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Thick-Market Effects and Churning in the Labor Market: Evidence from U.S. Cities*

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Abstract

Using U.S. Census microdata, we show that, on average, workers change occupation and industry less in more densely populated areas. The result is robust to standard demographic controls, as well as to including aggregate measures of human capital and sectoral mix. Analysis of the displaced worker surveys shows that this effect is present in cases of involuntary separation as well. On the other hand, we actually find the opposite result (higher rates of occupational and industrial switching) for the subsample of younger workers. These results provide evidence in favor of increasing-returns-to-scale matching in labor markets. Results from a back-of-the-envelope calibration suggest that this mechanism has an important role in raising both wages and returns to experience in denser areas.

Key words: agglomeration, churning, sector-specific skill.
JEL codes: J24, J31, J41, R23.

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1 Introduction

Workers in more densely populated areas, on average, earn higher wages. It almost has to be this way to compensate for the higher costs of living arising from congestion. But businesses have to pay these higher wages, on top of facing the same costs of congestion. Why then would firms choose to locate in dense areas, given these disadvantages? Evidently being in highly populated areas brings some productivity advantage that compensates for the higher cost structure. A typical first hypothesis is that densely populated areas enjoy some natural locational advantage, such as being a convenient transportation node (New York and Chicago, for example). While this seems a compelling hypothesis for the days when transportation was supremely costly, it is less so following the decline in transport costs and the rise of the service economy. And yet, these great agglomerations of people and enterprise persist and in many cases thrive. How has this been possible?

An intriguing hypothesis is that the very act of bringing together so many workers and firms can itself generate these productivity advantages. These so-called agglomeration economies might arise from mechanisms related to sharing, learning, or matching.[1] Sharing refers to the production externalities coming from large indivisible investments that enhance local productivity, in the spirit of Hirschmann's linkages.[2] The learning hypothesis posits that larger urban areas hold an advantage in either the creation of technology (Jacobs, 1969) or the formation of human capital (Glaeser and Maré, 2001). The present study, on the other hand, is concerned with the matching mechanism.

Denser areas also have thicker markets and might therefore benefit from improved search and matching, as in the seminal "coconut" model of Diamond (1982), which formalized increasing returns to scale in matching. And search and matching figure prominently in the market for labor, which is characterized by heterogeneous workers and jobs. This theory posits that, from the perspective of a worker, finding a job is cheaper in a thicker market. Put another way, workers in denser areas would be able to find a better job for the same cost of search.

Market thickness should matter particularly for specialized labor markets.[3] Consider a worker who

[1] This typology is drawn from Duranton and Puga (2004).

[2] In other words, if a product requires large capital outlays to produce, some markets might be too small to justify such an investment locally, and therefore firms in more sparsely populated areas that use the product will have a cost disadvantage.

[3] The idea of improved search because of thick markets being important for sustaining task-specific skill is typically attributed

loses his job in a thinner labor market. He might have to wait an appreciable amount of time before finding a position that will take advantage of his skills. But searching and waiting is costly, and it may make more sense to simply accept a job that is less suited to his skill set. The result would be a loss of human capital. Moreover, ex ante, such workers have a diminished incentive to accumulate skills that are sector and task specific, given that those skills have a more limited expected lifetime. The result is decreased specific investment, which augments the original effect of market thinness. This suggests that, by both mechanisms, we should expect to see less changing of sectors by workers in denser areas. (In Section 3, we review further the theoretical framework and discuss our empirical specification.)

The present study finds that the rate of occupational and industrial transitions is indeed lower on average in thicker labor markets. These results are presented in Section 4. We first consider data[4] from the U.S. census of 1970, and we show that observationally similar workers are less likely to change occupation and/or industry in areas with higher population densities. We further demonstrate that this result is not sensitive to controlling for standard demographic variables, aggregate measures of human capital, and sectoral mix. We also implement corrections for sorting across areas and for differences in the definition of area groupings across regions. These effects are also present in a sample of non-movers and are robust to controlling for a variety of other area-wide control variables related to income, quality of life, and demographics. As an additional check, we show that this thick-market effect is present in a sample of displaced workers (in the 1990s) whose job separations were due to plant closings.

On the other hand, cheaper search also implies that workers would want to shop around more for a good occupational match. By the usual Ben-Porathian logic, they should do this shopping early in their careers. In accordance with this prediction, we find that our result above is weaker for younger workers. In fact, it is actually reversed: those with less than 10 years of potential experience switch occupations and industries *more* in areas that are more densely populated. We see this in Section 5, where we decompose the estimates by different levels of potential experience in the labor market. This is consistent with the thick-market model: young workers take advantage of low search costs to search more intensively for the right occupational match. On the other hand, we argue that this is difficult to rectify with a simple model of

to Alfred Marshall.

[4]Section 2 and Appendix A describe the data sets employed.

specialization induced by some non-search reason (e.g., learning spillovers about specific skills, or greater returns to specialization because of improved division of labor).

We consider, in Section 6, the implications of our results for the widely documented wage premium earned by workers in more densely populated areas. Our calculations are based on two factors: (i) our results imply that specific skills fall into disuse faster in less dense areas, and (ii) numerous studies have demonstrated the importance of sector-specific human capital in worker productivity. The simple combination of these two facts implies that specific skills depreciate faster—and wages grow more slowly—in less dense areas. We compute that this mechanism accounts for around 35% of the faster wage growth in denser areas. We also consider the ex ante effect: If specific skills depreciate more slowly in denser areas, workers will invest more in human capital that is specific to their chosen industry and/or occupation. To quantify this effect, we calibrate a simple investment model characterizing the optimal choice of sector- or activity-specific skill and find that this ex ante investment mechanism could account for a significant portion of the density premium observed in the wage data.

2 Data

This study combines individual and aggregate data. The principal micro-level data set is the 1970 Form 1 Metro sample from the Integrated Public Use Microdata Series (IPUMS), a 1% random sample of the entire population (Ruggles et al., 2004). We draw aggregate data from a number of sources, including the IPUMS, the State and Metropolitan Area Data Book (SMADB) (U.S. Census, 1979), and the Historical United States County (HUSCO) Boundary Files (Earle et al., 1999). More information on these sources is available in the data appendix.

The key outcome is a change in an individual's reported occupation or industry. The 1970 IPUMS reports worker characteristics, including occupation and industry, for two years, 1964 and 1969. We record changes in these reported codes between years in our binary outcome variable.

We also consider the Displaced Worker Supplement (DWS) for the years 1994-2002 (U.S. Bureau of the Census, 1994, 1996, 1998, 2000, 2002). The DWS is an occasional supplement to the Current Population Survey, usually conducted in January or February of even-numbered years. The DWS comprises all persons displaced from a job within three years of the survey date. To construct the change in outcome, we compare characteristics of these workers' pre-displacement job to characteristics of their survey-year job.

Within the DWS, workers may cite reasons for job loss. Possible responses are: (1) their plant or company may have closed down or moved, (2) there may be insufficient work, (3) their position may have been abolished, (4) their job may have been seasonal in nature, or (5) their self-operated business failed. We form a separate "plant closing" sub-sample of the DWS data based on workers who cited reason (1) for their job loss. For these workers, job separation is arguably exogenous to their unobserved characteristics.

The unit of observation for the aggregate data is the metropolitan area. Geographic location data is subject to census confidentiality restrictions; therefore, in both samples, we are only able to identify metropolitan areas larger than a certain size. Fortunately, the IPUMS also identifies "county group" of residence for its entire sample. The county group, a collection of enough contiguous counties to satisfy the census confidentiality requirements, is conceptually comparable to the Public-Use Microdata Areas (PUMAs) in the 1990 and 2000 census. In 1970, county groups included, for example, county group 1302, consisting only of New York County (Manhattan), and county group 14002, consisting of 19 counties and an independent city in southwest Utah and northern Nevada. For the 1970 IPUMS, we assigned county group data to those individuals outside of one of the identified metropolitan areas. Individuals within identified metropolitan areas kept their affiliation with metropolitan-level aggregate data. In this way, we are able to obtain complete geographic coverage of the country.

