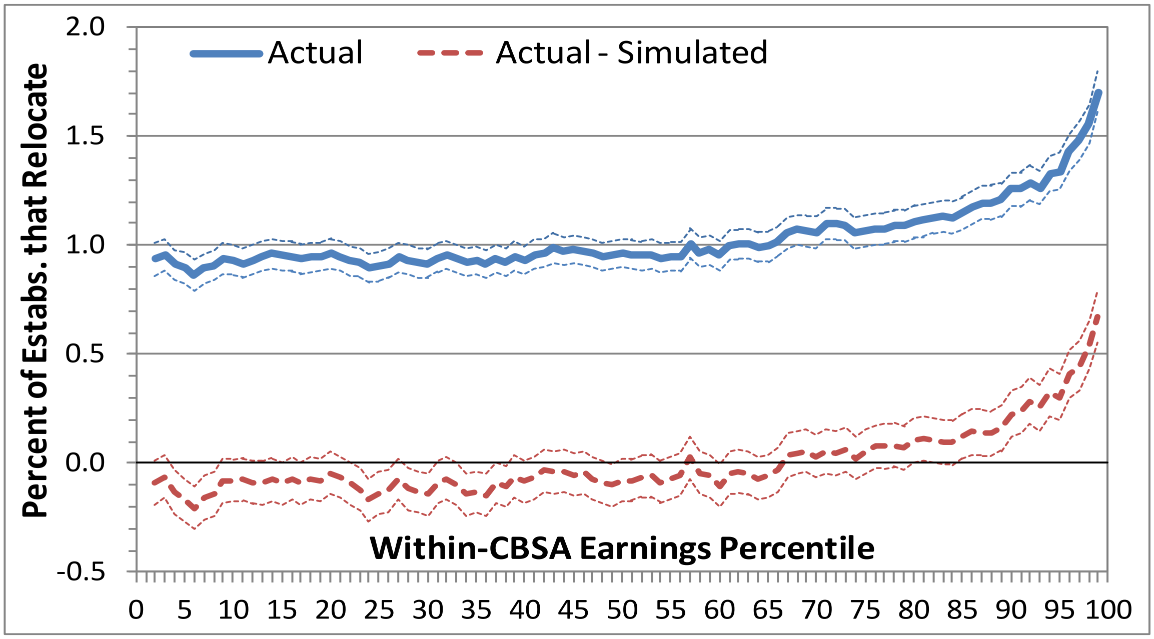
Figure 3. Establishment Exit Probabilities by CBSA Earnings Percentile



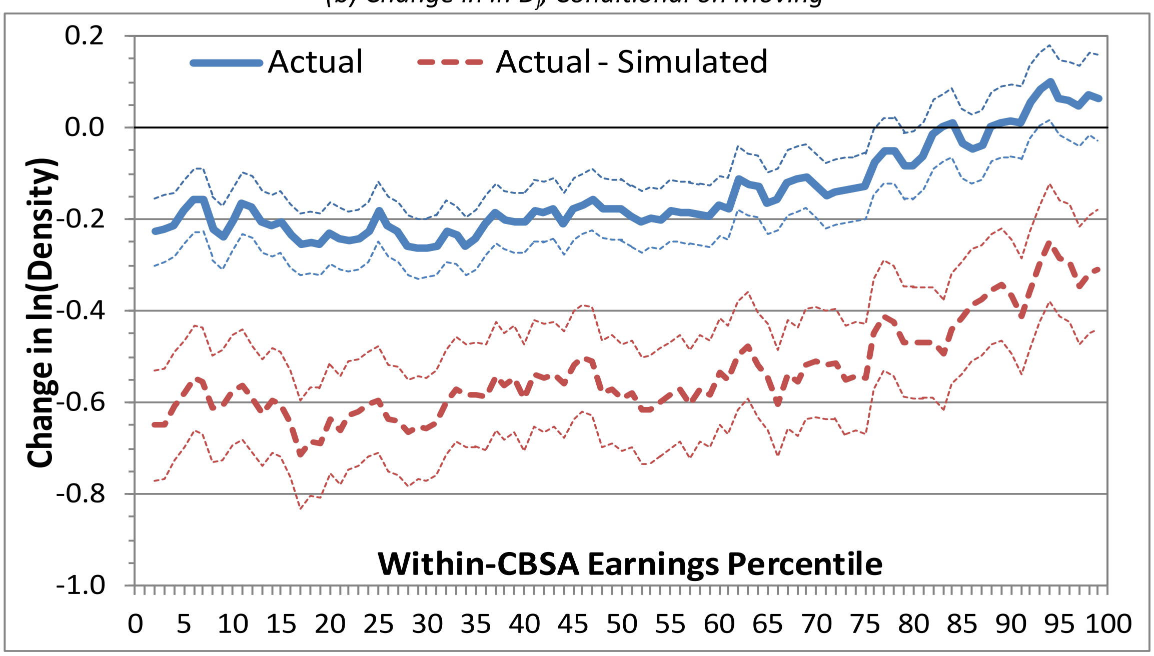
Note: Top panels report the probability of an establishment exiting by percentiles of the within-CBSA earnings distribution for CBSAs grouped into the highest and lowest quartiles of the CBSA density distribution. Bottom panels report the difference in exit probabilities between high-density and low-density CBSAs. The left panels are for all establishments while the right panels are for establishments aged 5 years or less. All probabilities and earnings are conditional on establishment characteristics (size, age, industry, multi-unit firm status). All panels report 3-percentile, centered averages to smooth the estimates.

Figure 4. Establishment Relocation Probabilities and Density Changes by CBSA Earnings Percentile