The key explanatory variable is local population density. For most individuals in our samples, this is the population density of their metropolitan area of residence. For the balance of the 1970 IPUMS, this is the population density of their county group of residence. Figure 1 presents a map of the 1970 county groups and metro areas with population density indicated via shading. These data come from the SMADB and the HUSCO. For the 1994-2002 DWS, we assign population density based on data from the 2000 census (U.S. Census, 2000).

We obtain most metropolitan-level variables (outside of population and area) by aggregating the individual-level data from the IPUMS and the DWS. Other individual-level controls also come from these microdata.

Further details on data and methodology are in the data appendix. Table 1 (Continued) provides summary statistics for the census and DWS samples.

3 Framework

3.1 Background and Related Literature

Labor-market density might have a simple, mechanical effect on occupational switching. This can be seen by considering occupational choice following the (exogenous) separation of a worker from his job at a particular firm. By revealed preference, we know that this worker had some skills, either by endowment or investment, that were specific to the activity and/or sector of the previous job. If the separation from the firm were permanent, the worker now faces a choice: seek employment doing the same tasks but in a different firm, or eschew his sector-specific skills while taking a job elsewhere in the economy.

A worker in a less dense labor market faces a "small numbers" problem. He happens to be without a job, but does there happen to be another firm that needs a worker with his skill set? A multinomial model serves as a mechanistic approximation to this process. As the market grows larger, the number of excess workers (or firms) shrinks in expectation like the square root of the market size.[5] The workers in denser markets benefit from the law of large numbers, leaving them less likely to be in a narrow labor market at a moment in which their skills are in excess supply. This ex post mechanism generates a lower probability that a worker would choose to leave his sector in denser markets, all else fixed, and therefore, in effect, his sector-specific skill depreciates at a lower rate.

This mechanism should also affect the skill-accumulation decision em ex ante as well. Murphy (1986) and Kim (1989) propose how density might change the market for sector-specific skill. In Kim's model, fixed costs are important in production, and consequently sparsely populated areas have fewer firms in each sector, and workers choose to invest less in narrow skills because there are fewer potential employers in the event of a separation. A result of this effect is that workers will choose to specialize more. Existing empirical work supports this contention for physicians (Baumgardner, 1988) and for lawyers (Garicano and Hubbard, 2007), as well as for a general index of specialization (Ades and Glaeser, 1999).

Thicker labor markets might also increase sector/activity turnover, since search is cheaper. But it might reduce it insofar as workers have already found good matches with their occupation and/or industry. Which

[5] See Shimer (2007), e.g., for a formal model of this process applied to the question of unemployment.

effect dominates is unclear a priori.[6] Having acknowledged this ambiguity, we note that search for a good occupational match is an investment. Therefore, like other human-capital investments, it should be done earlier rather than later in life. This implies that this positive effect of thick markets on activity switching should be strongest early in one's career.

3.2 Empirical Specification

The present study considers the effect of labor-market density on the probability that a worker changes activity and/or sector. The basic regression specification is as follows:

$$D^{\Delta}_{ijk} = \beta \,\text{density}_j \;+\; \delta_k \;+\; X_i\Gamma \;+\; Y_jW \;+\; \epsilon_{ijk} \tag{1}$$

for person i in area j who worked in occupation/industry cell k in the base period. The dependent variable, D^{Δ}_{ijk}, is an indicator for whether that individual has changed activity and/or sector since the base period. The central explanatory variable is the density of the area, which we define in the main specifications as the logarithm of population per square mile. Because this variable is defined over j, we cluster the standard errors at the area level. To adjust for differences in the granularity of occupational and industrial coding, we include fixed effects for each activity/sector cell (k). The specification also includes individual-level demographic controls (the X_i) and allows for area-level controls as well (Y_j).

We entertain a number of alternative specifications below. Our baseline is estimating equation (1) with ordinary least squares (OLS). We also address possible identification problems, including omitted regional characteristics and measurement error in local labor market density. In addition, workers with a propensity to acquire specialized skills may sort into dense cities. We implement an instrumental variables strategy that relies on the costs of moving from one region to another. And because workers may have other unobserved traits that lead to job separation, we analyze data on workers whose separations are plausibly exogenous to any of these characteristics (the displaced-worker sample from the CPS).

[6] A similar set of issues exists for employer/job switching. In keeping with this, evidence on the sign of the turnover effect of density has been mixed in recent work by Fallick, Fleischman, and Rebitzer (2006), Groen (2006), de Blasio and Di Addario (2005), Fox (2002), and the present study. Indeed, Petrongolo and Pissarides (2005) estimate a structural model using data on job searchers in the United Kingdom and find that reservation wages adjust just enough to leave search behavior unaffected by labor-market density. We return to the job-turnover question in Section 4.4. (Also see Coles and Smith (1996) and Shimer (2001) for evidence on increasing returns to scale in labor-market matching.)

4 Empirical Results

4.1 Main Results: Churning and Density

Using a sample of individuals from the 1970 census, we find that workers in areas with higher population density were less likely to have changed occupation or industry. We argue that the evidence presented in this section weighs in favor of a substantial decrease in sectoral churning as a result of being in a thicker labor market. The main result is seen in column 1 of Table 2, which contains estimates of equation 1. A change of one in log density affects this probability by 0.6%.

The magnitude of the thick-market effect is large enough to be relevant in understanding cross-area differences. In our sample, the distribution in log density across areas has a standard deviation of approximately 1.4. On the other hand, the standard deviation of average churning across regions is 0.029. Using the coefficients from Table 2, we compute that a one-standard-deviation change in density results in a decrease of one-third of a standard deviation in sectoral switching. (One standard deviation in density is the difference between Knoxville, Tennessee, and Philadelphia, Pennsylvania, for example.[7])

These results are not sensitive to the inclusion of a variety of individual- and aggregate-level controls. As seen in columns 2 and 3, this estimated effect of density is not affected substantially by the inclusion of demographic controls, such as age, gender, race/ethnicity, and education. The relationship between density and sectoral churning is shown in greater detail in Figure 2. In the figure, the churning measure on the vertical axis is an average residual from a regression of a dummy for occupation/industry switching on the controls in column 3. The relationship is similar using any of the sets of controls from Table 2. In columns 4 and 5, we also include several aggregate-level controls. In spite of the marked regional differences in density seen in Figure 1, including regional dummies changes the point estimate by less than a standard error.

We also include area-level information on educational attainment and find that having a more educated workforce in the area is associated with increased sectoral churning. An important alternative hypothesis is that cities also have more educated workforces, and learning spillovers provide workers with stronger incentives to accumulate human capital (in particular, to specialize their human capital). Glaeser and Maré

[7] One standard deviation is also the approximate difference in population density between San Diego, California, and San Francisco, California, or between Greenville, South Carolina, and Louisville, Kentucky. Note that these are 1970 numbers.

(2001) and Peri (2002) provide a treatment of these learning spillovers. Lin (2007) shows further that human capital contributes to occupational dynamism at both the micro and aggregate levels. Nonetheless, the resulting estimates of the effect of density are similar to those without aggregate controls.

The effect of labor-market thickness on sectoral switching is evident at various levels of occupational and industrial classification.[8] Above, we measure churning as a change in either the detailed occupation or the detailed industry. In Table 3, we report the estimated effect of population density on sectoral switching, but in each cell we use different levels of aggregation for occupation and industry. The bottom right cell in the table replicates the result from column 5 of Table 2, and this set of controls is used throughout Table 3. Coefficients are larger and generally more precisely determined for more aggregated measures of occupation and industry switching. Skills are presumably less transferable across aggregated sectors, and thick markets matter more for these transitions.

4.2 Sensitivity Analysis

The effect of labor-market density on sectoral churning that we observe is robust to a number of different alternative explanations.

4.2.1 Correction for Sorting

We first argue that these results do not arise from the endogenous sorting of individuals across areas. A plausible alternative hypothesis is that people whose comparative advantage involves greater specialization migrate to larger cities, where industries might be more at the "cutting edge." If so, we would expect less sectoral switching in thicker labor markets, but the effect is due to sorting, not search. To assess this alternative, we use a simple correction for sorting described below.

The methodology we employ is based on that of Evans, Oates, and Schwab (1992), who point out that regressing individual outcomes on local-area data is problematic in that individuals choose where to live. In their application, they consider the effect of neighborhood poverty on teen dropout decisions. Neighborhood-level variables are found to be statistically significant determinants of dropout. However,

[8] We repeat this exercise using a probit estimator and report the estimates in Appendix B. Results are similar to those presented here.

when metro-area poverty is used as an instrument for the neighborhood rate, the estimates of poverty are not significantly different from zero. They argue that the latter estimate is much less contaminated by sorting, and therefore the neighborhood-level result was due to endogeneity bias rather than a causal effect.

We implement this specification check by using the density of the individual's state of birth as an instrument for density of the current residence. The logic of doing so is similar to that just stated. The degree of bias induced by geographic sorting should be less for state of residence than for city of residence. Carrying the logic one step further, there should be even less sorting by state of birth. (It bears noting that this exercise is a correction for sorting, not a control for every conceivable channel through which density might affect sectoral switching. In addition, the Evans-Oates-Schwab method cannot correct for more complex error structures; see Bayer and Ross (2006).)

The estimates using this methodology suggest that our results are not driven by endogenous sorting. Table 4 displays the instrumental-variables (IV) estimates, along with results from the first stage. (Regressions reported in odd- and even-numbered columns contain the same controls as those in Table 2, columns 3 and 5, respectively.) We consider three higher aggregations of density, all at the state level: contemporaneous density in the state of residence or state of birth, and 1880 density in the state of birth.[9] For each variable, there is strong first-stage relationship between state density and density in the current area of residence. Density from the state of residence shows the highest elasticity in predicting local-area density. More to the point, the IV estimates of local density tend to be larger than the OLS estimates presented above. (Regressions using state-of-birth density as the IV and the additional metro-area characteristics are no longer significantly different from zero, but neither can they reject that they are equal to the comparable OLS estimates.) This suggests that sorting, at least within states, is not driving our estimates. (The large IV estimates also suggest that the main results may be contaminated by measurement error, particularly in measuring local

[9] Our use of the historical measure of density follows the work of Ciccone and Hall (1996), who instrument current density with several variables from the 1800s (1880 population density, distance to the Atlantic coast, 1850 population, and the presence of railroads in 1860). In preliminary work, we also included these other three variables in the analysis but obtained insignificant results and/or inappropriate signs for those other variables in the first stage. To avoid possible biases, including the well-known small-sample bias of 2SLS when the system is overidentified, we use only the 1880 density variable as an historical IV. We also note that Rosenthal and Strange (2005) have more recently introduced into the literature a geological instrument, which is based on the appropriateness of the local geological formations (bedrock, e.g.) for supporting skyscrapers. That study focuses on areas (PUMAs) within cities, and the instrument seems to have some power in explaining the highly concentrated business districts within metro areas. However, these effects play out over much smaller areas relative to the comparatively low spatial frequency of the present study. We therefore do not consider the Rosenthal-Strange instrument here because it does not address the relevant problem of this subsection: sorting of workers across metro areas and county groups.

labor-market density. This possibility is explored below.)

4.2.2 Measurement Error

Because the atomistic unit in forming metropolitan areas and county groups is *counties*, very large counties, or the uneven distribution of population within large counties, may affect our estimates. For example, in our 1970 data, the Los Angeles metropolitan area includes the counties of Los Angeles, Orange, Riverside, and Ventura. The densities of northern Ventura county or eastern Riverside county (bordering Arizona) are very low relative to the balance of the metropolitan area.

Other measures of density yield estimates that are similar to the main results but reflect the larger magnitudes of the IV results. In Table 5, Panel A, each row contains estimated coefficients on log density for a different density concept. Each cell is a separate regression, either on the entire sample or one of four census regions. The first row uses our original density measure, calculated for consolidated metropolitan areas and county groups. Log density predicts reduced switching between sectors in the full sample and across regions. However, in the South and West, this estimate is less precise and not significantly different from zero. These regions, especially with the West's large counties, may be especially sensitive to the uneven distribution of population within metropolitan areas and county groups.

The second row contains estimates using an adjusted measure of density. Here, county group densities remain the same as the original measure. However, within metropolitan areas, density is calculated as a weighted average of component county group densities. For example, density for the Los Angeles metropolitan area is determined by a weighted average of the densities of Los Angeles, Orange, Riverside, and Ventura counties—each of which constitutes a separate county group. The weights are determined by county population; in effect, we are calculating the "average" county-group density experienced by a worker in the Los Angeles metropolitan area. Estimates using this measure are similar to the main results. In the West, the effect of density on switching is now significant.

We calculate the third and fourth density concepts based on workers' county group of residence. The former is a weighted average of component county densities, using data from the 1972 City and County Data Book (ICPSR, 1984). The latter is a weighted average of component census tract data, using data from the CensusCD Neighborhood Change Database, a commercial product containing U.S. census tract data for

1970 (GeoLytics, 2001). Results using these measures echo earlier ones. In sum, we conclude that errors in density measurement do not drive our results.

Alternatively, we use these adjusted density measures as instruments for log density. The baseline density measure may under-report actual local labor-market density for metropolitan areas or county groups where population centers are small relative to the size of the county or county group (bias toward zero). The IV procedure should correct for this sort of bias.

In Table 5, Panel B, each column contains separate regression estimates using alternative density measures as instruments. Measures are weighted averages of component densities (tracts, counties, or county group) of workers' county group of residence. Column 4 uses all three alternative measures as instruments. We find strong effects of log density on sectoral switching using the adjusted density measures as instruments. The IV estimates here are also similar to the estimates that use the Evans-Oates-Schwab sorting correction. In sum, corrections for measurement error suggest that the OLS results understate the effect of local density on sectoral switching.

Finally, we find further support for negative thick-market effects on switching when adding sectoral and occupation employment shares to the model, as seen in Table 5, Panel C. According to our logic above, activities with higher employment shares are in effect thicker labor markets. To test this importance of this dimension of thickness, in columns 2–4 of Panel C, we add the log employment shares for three-digit occupation and industry. (Recall that these regressions already contain dummies for lagged occupation$\times$industry at the three-digit level, so estimates are being made within sectors and activities.) Consistent with the results above for metro-area density, we estimate negative coefficients on employment shares.[10]

4.2.3 Additional Specification Checks

The results above are not sensitive to controlling for a variety of alternative aggregate-level variables. These results are seen in Panel A of Table 6. For reference, the first row repeats the density estimates from above. Subsequent rows also include estimates of the density effect after including in the regression the specified

[10] We do not base the main analysis of the paper on employment share because this measure strikes us as more prone to endogeneity problems: sorting can occur *both* across areas *and* within areas among sectors and activities. Also, while we present several plausible corrections for area-wide density in Table 4 above, it is harder to imagine implementing comparable strategies for area$\times$industry/occupation density.

control variables. (The sources for these additional controls are described in Appendix A.2.) The next row displays results after controlling for a set of demographic variables: race and age composition and decennial population change. The third row of Panel A controls for a set of employment and income variables: the local unemployment and poverty rates, and median income and rent levels.[11] For the fourth row, we include controls for amenities such as average January and July temperatures, July humidity, and the local receipt-share of recreation-related industries. The final row contains estimates of density controlling for all of these additional variables. The estimates with additional controls are within approximately one standard error of the baseline results, sometimes higher and sometimes lower. Nevertheless, the specification with the most thorough set of controls yields estimates that are uniformly lower than the baseline results.

Given the concerns about the mismeasurement of density expressed above, we repeat this exercise, but use the alternative measures of density as instruments to correct for measurement. The 2SLS results are seen in Panel B of Table 6. The estimates are indeed higher than comparable OLS results, as expected if the measurement error were classical. However, the magnitudes of the density effect, when both controlling for the additional variables and using instruments for measurement error, are quite similar to the baseline results.