(a) Probability of Moving

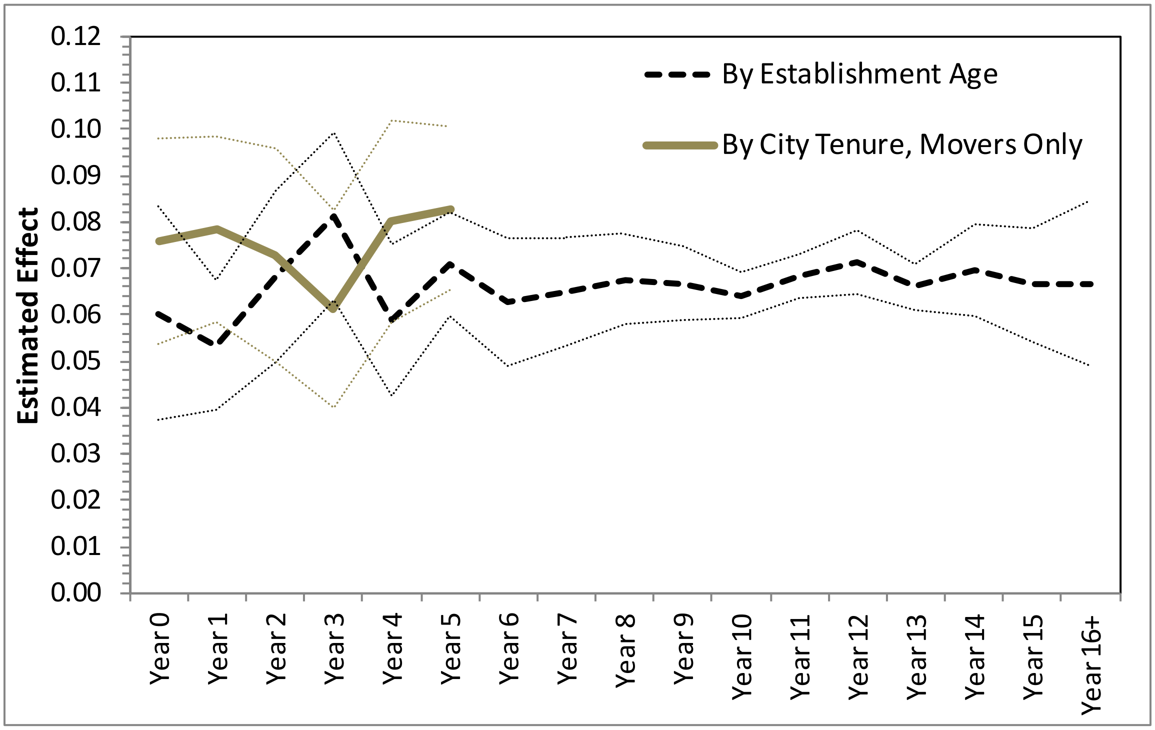


(b) Change in ln D_j, Conditional on Moving



Note: Top panel reports the probability of an establishment relocating from one CBSA to another by percentiles of the earnings distribution of the origin CBSA. Bottom panel reports the change in an establishment's CBSA (log) density, conditional on relocating, by the same percentile measure. Thick solid blue lines represent outcomes from the data using an earnings and move probability measure that conditions out establishment characteristics (size, age, industry, multi-unit firm status). Thick dashed red lines represent estimates from the data less the outcome predicted from a simulation where all establishments have an equal probability of a move to a random CBSA. Thin dashed lines represent 95 percent confidence intervals. All panels report 3-percentile, centered averages to smooth the estimates.

Figure 5. Estimated Elasticity of Earnings with respect to Density by Age and City Tenure



Note: The figure plots the predicted elasticity of earnings with respect to density as a function of age and as a function of CBSA tenure, independent of age and conditional on moving to the CBSA within the previous 6 years. Estimates come from equation (4) in the text. See text for details. Thin dashed lines represent standard error bands, with standard errors clustered by CBSA.

Web Appendix for "The Urban Density Premium across Establishments"

A. Measuring Average Earnings

As described in Section 2, we measure average earnings for establishments as payroll per worker in a way that accounts for the timing of the data reported and establishment entry and exit. We then evaluate our average earnings measure for potential outliers and impute a new estimate where appropriate.

In general, our procedure evaluates the average earnings measure with two criteria. The first is whether the earnings measure exhibited extreme changes in from the preceding period and to the next period. The second is whether the earnings measure is an extreme value. We then impute a value that attempts to use as much information as possible from the leading and lagging earnings measures, conditional on those measures themselves not being extreme values. If this criterion fails, we impute the median earnings for an establishment's industry.

The algorithm for evaluation is as follows. Let $g_{eit}^{w} = \frac{w_{eit} - w_{ei,t-1}}{\frac{1}{2}(w_{eit} + w_{ei,t-1})}$ equal the growth rate of average earnings for establishment *e* in two-digit SIC industry *i* between year *t* – 1 and *t.* It uses the growth measure of Davis, Haltiwanger, and Schuh (1996) because it provides a symmetric treatment of increasing and decreasing growth rates that is bounded within [-2, 2]. Let $\bar{w}_{it}$ be median average earnings in industry *i* in year t, and let $\widetilde{w}_{ei,s}^{t} = \frac{w_{ei,s} - \bar{w}_{it}}{\frac{1}{2}(w_{ei,s} + \bar{w}_{it})}$ be a measure of the average earnings of an establishment in year *s* relative to the median average earnings in its industry in year t. The measure is scaled so that extremely high and extremely low values (in percentage terms) receive symmetric treatment.

Our evaluation method depends on whether the establishment has positive employment in the preceding and proceeding years. If an establishment has positive employment in both years, we impute its average earnings in year *t* if

i) $|g_{eit}^{w}| > 1.96$ and $|g_{ei,t+1}^{w}| > 1.96$, or

ii) $|\widetilde{w}_{ei,t}^{t}| > 1.96$.

In other words, we impute the value if the change in average earnings if it is within 4 percent of the maximum absolute value of the growth rate measure, or if the value relative to the industry median is within 4 percent of its maximum absolute value using our relative earnings measure. The value that we choose for imputed average earnings, $\widehat{w}_{eit}$, depends on whether the leading and lagging average earnings estimates exhibit extreme values:

$$\widehat{w}_{eit} = \begin{cases} \frac{1}{2}(w_{ei,t-1} + w_{ei,t+1}) & \text{if } \left| \frac{\frac{1}{2}(w_{ei,t+1}+w_{ei,t-1})-\overline{w}_{it}}{\frac{1}{2}\left[\frac{1}{2}(w_{ei,t+1}+w_{ei,t-1})+\overline{w}_{it}\right]} \right| \leq 1.96, \text{ and} \\ \overline{w}_{it} & \text{otherwise.} \end{cases}$$

In words, if the average of average earnings in t + 1 and t – 1, relative to median industry earnings is not an extreme value (as defined by a modified version of our relative earnings measure $\widetilde{w}_{ei,t}^{t}$), we use the average of the leading and lagging average earnings estimates. Otherwise, we use the median industry earnings.

If an establishment only has positive employment in *t* – 1, we impute the value of average earnings in *t* if

i) $|g_{eit}^{w}| > 1.96$, or

ii) $|\widetilde{w}_{ei,t}^{t}| > 1.96$.

The value we use in the imputation depends on whether the average earnings measure in *t* – 1 is an extreme value, relative to median industry earnings:

$$\widehat{w}_{eit} = \begin{cases} w_{ei,t-1} & \text{if } |\widetilde{w}_{ei,t-1}^{t}| \leq 1.96, \text{ and} \\ \overline{w}_{it} & \text{otherwise.} \end{cases}$$

Similarly, if an establishment only has positive employment in $t + 1$, we impute the value of average earnings in t if

i) $\left|g^{w}_{ei,t+1}\right| > 1.96$, or

ii) $\left|\widetilde{w}^{t}_{ei,t}\right| > 1.96$.

The value we use in the imputation depends on whether the average earnings measure in $t + 1$ is an extreme value, relative to median industry earnings:

$$\widehat{w}_{eit} = \begin{cases} w_{ei,t+1} & \text{if } \left|\widetilde{w}^{t}_{ei,t+1}\right| \leq 1.96, \text{ and} \\ \overline{w}_{it} & \text{otherwise.} \end{cases}$$

Finally, for establishments that only have positive employment in year t, we only impute the average earnings value if $\left|\widetilde{w}^{t}_{ei,t}\right| > 1.96$, in which case we use $\overline{w}_{it}$was the imputed value.

Combined, all four cases of the imputation algorithm affect relatively few establishments, with less than one-tenth of one percent of establishments affected in any given year in our sample.

B. Average Earnings as a Proxy for Productivity

We replicate the Syverson (2004) study using the LBD data in an identical subsample: plants in the ready-mix concrete industry (SIC 3273) with at least 5 employees in locations with at least 5 plants for the years 1982, 1987, and 1992. Our analyses differ in only three regards: i) we use data from the LBD rather than from the Census of Manufactures, ii) we use the CBSA definitions rather than the Component Economic Area (CEA) definitions of a metropolitan area, and iii) we use the log of average earnings instead of the log of TFP. The first difference is negligible as, during economic census years, the coverage of the LBD and Census of Manufactures is nearly identical. The main implication of the second difference is that, unlike Syverson's analysis, our analysis excludes rural locations (CEA definitions cover non-metropolitan areas). The third difference is the margin of interest.

Syverson focuses on six moments: the (weighted) mean, median, and interquartile range of the TFP distribution; the TFP of the plant at the tenth percentile of the TFP distribution; (log) average plant size; and the producer-demand ratio (the number of plants per 1,000 construction workers). He regresses each moment separately on (log) density. He finds that areas with greater demand density have a less disperse TFP distribution that exhibits greater lower truncation. These areas also have higher average TFP, larger plants, and a lower producer demand ratio.

C. Additional Estimates of the Density Premium

Figure C.1 shows the scatter plot of the relationship between the log of average establishment earnings and the log of population density across CBSAs. The relationship implies an elasticity of average earnings with respect to density of 8.1 percent, with a standard error of 0.7 percent. Controlling for college share only reduces the elasticity to 7.8 percent (with a standard error of 0.7 percent).[1]

Figure C.2 shows the full distribution of earnings for two subsets of the data: establishments in the top quartile and in the bottom quartile of CBSAs, ranked by their population density.[2] The data are pooled over both years and the kernel density estimates are based on an unconditional earnings measure. The figure clearly shows a rightward shift of the entire earnings distribution for establishments in the high-density CBSAs. Among continuing establishments, median earnings are 23 percent higher in high-density CBSAs unconditionally, and 14 percent higher when controlling for establishment characteristics. The earnings distribution in the densest CBSAs also exhibits greater dispersion. The 90-10 ratio is 9.8 log points larger in high-density CBSAs unconditionally and 14.6 log points larger after controls. With such differences in both the levels and dispersion of average earnings across CBSAs, it is natural to examine whether the establishments experience a greater density premium at different points of the earnings distribution. Notably, the earnings distribution across high-density and low-density CBSAs among just entering establishments, shown in Figure C.3, appear very similar to those for the full sample, consistent with our finding that the gains to agglomeration are largely realized at entry.

[1] The coefficient on the college share is 0.33 with a standard error of 0.10.
[2] The least-dense CBSA in the top quartile is Louisville-Jefferson County, KY-IN and the densest CBSA in the top quartile is Niles-Benton Harbor, MI.

Figure C.4 plots the predicted value of earnings from the regression of equation (3) in the main text, ignoring controls for college share and establishment characteristics. Specifically, it plots $\hat{\varphi}(a) + \left(\hat{\beta}^1 + \hat{\zeta}(a)\right) \ln D_j$, with density evaluated at its value for the CBSAs ranked at the 90th, 50th, and 10th percentiles of the population density distribution.[3] The figure shows that earnings are higher in more dense areas and that earnings rise with establishment age. Notably, there is no evidence of fanning out of the earnings-age profiles.

Figure C.5 plots the estimated density premium with respect to age using the restricted sample of establishments where we have data available for our instrumental variables. With respect to equation (3), it plots the coefficients $\hat{\beta}^1 + \hat{\zeta}(a)$ from an OLS and 2SLS estimation. To maintain the rank and order conditions of the 2SLS regression, we treat all interactions of establishment age with log density as endogenous and add interactions of the age dummy variables with our climate and geology variables as additional instruments. Estimates are nearly identical, and the estimated density premium is essentially independent of age in both cases.

In Table C.1, we present estimates from CBSA-level regressions of (log) density and college share on the instruments used in the first-stage of our 2SLS regressions (Table 6 in the paper). Since all instruments are at the CBSA level, these regressions provide a better sense of the explanatory power of our instruments. We also present the diagnostic statistics of the instruments from the (establishment-level) first-stage regressions themselves. The geological, climate, and soil instruments are based on the instruments used by Combes et al. (2010). Most have some explanatory power, and both the R-squared of the CBSA-level regression and the F-statistic on the instruments from the first-stage regression suggest they are fairly strong instruments for log density. The instruments have substantially less power in explaining the variation in CBSA college share.

[3] These CBSAs correspond to the Santa Cruz-Watsonville, CA CBSA, the Des Moines-West Des Moines, IA CBSA , and the Yakima, WA CBSA, respectively. While not reported, the predicted earnings estimates for the two specifications with additional controls produce qualitatively similar results.

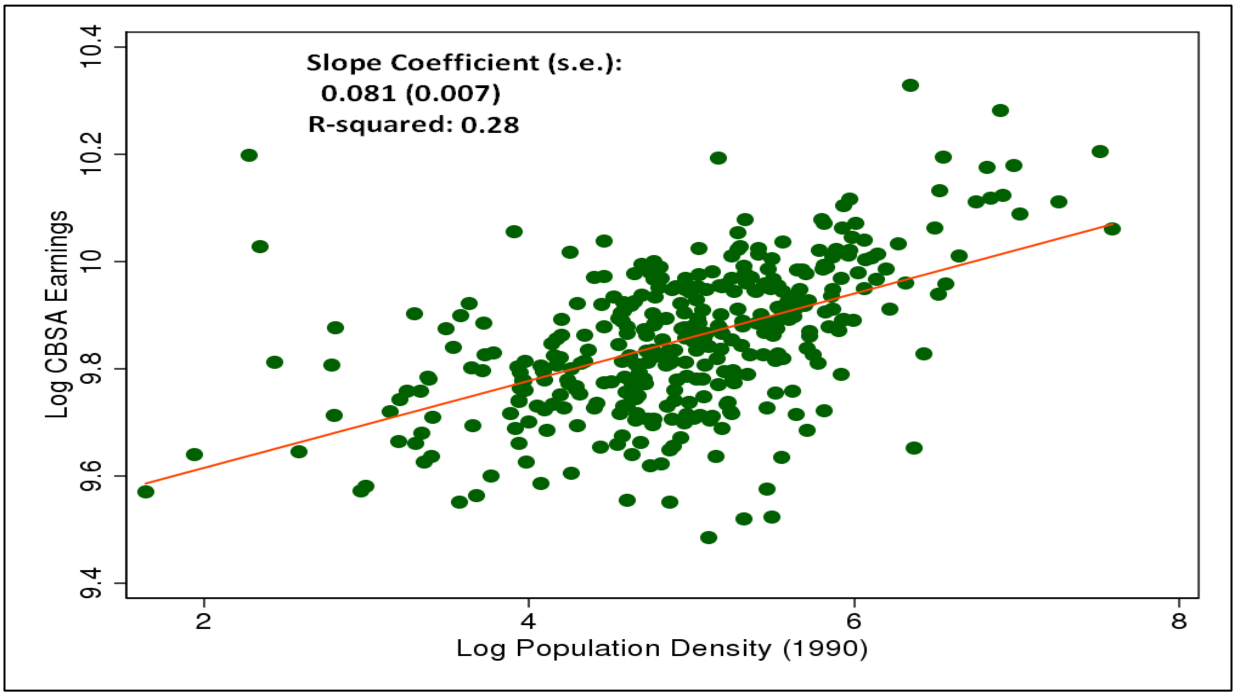
Tables C.2 and C.3 presents additional estimates of the urban density premium by quintiles of the within-CBSA earnings distribution. The exercise seeks to confirm evidence of *productivity-biased* returns to agglomeration originally found by Combes et al. (2012) when they examined the returns to TFP of French firms. It is related to findings of differential returns to density by worker skill by Glaeser and Mare (2001), Gould (2007), and Glaeser and Resseger (2010). To test for the presence of such returns in our data, we split the earnings distribution of each CBSA into quintiles and create five estimation subsamples that pool together all establishments within the same quintile of their respective CBSA. We then estimate the density premium using equation (2) for each subsample.