In Panel C of Table 6, we address several other specification issues related to selection. Information from the census on migration provides a check for problems of spatial sorting. By observing metropolitan area/county group of residence five years ago (in 1965), we separate the 1970 census sample into non-movers and movers. Movers may be those with a comparative advantage in specializing who self-select into thicker labor markets, as discussed earlier. Results in the first row of Panel C using only non-movers confirm the main result. In the second row of that panel, we present results from a subsample that excludes observations that have been edited or allocated by the census. These estimates are essentially the same as those found above. As an additional specification check, we also consider the role played by censoring of the sectoral data. The basic sample used above contains individuals whose occupation and industry data are non-missing for both the census year and five years prior. This sample used in the third row of Panel C is of all individuals for whom we observe prior occupation and industry. Density does not predict censoring at

[11] Unionization is a plausible determinant of occupational and industry switching, but data by county were not readily available for 1970. However, we can construct such measures using the displaced-workers sample and implement the specification check with those data. These results are shown in Appendix C.

conventional levels of statistical confidence. (Student's t statistics are all less than one in absolute value.) In any case, the magnitude of the estimate is much smaller than the effect of density on sectoral switching.

Finally, we find that the negative effects of density on churning are present across the gamut of one-digit sectors and activities. These results are shown in Appendices D and E for occupations and industries, respectively. Apart from farming/farmers, the coefficients on density are uniformly negative and, in almost all cases, statistically significant. This indicates that this switching effect of density is at play for various activities.

4.3 Displacement

We find a similar effect of density on sectoral switching using samples from the Current Population Survey's Displaced Worker Supplement between 1994 and 2002. For example, column 3, row 3 of Table 7 shows that a change of one in log density decreases the probability of changing detailed occupation or detailed industry by 1.6%. The magnitude of this estimate is comparable to that of the 1970 result. Again, a one-standard-deviation increase in density results in a decrease of one-third of a standard deviation in sectoral switching.

However, this estimate is imprecise. Standard errors reported for changes in detailed occupation and detailed industry group in Table 7 are large, relative to the magnitude of the coefficient estimate. In contrast, estimates for the effect of density on the probability of another type of sector change, changing only detailed occupation, have smaller standard errors. As seen in row 3, the estimated effect of density is of similar magnitude, but it is statistically significant at the 95% confidence level. The Displaced Worker results are robust to different levels of aggregation for occupation and industry.

The effect of density on sectoral switching is present even when workers leave their jobs involuntarily. In the Displaced Worker sample, we can identify the reason each worker left his or her previous job. One-third of workers in the sample lost their jobs because of a plant closure. Importantly, their job separation can be thought of as exogenous to any unobservable worker skill. (Other reasons for displacement, such as layoff or seasonal employment, may be related to unobserved skill, which may in turn affect churning.)

Panel B of Table 7 shows estimates using only workers whose plants closed. According to the estimate in column 1, row 3, a change of one in log density decreases the probability of changing detailed occupation by

3.3%. It is important that our main result is robust to involuntary job separation. An alternative explanation is that unobserved shocks, correlated with density, also affect the probability of job separation. The plant closing data show that our results are not driven by such shocks.

The magnitudes of the estimates using workers displaced by plant closings seem larger than those obtained using other data. A one-standard-deviation change in density results in a decrease of one-half of a standard deviation change in sectoral switching. It is plausible that thicker markets matter more in the case of a negative shock to demand for a particular specialized skill. However, the magnitudes of the standard errors prevent a definitive conclusion.

4.4 Relation to Job Changing

The Displaced Worker Supplement is also paired with the Job Tenure Supplement, which records additional information on workers' job histories. For example, we can use the Tenure Supplement to examine the relationship between job changing (i.e., changing employers) and sector switching (changing from one industry-occupation to another). Using the Tenure Supplement, we record a dummy variable indicating whether a worker has changed employers in the previous three years.

An alternative explanation for our results is that workers in thicker markets change employers less, leading to reduced sector switching. This implies a somewhat different mechanism than skill matching in thicker labor markets. We find that workers in dense regions are indeed less likely to change employers. The regressions presented in Table 8, Panel A use employer change as the dependent variable, with log density and other controls as explanatory variables. The coefficient on log density is negative and precisely estimated. One interpretation of this result is that workers in thicker markets, by some agglomeration mechanism, face a lower risk of being separated from their employers.[12] A specifically thick-market interpretation is that workers easily find good employer matches the first time around and therefore have less need to re-match down the road.

Importantly, however, the addition of this variable leaves the estimated effect of log density on sector switching unchanged. This employer change variable is included separately from log density in the sector

[12] This density effect on employer transitions is similarly negative across potential experience categories, as seen in Appendix G. This suggests an area-wide job-changing effect that is also distinct from the sector-switching effects in Figure 3 (discussed below).

switching regressions presented in Table 8, Panel B. As expected, workers that change employers also tend to switch sectors. The coefficient on the employer-change variable is positive and estimated precisely. Nevertheless, the magnitude of density effect on sectoral/activity switching is comparable to those presented in Table 2. This suggests that even when controlling for the lower rate of employer transitions in dense cities, we still observe that workers are less likely to abandon their sector or activity in thicker labor markets. We conclude that skill matching is still an important mechanism operating in thicker labor markets and that it is distinct from specific employer-employee matching.

5 Decompositions by Potential Experience

We find heterogeneity in the effect of density on occupational/industrial switching across different levels of potential experience in the labor market. These results are found in Figure 3, which presents the density coefficient from switching regressions that are estimated for each level of potential experience.[13] In Panel A, each point displays the results from a separate regression whose dependent variable is an indicator variable for a change in detailed occupation or industry group (the most disaggregate classification). The solid line is a smoothed version of the estimated coefficients. Panel B reports similar, smoothed estimates for the full set of aggregations of industry and occupation codings (as in Table 3). The density coefficients tend to be negative after around 10 years of potential experience. On the other hand, the effect of density tends to be positive before reaching 10 years in the labor market for all measures of switching but one (the exception being one of the most aggregated measures).

The positive effect of density on switching early in one's career is perfectly consistent with a model of thick-market effects in job search, but difficult to rectify with a simple model of induced specialization from the production side (via labor demand). A model with increasing returns to labor-market search could predict that workers take advantage of low search costs to search more intensively for the right occupational match. Depending on the parameters of the model, this effect could dominate the negative, mechanistic effect

[13]The specification parallels equation 1 above. All regressions include dummies for gender, race, marital status, citizenship, and years of education. Because of the limited sample size when partitioning by potential experience, the average effects of the lagged detailed industry and occupation dummies were removed in a first-step regression using the whole sample. Note, however, that the sample differs from that of the main analysis in that observations are included from the full census based on potential experience rather than age.

discussed above. Moreover, because search intensity is an investment whose gains are realized throughout the working lifetime, this new, positive effect would be strongest at younger ages. Contrast this with a simple model in which urban workers are more specialized for some non-search reason (e.g., faster learning about specific skills, or greater returns to specialization because of improved division of labor). This might generate a zero effect in the early years (before workers have gotten locked in by their specialized capital). However, this would not generate a positive effect at low levels of labor-market experience.[14]

6 Implications for Wages

We discuss several channels through which the results above could also have implications for wage differences across areas with differing labor-market densities. We consider mechanisms that are either em ex post or ex ante relative to the potential occupation/industry change. For comparison purposes, we present two facts about the effect of labor-market density on wages: (i) at low levels of experience, wages are around 7% higher per a one-logarithm increase in density; (ii) over the working lifetime, workers in denser areas see higher returns to experience, and this wage gap grows to 9%. (See Appendix F for these results.)

6.1 Ex post Mechanism

The main results of the present study imply lower growth rates for wages in less dense areas, through a simple, ex post mechanism: specific skills fall into disuse faster. We show above that occupation and industry switching is lower in areas with higher population density. In more sparsely populated areas, this mechanism increases the depreciation rate of skills that are specific to a worker's starting sector and/or

[14] More complicated models of specialization could be generated that produce the positive effect of density on switching in the early career. A sensible point of departure would be from the model of Neal (1999), who argues that occupations are in effect "experience goods": Workers need to spend time in a particular occupation to learn about their idiosyncratic match quality. If some agglomeration economy on the production side increases the variance on the *unobserved component* of the idiosyncratic worker/activity match, this would raise the benefit of further searching for the right occupation/industry. While this contrasts with the increasing-returns-to-scale model of search and matching, which reduces the cost of search, the reduced-form effect would be the same: more switching earlier in one's career. Note, however, that density-related increases in the predictable component of that worker's potential gains from specialization would not generate this positive effect on switching, because the worker would have gone to the highest-value job in the first place.

activity. Consider the law of motion for sector-specific skill, H_s:

$$\dot{H}_s = I_s - \delta H_s \tag{2}$$

where I_s is skill investment and δ is the skill depreciation rate. From this equation, we see that an increase in the depreciation rate reduces the growth rate of skills, absent any change in investment behavior. (Below we show that faster depreciation reduces investment.)