Table C.2 presents the results for three specifications, equivalent to the specifications in the first, second, and fourth columns of Table 3 of the text.[4] Across all specifications, the estimates show an increase in the estimated density premium when moving from the lowest to the highest earnings quintile. Without controls, the difference in the estimated elasticity between the lowest and highest quintile is 6.4 percentage points, with the estimate of the highest quintile (14.4 percent) about 80 percent higher than the estimate of the lowest quintile (8.0 percent). With all controls included, the difference is 3.5 percentage points, and the estimated premium in the highest quintile (10.2 percent) is about 52 percent higher than the estimated premium in the lowest quintile (6.7 percent). Thus, like Combes et al. (2012), we find strong evidence of "productivity-biased" returns to agglomeration, though we estimate a smaller difference between high-productivity and low-productivity establishments. We do so despite using average earnings rather than TFP as a productivity measure and despite examining urban density rather than city size.

[4] We also experimented with an alternative estimation strategy that first conditioned out observable establishment characteristics from the average earnings measure then sorted establishments into their CBSA quintiles based on the resulting residual earnings measure prior to estimating the density premium. The approach produced very similar results to the ones reported in Table 4.

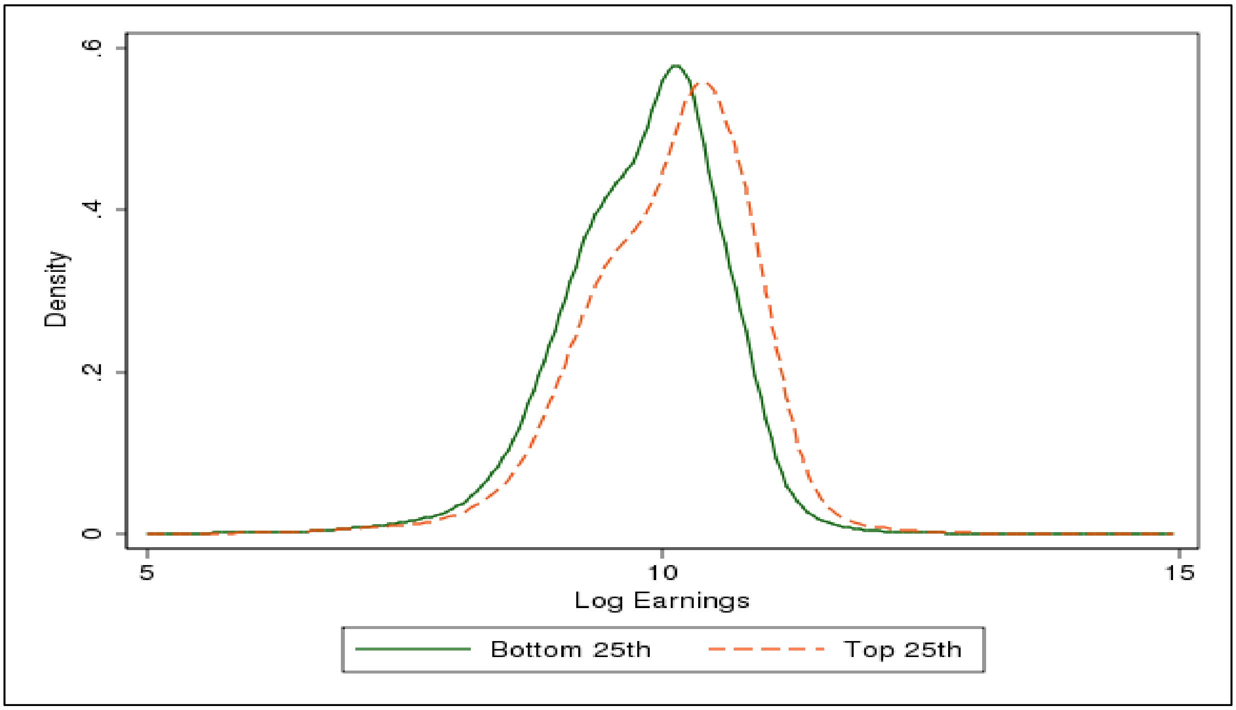
Table C.3. presents additional estimates of the urban density premium by earnings quintile using alternative measures and different subsamples. These include regressions in which we weight the regressions by establishment employment, measure density as the population level as opposed to the log, measure density as log employment, use area-weighted log population density. We find very similar results across these different specifications. Specifically, we find a large and statistically significant urban density premium that is generally increasing in establishment earnings.

Figure C.1. The Relationship between CBSA Earnings and Density



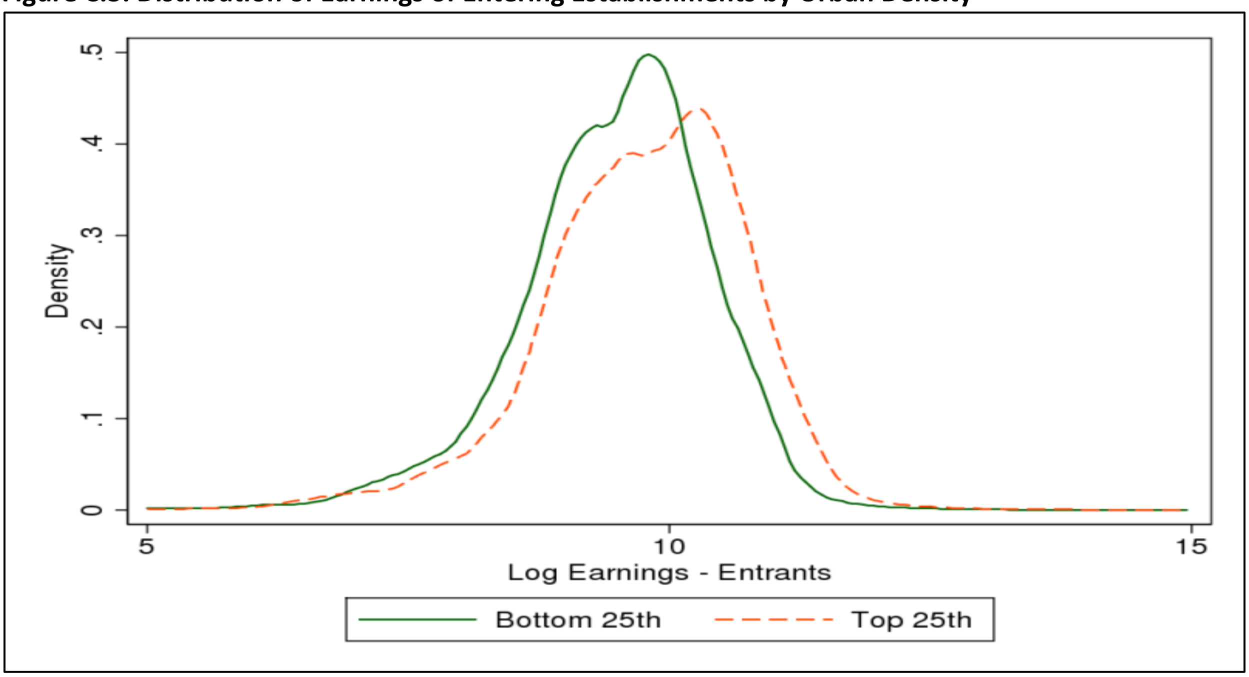
Note: The figure plots the relation between the log of average earnings on log 1990 population density for the 363 CBSAs of our sample, along with the fitted linear trend and its slope and *R*-squared value.