To understand the first-order impact of this mechanism on the wage, we need to know what fraction of skill is industry/occupation specific.[15] Using the Displaced Worker Surveys, Neal (1995, p. 665) estimates that 10% of their income was derived from industry-specific skill for men with 10 years of post-displacement experience. On the other hand, Parent (2000, p. 317) uses detailed work-history data to estimate simultaneously returns to both industry and total labor-market experience. For workers with 10 years of continuous industry experience, 10 to 20% of their income was derived from industry-specific skill.[16] We consider fractions between 5 and 25% in the analysis below.

We can account for 10 to 60% of the higher return to experience in denser areas with this ex post mechanism. We start with the typical estimate of the effect of log density on three-digit industry/occupation switching: approximately 0.6%, measured over a five-year horizon, or about 4.8% over a 40-year career. We take this latter number and multiply it by the various estimates for the baseline fraction of sector-specific skills. The calculations indicate that, over a 40-year career, a reduction of one logarithm of labor-market density implies somewhere between 0.2% and 1.2% lower wage growth through this mechanism of accelerated skill depreciation. (Note that this is purely a mechanical effect that comes from the differential depreciation of specific skills. No behavior has been assumed to change, yet.) In comparison, the extra growth in dense-area wages, in the same units, amounts to around 2% over 40 years.

[15] There is most likely more than one number characterizing this fraction. First, the specific/general dichotomy is perhaps too stark. Some skills might transfer to a limited number of other occupations or industries, but not beyond that. (See Gathmann and Schönberg, 2006.) Second, this fraction certainly must vary across workers. More experienced workers will probably have a higher fraction of specific skill than newly minted graduates, for example. And of course this fraction will eventually be higher for workers in dense areas, for precisely the mechanism discussed here. We present this static framework in the hope that, for what it lacks in realism, it makes up for in transparency.

[16] Shaw (1984, 1987) also discusses the importance of occupational skills, but we did not see a clear way to translate her estimates into the desired number.

6.2 Ex ante Mechanisms

The results above could also raise labor productivity in more densely populated areas through several ex ante mechanisms. The differential effects on switching by experience (seen in Section 5) suggest that thicker markets allow for better occupational matching early in one's career, although it is not clear whether the associated gains would take the form of higher productivity or just more satisfied workers. On the other hand, better preservation of specific skill in denser areas affects comparative advantage across space. Because cities are like the small open economies of the textbook trade models, we expect that high-specific-investment occupations would concentrate in denser areas. Indeed, we do find that occupations with higher returns to experience are more likely to be found in more densely populated areas.[17]

An additional ex ante effect of reduced depreciation of specific skills is that workers will choose to invest more in human capital that is specific to their industry and/or occupation. We calibrate a simple investment model characterizing the optimal choice of sector/activity-specific skill, H_s. If we think of this skill as an asset with a time-invariant return, as in Ben-Porath (1967, 1970), it has a present value that will be proportional to $\gamma H_s/(r+\delta)$, for an interest rate of r, a skill-depreciation of rate δ, and a return to skill of γ. Again following Ben-Porath,[18] we define the cost of skill-acquisition to be $c\left(H_s+\bar{H}\right)^{\alpha}$, where $\bar{H}$ is a given quantity of general skill.[19] We impose the usual convexity assumption: $\alpha > 1$. These two terms

[17]Specifically, we use the 1970 census data to estimate the following wage equation:

$$\ln w_{ik} \;=\; \gamma_k \times \text{potexp}_i \;+\; \delta_k \;+\; \beta_{d\times e}\left(\text{density}_k \times \text{potexp}_i\right) \;+\; \beta_d \text{density}_k \;+\; \sum_{m=1}^{5} \alpha_m \times \text{potexp}_i^m + \epsilon_{ik}$$

for individual i and occupation k. The left-hand side, $\ln w$, is the natural logarithm of the hourly wage, "potexp" is potential experience, and the γ_k and δ_k are occupation-specific slope and level effects, respectively. Note that a fifth-order polynomial in potential experience is among the controls, as is the linear interaction of potential experience with local-area density (as defined for the main results of the paper). This means that γ_k measures the returns to experience in that occupation, relative to other occupations, and over and above any direct effect of labor-market density on wage growth. (Results are similar if we control for selection via either a Heckman two-step procedure or by including the fraction of that occupation's employment represented at worker i's level of potential experience. For computational reasons, we run one regression for each occupation k using the full sample, rather than a single regression with the full set of dummies and interactions.) The resulting estimates of γ_k are compared with the average labor-market density by occupation and found to be correlated positively and significantly at conventional levels of statistical confidence.

[18]This is a modest departure from his model in that we treat H_s as the result of a one-shot, early-career investment, while Ben-Porath models the life-cycle timing of such investments. The form of the cost function is nevertheless similar because Ben-Porath imposes curvature based on the current stock of skill rather than on the period-specific investment flow. Also, one of the central results of Ben-Porath's model is that training investments are concentrated early in life. We have experimented with specifications that allow for a dynamic element in the skill investment decision and obtain results similar to those below.

[19]To keep units consistent, we treat H_s in years-of-schooling equivalents. Therefore, again by Ben-Porathian reasoning, we take the return to skill to be proxied by the return to schooling.

are both denominated in units of wages, consistent with the return to and opportunity cost of human capital being related to the wage.

In this framework, the worker solves the following maximization problem:

$$\max_{H_s} \left(\frac{\gamma \left(H_s + \bar{H}\right)}{r+\delta} - c \left(H_s + \bar{H}\right)^{\alpha} \right), \tag{3}$$

which defines the optimal stock of sector-specific human capital as

$$H_s^* = \left[\frac{\gamma}{(\alpha c)(r+\delta)} \right]^{\frac{1}{\alpha-1}} - \bar{H}. \tag{4}$$

The elasticity of H_s^* with respect to the depreciation rate for skills is therefore

$$\frac{\partial H_s^*}{\partial \delta} \frac{\delta}{H_s^*} = \frac{-\delta}{\lambda(\alpha-1)(r+\delta)} < 0, \tag{5}$$

This last equation[20] gives us the response of specific skill in terms of the skill depreciation rate, the curvature of the skill production function, the fraction of skills that are sector-specific ($\lambda = H_s/(H_s + \bar{H})$), and the interest rate. The interest rate is a commonly observed parameter, but the other three are not so ubiquitous. The literature discussed above suggests that λ is between 10 and 20%. We now review the literature on the other two parameters:

1. What is the depreciation rate (δ) for skill? Using U.S. data, Heckman (1976) presents an estimate of 3.7% (on a yearly basis) for the skill depreciation rate. Arrazola and de Hevia (2004) estimate δ to be around 1.4% per annum in Spanish data. Groot (1998) estimates numbers that are considerably larger

[20] Note that this calculation was based on an infinite-horizon approximation to the present value of H_s^*. Solving the model with a finite-career assumption makes a neglible difference. Defining $\tilde{H}_s^*$ to be the optimal choice of sector-specific human capital with a finite horizon, we derive that skill/depreciation elasticity to be

$$\frac{\partial \tilde{H}_s^*}{\partial \delta} \frac{\delta}{\tilde{H}_s^*} = \frac{\partial H_s^*}{\partial \delta} \frac{\delta}{H_s^*} + \left(\frac{1}{\lambda(1-\alpha)} \right) \left(1 - e^{-(r+\delta)T}\right)^{\frac{2-\alpha}{1-\alpha}}$$

where T is the length of the career and $\frac{\partial H_s^*}{\partial \delta} \frac{\delta}{H_s^*}$ is characterized in equation 5. In words, this finite-horizon elasticity can be decomposed into two terms: the infinite-horizon elasticity plus a second, horizon-adjustment term. When we calibrate this equation using the parameters below and a horizon of 40 years, the first term is of order 10 while the second term is around 0.003. Because the finite-horizon adjustment is three to four orders of magnitude smaller than the main effect, we opt for simplicity and present the infinite-horizon approximation.

in the United Kingdom and the Netherlands (around 10%–15%), but that study does not account for the tendency for skills investment to decline later in one's career (as observed by Ben-Porath (1970), for example). Mincer and Ofek (1982) estimate depreciation rates between 3%–7% per year, but they measure this effect for workers who have just completed a non-employment spell. For this reason, their estimates are presumably an upper bound on the estimate of δ for workers that are more-or-less continuously employed. Below, we consider estimates of δ between zero and four.