Figure C.2. The Distribution of Earnings in High- and Low-Density Metropolitan Areas



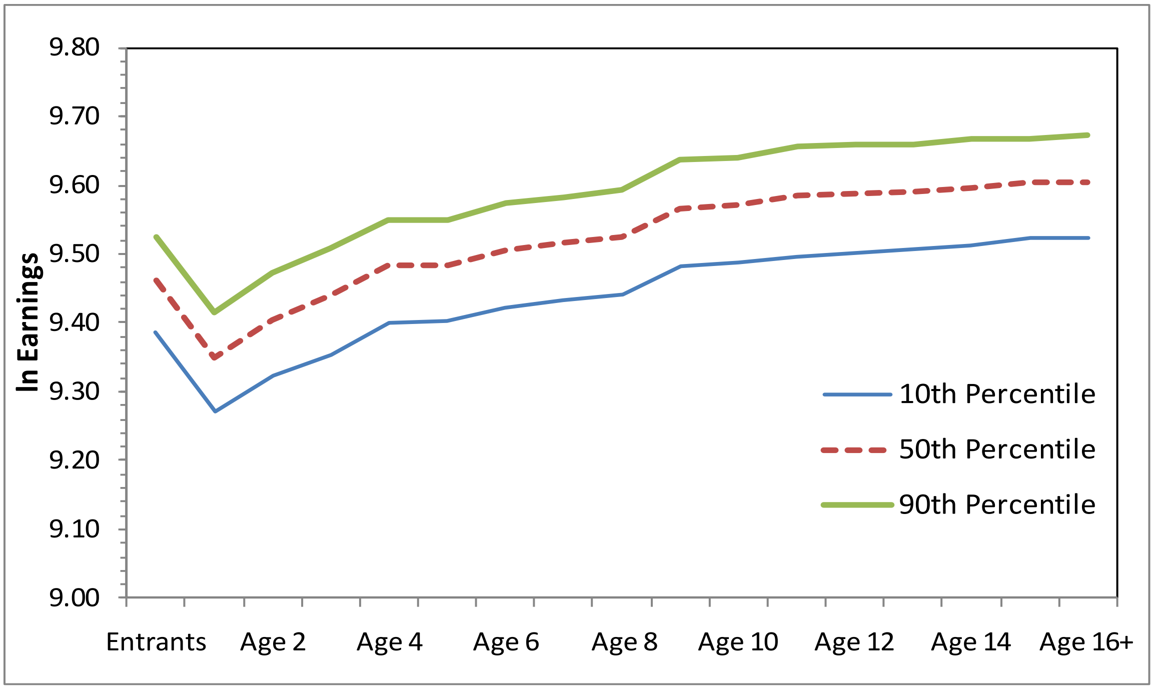
Note: The figure plots the kernel density estimates of the distribution of log average earnings for the 91 CBSAs in the bottom quartile of the density distribution (solid line) and the 91 CBSAs in the top quartile of the density distribution (dashed line), respectively.

Figure C.3. Distribution of Earnings of Entering Establishments by Urban Density



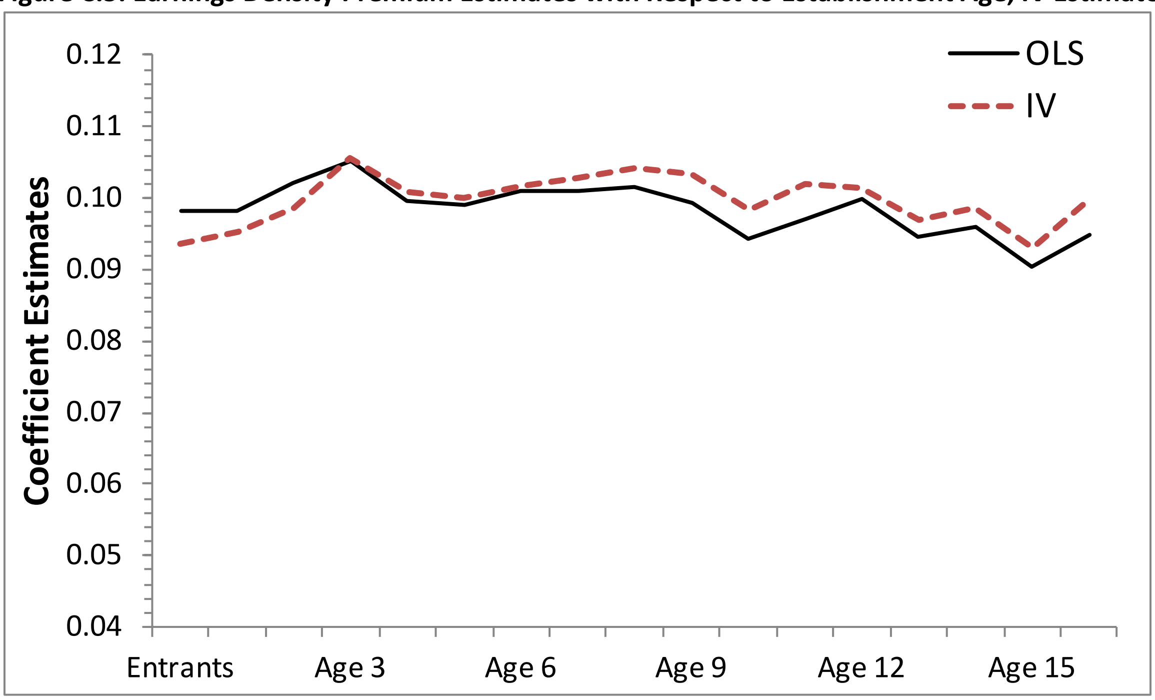
Note: The figure plots the kernel density estimates of the distribution of log average earnings for entering establishments in CBSAs in the bottom (solid line) and top (dashed line) quartiles of the density distribution, respectively. The top panel shows the unconditional distributions, while the bottom panel shows the distributions of earnings relative to mean CBSA earnings.