2. What is the degree of curvature (α) of the skill cost function? Ben-Porath (1970) uses data on training over the life-cycle to estimate $1/\alpha$ around 0.93 (*i.e.*, close to linear). Heckman (1976) fits Ben-Porath's model using the age-earnings profile and estimates $1/\alpha$ to be 0.812. Furthermore, when Heckman augments the model to allow for reduced-form time variation in the value of leisure, he finds $1/\alpha$ to be 0.52, although this parameter is less precisely estimated than in the previous case.

The model also places restrictions on the choice of parameters. In particular, given a skill-depreciation rate (δ) and a sector-specific-skill share (λ), the model implies a particular curvature for the skill cost function (α). For example, if λ is large in the presence of a high δ, it must be the case that it is easy to scale up one's human capital investment (i.e., α closer to one). This relationship can be seen in Panel A of Figure 4. We consider two cases: an upper bound on the fraction of sector-specific skill ($\lambda = .25$) and a lower bound ($\lambda = .05$).[21] Both lines are downward sloping, as expected from the logic above. Because we wish to avoid nonsensical combinations of parameters, we calibrate the model with various plausible choices of δ and λ, and use these model-implied restrictions on α in the process.

We now have enough ingredients for approximating the effect of density on ex ante investments in sector-specific skill. The empirical results in Section 4 provide estimates of $\frac{\partial \delta}{\partial \ln D}$, where D is labor-market density. The maximization problem above itself defines $\frac{\partial \ln H_s^*}{\partial \delta}$, and the parameter selection was just discussed. The product of these two numbers yields $\frac{\partial \ln H_s^*}{\partial \ln D}$, the effect of density on specific skill (and, via returns to skill, the wage).

The calibrated model implies economically important effects of density on investment in sector-specific

[21] We consider δ on the range of estimates identified above. The other parameters are set as follows. We choose an interest rate of $r = .02$, the returns to skill of $\gamma = .1$, average schooling of $\bar{H} = 11.38$. We use $c \approx 1$, for which the range of implied α match the estimates above.

skill, although the uncertainty associated with these parameters leaves a somewhat wide range of possible values for this computation. These results can be seen in Panel B of Figure 4, where we measure the effect of density-induced skill investment on the wage. As above, we consider ranges of sectoral-skill fractions (λ) and baseline skill-depreciation rates (δ) consistent with the available empirical work. Across this set of possible parameter values, the implied elasticity from density to the wage varies from between 0.14 and 0.22. In words, we expect an increase in labor-market density of one natural logarithm to cause additional sectoral-skill investments that would raise the worker's productivity by around 14 to 22%. This compares with an estimated 7–10% density premium for wages and suggests that this ex ante investment mechanism can account for perhaps all of the dense-area wage premium.

A few caveat lectors are in order. First, to calibrate the model, we used the OLS estimates from Section 4, but these were contaminated by sorting and measurement-error biases. As seen above, these biases seem to offset each other, leaving an IV estimate of β that was somewhat higher than the OLS number. This suggests that the wage effects might be higher than those calibrated here. Second, we model the agent above as maximizing expected value, but idiosyncratic wage uncertainty is a textbook example of non-diversifiable risk. If workers are risk averse, market thinness will presumably depress sector-specific investment even further. Finally, the estimates of differential depreciation by density (β) build in both the direct effect of thick markets on switching (i.e., easier matching to a new job in the same sector/activity) and indirect effects (e.g., that specific investments make it less likely that a worker will choose to switch activities). Ideally we would calibrate this model with only the direct component, but it is unobserved. Because the direct and indirect components are of the same sign, our calibration above produces an over-estimate of the impact on wages. It is worth noting, however, that the calibrated wage effect via ex ante investment scales down proportionately with the estimate of $\frac{\partial \delta}{\partial \ln D}$. So, if the direct impact of density on the depreciation of sector-specific skill were one-tenth of the parameter we estimate in Section 4, the effect of density on skill investment would nevertheless account for about a quarter of the observed density effect on wages.

7 Conclusion

Observationally similar workers change occupation and industry less in more densely populated areas. This result is not sensitive to controlling for standard demographic variables, aggregate measures of human capital, and sectoral mix. We also implement corrections for sorting across areas and for differences in the construction of census areas across regions. Furthermore, we show that this thick-market effect is present in a sample of displaced workers whose job separations were involuntary.

We interpret these results as evidence of increasing-returns-to-scale matching in local labor markets (in the sense of Diamond's (1982) "coconut" model). A worker in a less dense labor market faces a small numbers problem: is there a similar job available right after he happens tolose his? In contrast, workers in denser markets benefit from the law of large numbers, leaving them less likely to be in a narrow labor market at a moment in which their skills are in excess supply. This ex post mechanism generates a lower probability that a worker would choose to leave his sector in denser markets. Put another way, from the perspective of a worker, finding a job is cheaper in a thicker market. This interpretation is further supported by results decomposed by different levels of potential experience in the labor market. The positive switching/density result in the very early career is consistent with the thick-market model, but it is difficult to rectify with a simple model of specialization induced by some non-search reason.

This mechanism has an important role in raising both wages and returns to experience in denser areas. Workers in more densely populated areas, on average, earn higher wages and experience faster wage growth. The thick-market model matches these facts qualitatively, and we use a calibrated model to assess its quantitative contribution. The faster depreciation of specific skills estimated above account for around 35% of the faster wage growth in denser areas. Moreover, facing this diminished rate of specific skill depreciation, workers in denser areas will invest more in human capital that is specific to their chosen industry and/or occupation. The calibrated model suggests that this ex ante investment mechanism accounts for a significant fraction of the density premium observed in the wage data, although uncertainty about the model parameters leaves a fairly wide range of possible values for this computation.