Figure C.4. Estimated Elasticity of Earnings with respect to Density by Establishment Age



Note: The figure plots predicted earnings from the estimation of equation (3) in the text for CBSAs at the 10^{th}, 50^{th}, and 90^{th} percentiles of the population density distribution. See text for estimation details.

Figure C.5. Earnings Density Premium Estimates with Respect to Establishment Age, IV Estimates



Note: The figure plots the predicted elasticity of earnings with respect to density as a function of age for both an OLS and IV estimation using observations where we have data on CBSA geology and climate. Estimates come from either an OLS or 2SLS estimation of equation (3) in the text. See text for details.

Table C.1. CBSA-Level Regression of CBSA Characteristics on Instruments and First-Stage Regression Diagnostics

CBSA-Level Regressions		
Dependent Variable	**Density, $\ln D_j$**	**College Share, C_j**
Fraction of CBSA Water-Covered	0.457** (0.142)	-0.009 (0.013)
Fraction of CBSA > 1000m Elevation	0.832 (0.815)	-0.051 (0.073)
Mean CBSA Elevation	-0.0012* (0.0004)	-0.0001 (0.0000)
Ruggedness Index	0.0001 (0.0002)	0.0001** (0.0000)
Mean Annual Temperature	-0.008 (0.043)	-0.004 (0.004)
Mean Annual Moisture	0.0052* (0.0026)	-0.0001 (0.0002)
Number of Growing Days	-0.0008 (0.0039)	0.0002 (0.0004)
Soil Type Dummies	Yes	Yes
F-test: Joint Significance of Soil Types (*p*-value)	3.75 (0.000)	1.61 (0.021)
R-Squared	0.280	0.098
Establishment-Level Regressions, First Stage		
F-test: Joint Significance of Instruments in First Stage (*p*-value)	15.30** (0.000)	2.21 (0.138)
R-Squared, First Stage Regression	0.447	0.384

Notes: Table reports estimates comparable first stage regressions for the instrumental variables estimates in Table 4 of the text. Regressions are all at the CBSA level (*N* = 283 CBSAs). The first column reports results for the regression of (log) 1990 population density on the listed statistics. The second regression reports the results for the regression of the 1990 CBSA college share on the listed statistics. The ruggedness index the maximum-minimum difference in elevation (in meters). Soil type dummies represent fixed effects for the presence of the following soils: alfisol, aridisol, entisol, histosol, inceptisol, mollisol, spodosol, ultisol, and vertisol. Standard errors are in parentheses.

** Significant at the 1 percent level. * Significant at the 5 percent level.

Table C.2. Establishment-Level Relations between Earnings and Density across the Earnings Distribution

	Lowest Quintile	Second Quintile	Middle Quintile	Fourth Quintile	Highest Quintile
I. Within-Quintile Regression of Earnings on Density, Unconditional					
$\ln D_j$	0.080	0.083	0.096	0.110	0.144
	(0.011)	(0.009)	(0.008)	(0.007)	(0.008)
R^2	0.022	0.212	0.294	0.332	0.086
II. Within-Quintile Regression of Earnings on Density, Controlling for College Share					
$\ln D_j$	0.067	0.064	0.072	0.084	0.117
	(0.011)	(0.008)	(0.007)	(0.007)	(0.009)
College Share, C_j	0.637	0.919	1.103	1.213	1.285
	(0.119)	(0.101)	(0.107)	(0.119)	(0.145)
R^2	0.023	0.270	0.381	0.422	0.102
III. Within-Quintile Regression of Earnings on Density, Controlling for College Share and Characteristics					
$\ln D_j$	0.067	0.063	0.071	0.083	0.102
	(0.012)	(0.008)	(0.007)	(0.007)	(0.007)
College Share, C_j	0.640	0.913	1.089	1.188	1.116
	(0.107)	(0.099)	(0.104)	(0.116)	(0.133)
Controls for establishment characteristics?	Yes	Yes	Yes	Yes	Yes
R^2	0.104	0.296	0.407	0.446	0.278
Number of Observations	2,034,039	2,051,268	2,057,161	2,057,383	2,056,753

Notes: Table reports estimates from the regression of the log of average establishment earnings on log 1990 population density, and 1990 college share, where listed, within each quintile an establishment-year observation's CBSA-specific earnings distribution. All regressions include a year dummy. Establishment characteristics include the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC. Standard errors, clustered by CBSA, are in parentheses.

Table C.3. Estimates of the Urban Density Premium by Earnings Quintile, Alternative Measures

	Lowest Quintile	Second Quintile	Middle Quintile	Fourth Quintile	Highest Quintile
I. Using Population Density, Employment-Weighted Regressions					
$\ln D_j$	0.057	0.061	0.068	0.080	0.091
	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)
College Share, C_j	0.812	0.874	1.098	1.074	0.961
	(0.121)	(0.090)	(0.109)	(0.112)	(0.110)
R^2	0.151	0.313	0.439	0.471	0.347
II. Using Population (Level)					
D_j	0.049	0.049	0.056	0.067	0.083
	(0.008)	(0.004)	(0.004)	(0.004)	(0.005)
College Share, C_j	0.583	0.831	0.986	1.051	0.945
	(0.120)	(0.110)	(0.114)	(0.124)	(0.148)
R^2	0.104	0.308	0.430	0.480	0.286
III. Using Employment Density					
$\ln D_j$	0.067	0.065	0.074	0.085	0.104
	(0.011)	(0.008)	(0.007)	(0.007)	(0.007)
College Share, C_j	0.556	0.818	0.977	1.065	0.978
	(0.112)	(0.102)	(0.102)	(0.111)	(0.125)
R^2	0.105	0.308	0.425	0.463	0.278
IV. Using Area-Weighted Population Density					
$\ln D_j$	0.077	0.071	0.083	0.100	0.124
	(0.011)	(0.006)	(0.008)	(0.012)	(0.017)
College Share, C_j	0.660	0.947	1.119	1.187	1.098
	(0.132)	(0.119)	(0.121)	(0.135)	(0.159)
R^2	0.102	0.277	0.391	0.434	0.275
Number of Observations	2,034,039	2,051,268	2,057,161	2,057,383	2,056,753
V. Using Population Density, Restricted Sample, OLS					
$\ln D_j$	0.086	0.082	0.093	0.107	0.122
	(0.008)	(0.004)	(0.006)	(0.008)	(0.008)
College Share, C_j	0.699	0.954	1.093	1.170	1.130
	(0.096)	(0.098)	(0.108)	(0.123)	(0.148)
R^2	0.112	0.350	0.465	0.497	0.281
VI. Using Population Density, Restricted Sample, Two-Stage Least Squares					
$\ln D_j$	0.089	0.071	0.078	0.087	0.097
	(0.012)	(0.010)	(0.010)	(0.011)	(0.015)
College Share, C_j	0.878	1.304	1.471	1.588	1.524
	(0.177)	(0.225)	(0.275)	(0.314)	(0.360)
R^2	0.107	0.293	0.382	0.400	0.260
Number of Observations	1,538,292	1,552,522	1,556,699	1,556,821	1,556,928

Notes: Table reports estimates from the regression of the log of average establishment earnings on log 1990 population density, and 1990 college share, where listed, within each quintile an establishment-year observation's CBSA-specific earnings distribution. All regressions include a year dummy. Establishment characteristics include the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC. Standard errors, clustered by CBSA, are in parentheses.

Table C.3. Earnings-Density Relationship Estimates based on Establishment Relocations

	Continuous Establishments			
	Levels Specification		**First Difference Specification**	
	(1)	(2)	(1)	(2)
(*change in*) $\ln D_j$	0.101 (0.007)	0.072 (0.008)	0.008 (0.004)	0.007 (0.003)
(*change in*) *College Share,* C_j		0.915 (0.091)		0.008 (0.030)
Year effects?	Yes	Yes	Yes	Yes
Controls for establishment characteristics?	No	Yes	No	Yes
R^2	0.017	0.354	0.001	0.167
Number of Observations	7,881,354			

Notes: Table reports estimates from the regression of the log of average establishment earnings on the listed variables, or the change in (log) earnings on the change in the listed variables, for our sample of establishment-year observations from the LBD. Establishment characteristics in the levels specification include the log of establishment employment, a dummy for whether the establishment is part of a multi-unit firm, fixed effects for age, and fixed effects for four-digit SIC. Establishment characteristics in the first-difference specification include the change in establishment employment and age fixed effects. First differences are measured year-over-year (1991-92 or 1996-97 for continuous establishments observed in 1992 or 1997, respectively). Standard errors, clustered by CBSA, are in parentheses.

D. Establishment Relocations: Additional and Simulated Results

Additional Results on Relocation Behavior

We also estimate the probability of relocating and the average change in CBSA density, conditional on relocating, based on the earnings distribution of the full establishment sample. These estimates are in Figure D.1. The results are qualitatively similar to those in Figure 8 of the main text. The notable exception is that, based on the full distribution, there is no observed difference in the change in CBSA density with respect to establishment earnings. Establishments in the top 20 percent of their within-CBSA distribution are interspersed across the earnings distribution of the full sample because CBSAs vary in their mean earnings. Once we control for what density changes would look like under completely random relocations across CBSAs, however, we obtain results that are very similar to those in the main text.

Generating Simulated Relocation Results

We simulate what establishment relocation patterns would look like under the hypothesis that relocations are completely random with respect to destination and establishment earnings, assuming that we start with the empirical distribution of the number of CBSAs, CBSA population densities, and mean CBSA sizes (by number of establishments) and earnings distributions for high-, middle-, and low-density CBSAs. The exercise provides a baseline to judge how much the relocation patterns observed in the data deviate from purely random relocation patterns. The patterns of random relocation are not obvious because CBSAs vary widely in both their size and the earnings distributions of their establishments.

Each establishment is assigned to one of 363 CBSAs allocated within one of three groups: those in the highest quartile of CBSA density, those in the lowest quartile, and those in the interquartile range. We run the simulation on over 7.8 million establishments, the same number that we observe in the data. Establishments are divided evenly among CBSAs within each density group, so that mean CBSA size is the same within each group, but differs across groups. CBSAs are then assigned a population density and college share pair in accordance with the density-college share pairs observed within their group in the data. Thus, the full empirical distribution of CBSA densities and college shares are represented in our simulation. Finally, establishments draw their earnings from an earnings distribution with the same mean and standard deviation as the empirical distribution of its CBSA group. Each establishment has an equal probability of moving, equal to the empirical average of 1.03 percent. Conditional on moving, the probability that an establishment moves to a particular CBSA is proportional to the size of the CBSA (measured in number of establishments). The weighted probability of moving provides a “steady-state” interpretation of the relocation dynamics, since they would keep the distribution of CBSA sizes constant. In contrast, if move probabilities were uniform across CBSAs, the CBSAs would converge to the same size in the limit.

We then calculate the fraction of establishments who move within each percentile of the earnings distribution, as well as their change in CBSA population density conditional on the move, just as we do with the LBD data. The simulation methodology allows us to generate these estimates by percentiles of each establishment's origin-CBSA earnings distribution or by percentiles of the full sample's earnings distribution.

Figure D.2 reports the estimated move probabilities and changes in density of the simulation alone. The thick solid lines represent estimates based on the earnings distribution of the origin CBSA and the dashed lines represent estimates based on the earnings distribution of the full sample.

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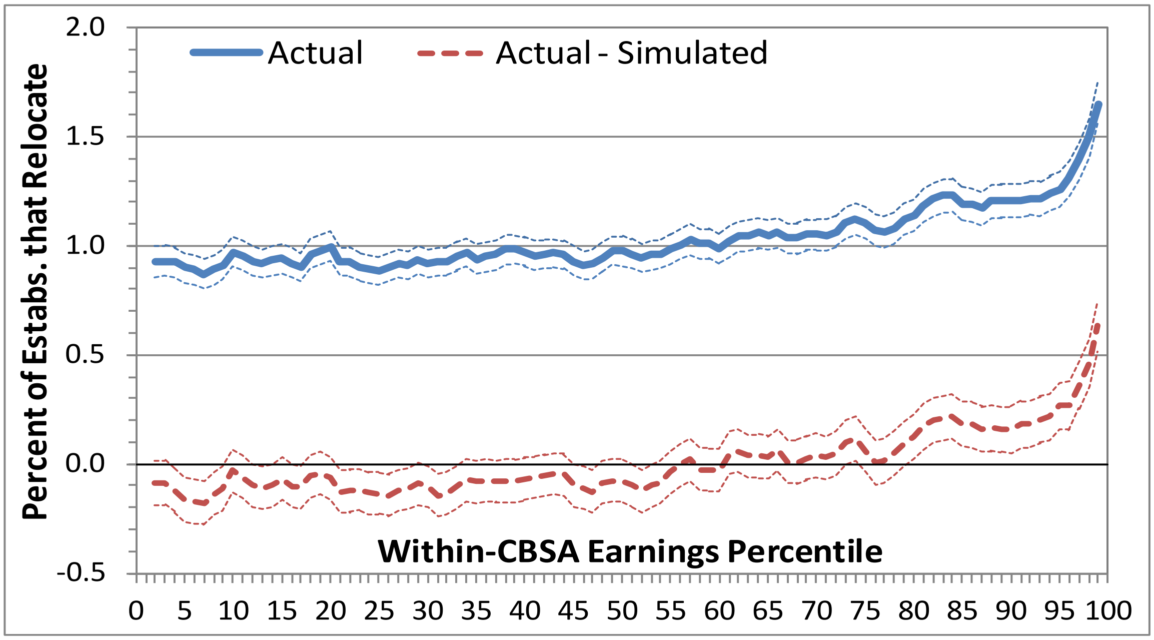
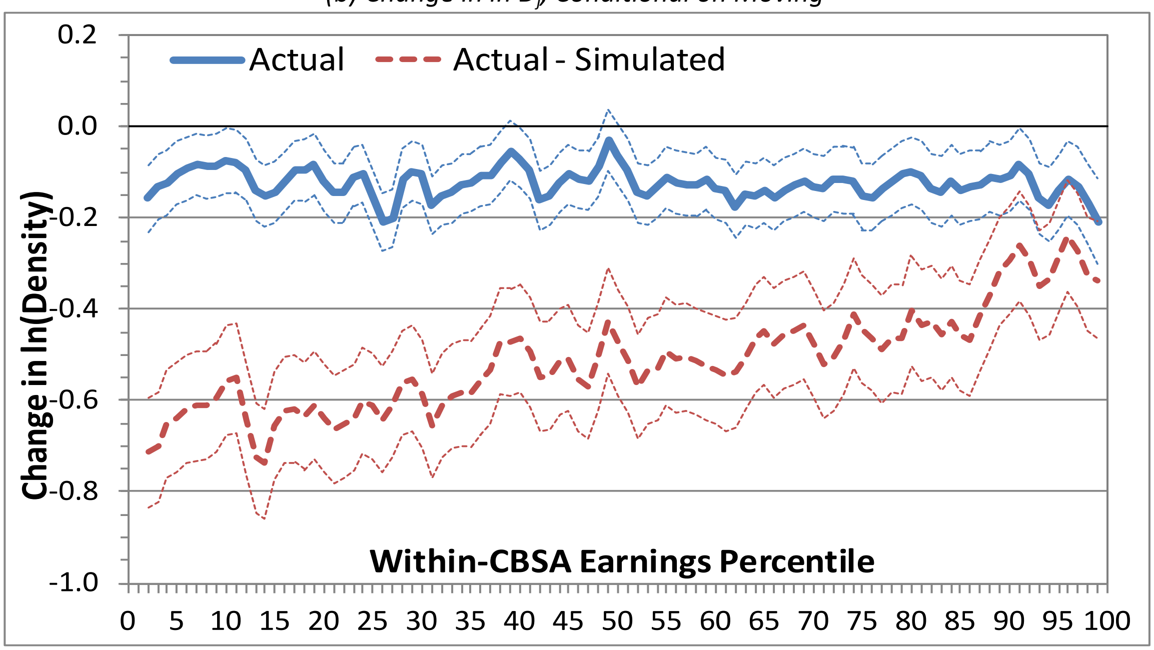
Figure D.1. Establishment Relocation Probabilities and Density Changes by Percentile of Full Sample's Earnings Distribution