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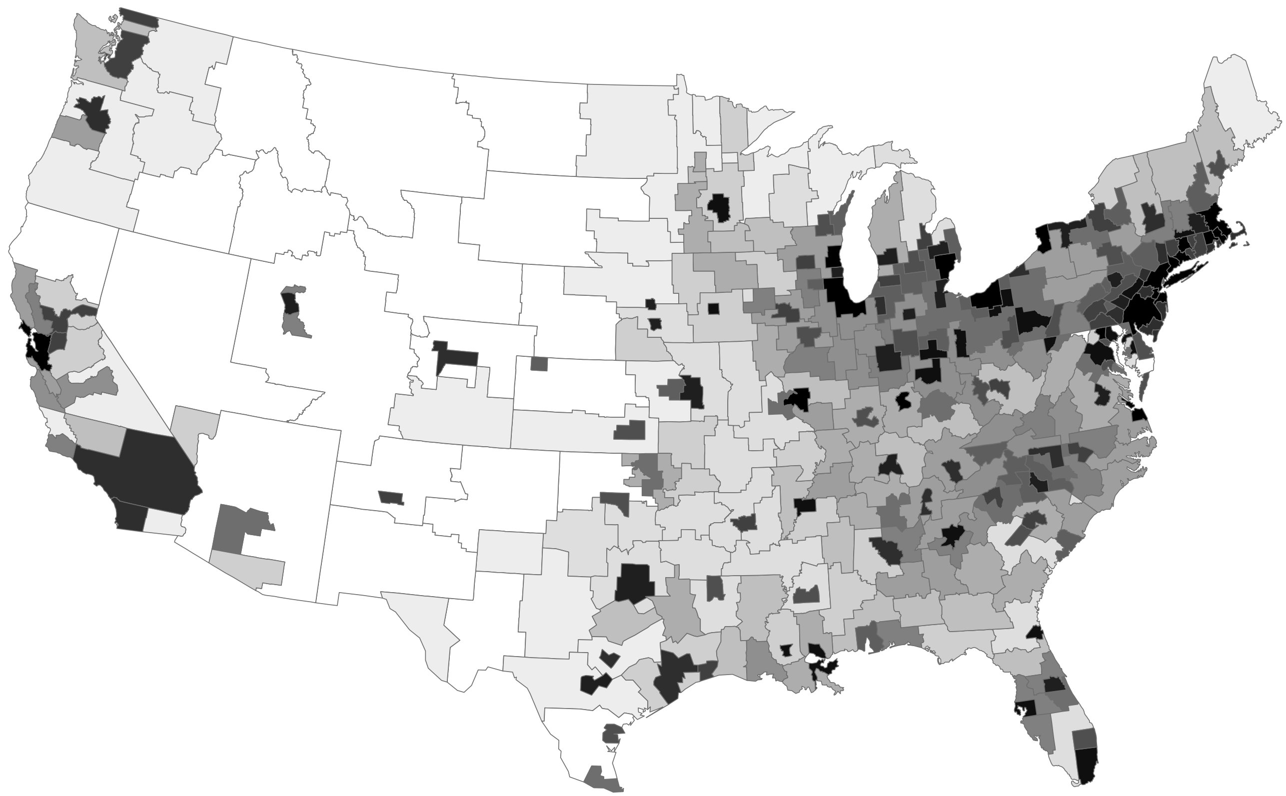
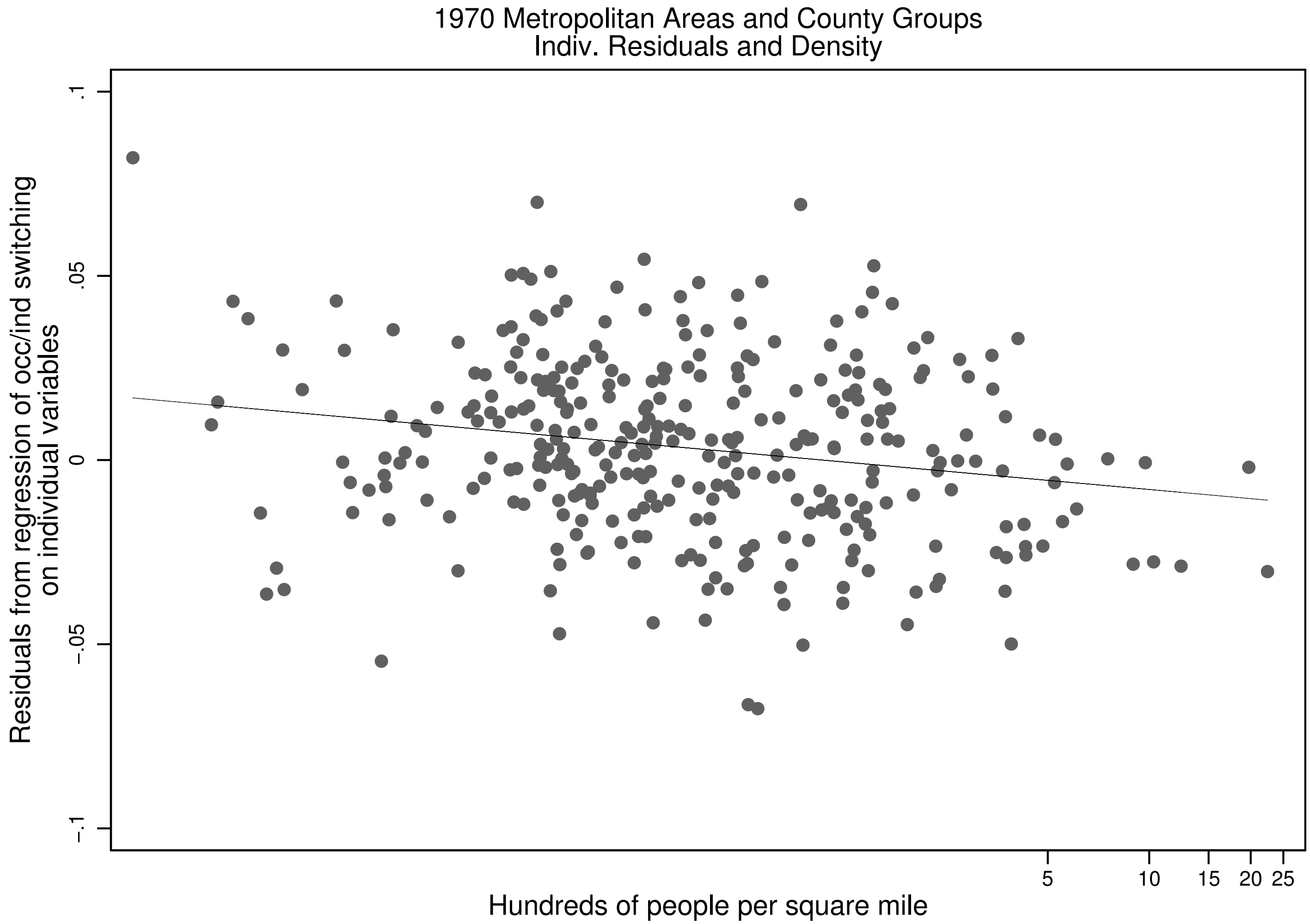
Figure 1: Population Density by County Groupings, 1970



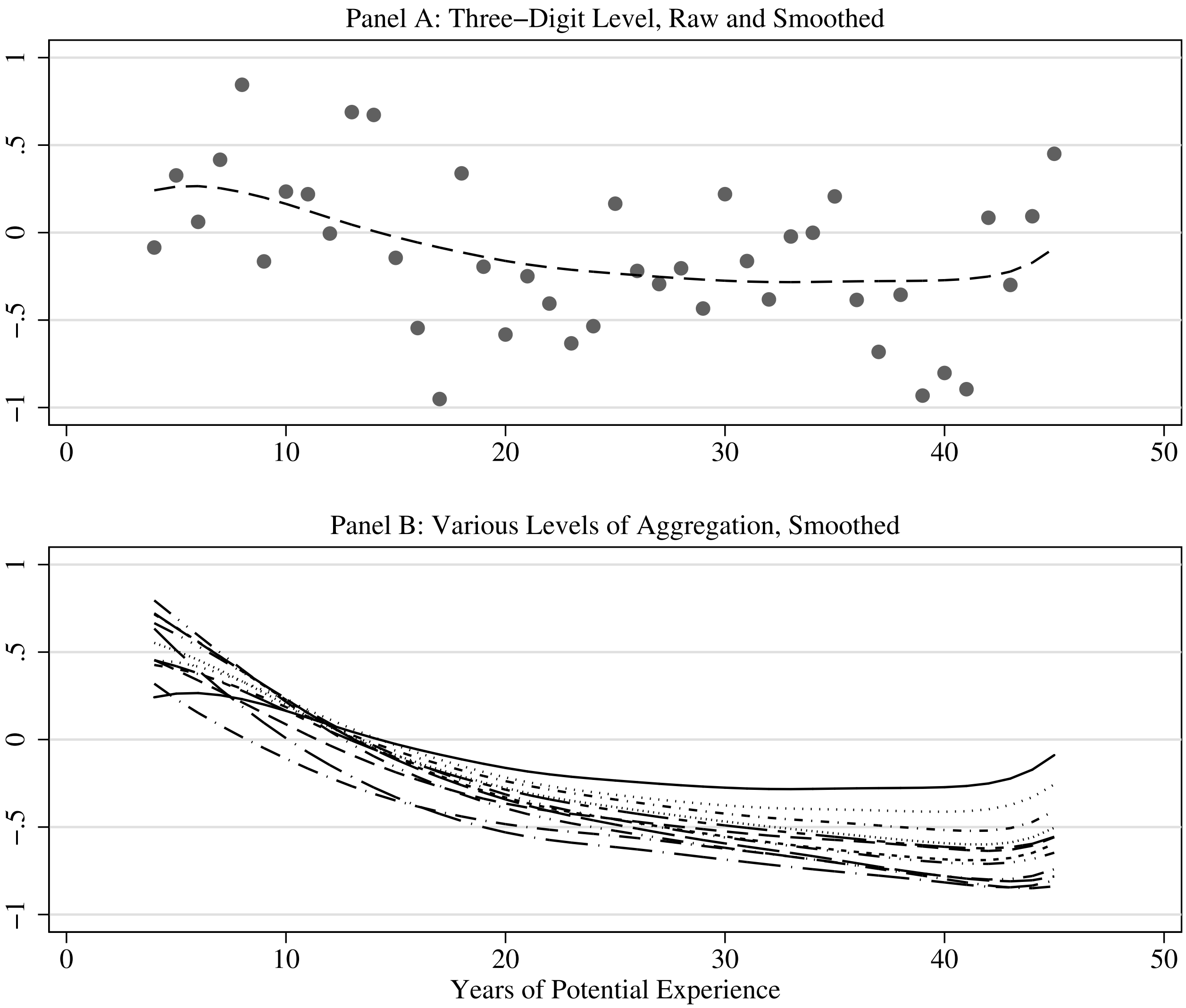
Notes: This map displays population density in 1970 for the aggregations of counties (county groups plus CMSAs) described in the text. Darker shades indicate more population per square mile.