(a) Probability of Moving

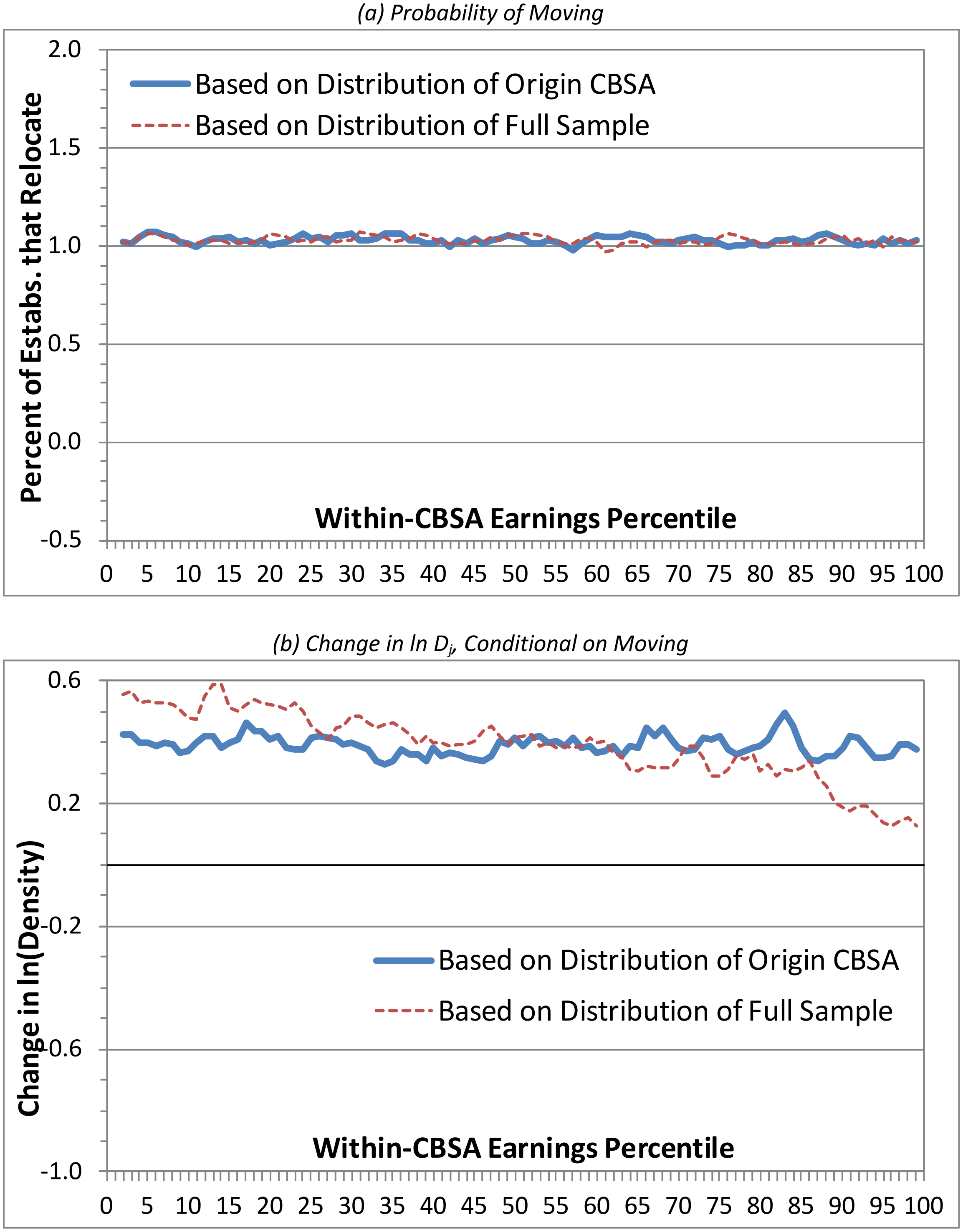


(b) Change in ln D_j, Conditional on Moving



Note: Top panel reports the probability of an establishment relocating from one CBSA to another by percentiles of the earnings distribution of the full sample of establishment. Bottom panel reports the change in an establishment's CBSA (log) density, conditional on relocating, by the same percentile measure. Thick solid blue lines represent outcomes from the data using an earnings and move probability measure that conditions out establishment characteristics (size, age, industry, multi-unit firm status). Thick dashed red lines represent estimates from the data less the outcome predicted from a simulation where all establishments have an equal probability of a move to a random CBSA. Thin dashed lines represent 95 percent confidence intervals. All panels report 3-percentile, centered averages to smooth the estimates.

Figure D.2. Simulated Establishment Relocation Probabilities and Density Changes by Percentile



Note: Top panel reports the probability of an establishment relocating from one CBSA to another by percentiles of the earnings distribution, based on the listed definition (origin CBSA or the full sample). Bottom panel reports the change in an establishment's CBSA (log) density, conditional on relocating, by the same percentile measures. All panels report 3-percentile, centered averages to smooth the estimates.

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