Figure 2: Average Occupational and Industrial Switching Versus Local Population Density



Notes: Each point represents a county group, and the OLS regression fit is drawn as a black line. The y axis displays the average residual from a regression of 2-digit occupational and industry switching on the individual gender, race, marital status, and citizenship, along with dummies for age and original occupation/industry cell. The x axis is the 1970 population density, on a natural-log scale.

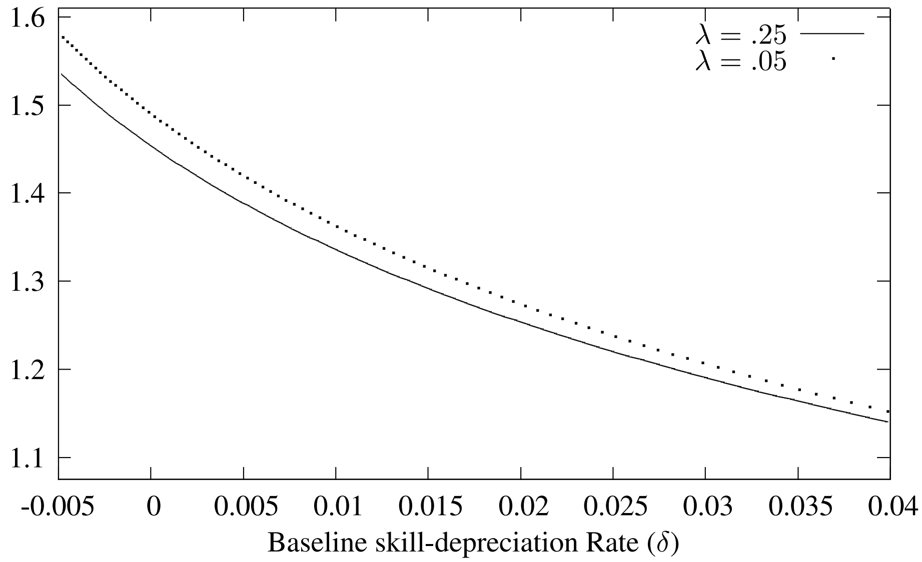
Figure 3: Effect of Density on Switching, by Potential Labor-Market Experience



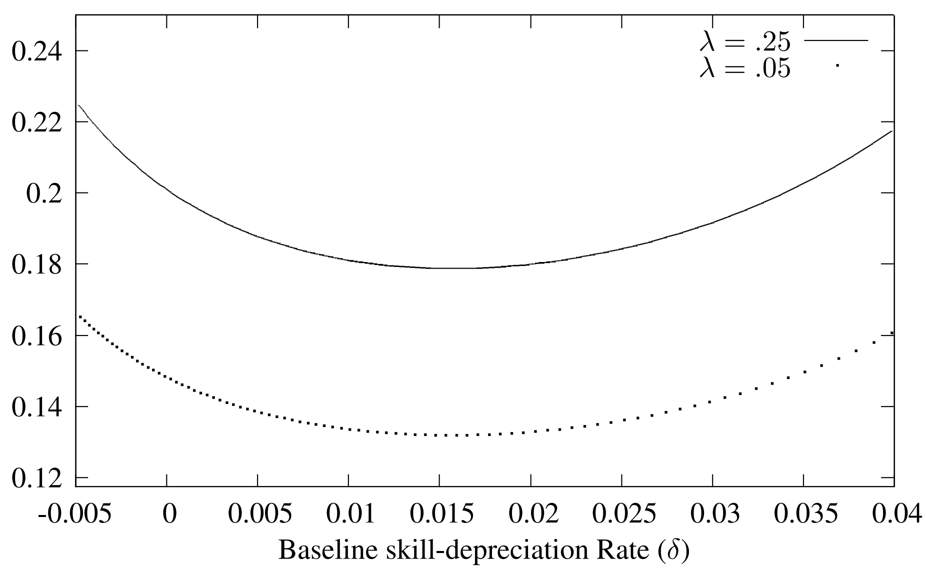
Notes: In Panel A, each point displays the results from a separate regression whose dependent variable is an indicator variable for a change in detailed occupation or industry group. The y axis measures the density coefficient from these regressions. The x axis is years of potential experience in the labor market. All regressions include dummies for gender, race, marital status, and citizenship, years of education. Because of the limited sample size when partitioning by potential experience, the average effects of the lagged detailed industry and occupation dummies were removed in a first-step regression using the whole sample. The solid line is a smoothed version of the estimated coefficients, produced using Stata's "lowess" procedure. Panel B reports similar, smoothed estimates for the full set of aggregations of industry and occupation codings (as in Table 3). Note that the sample differs from that of the main analysis in that observations are included based on potential experience rather than age.

Figure 4: Approximate Effects on Labor Productivity; Calibrations and Sensitivity Analysis

Panel A: Implied Curvature of the Cost Function (α)



Panel B: Wage/Density Elasticity $\left(\frac{\partial \ln w}{\partial \ln D}\right)$ *via the* ex-ante *Investment Mechanism*



Notes: This figure reports results from the calibrated model of investment in sector-specific skill from Section 6. Panel A shows the model-implied relationship between the skill-depreciation rate (δ) and the curvature of the cost function (α). Solid line indicates the relationship between δ and α when the fraction of sector-specific skills is high ($\lambda = 0.25$). Dotted line represents the case when the fraction of sector-specific skills is low ($\lambda = 0.05$). Panel B considers the same cases for λ and reports calibrated estimates of the wage/density elasticity, which are constructed from equation 5 and the model-implied α shown in Panel A. Following the results in Section 4, we assume the effect of log density on sector-specific skill depreciation to be 0.6% per five years, or 0.12% in continuously compounded terms. Calculations also assume a continuous-time, real interest rate of 2% per year and a return to skill of 10% per year. The sources for the other parameters are detailed in Section 6.

Table 1: Summary statistics

Variable:	1970 PUMS	'94-'-02 DWS
Panel A. Occupation and industry changes		
Detailed occupation or industry group	0.414	0.747
Detailed occupation group	0.358	0.607
Minor occupation group	0.241	-
Major occupation group	0.207	0.423
Detailed industry group	0.262	0.617
Minor industry group	0.213	-
Major industry group	0.165	0.407
Panel B. Metropolitan-area controls		
Log density	3.761	5.520
	(1.358)	(0.731)
Average educational attainment, years	11.176	13.375
	(0.744)	(0.699)
Share of workforce with bachelor's degree	0.124	0.094
	(0.038)	(0.050)
Share of workforce with some college	0.121	0.477
	(0.038)	(0.095)
Share of workforce with HS diploma	0.337	0.330
	(0.065)	(0.094)
Share of workforce employed in mfg. ind.	0.261	0.160
	(0.114)	(0.087)
Share of workforce in professional occ.	0.139	0.311
	(0.036)	(0.083)

Note: Table continues next page.

Table 1 (Continued): Summary statistics

Variable:	1970 PUMS	'94-'-02 DWS
Panel C. Individual controls		
	(share of population)	
Male	0.648	0.571
Black	0.089	0.103
Hispanic	0.108	0.107
Married	0.814	0.586
Citizen	0.980	0.919
Age 25-34	0.244	0.337
Age 35-44	0.255	0.328
Age 45-54	0.275	0.240
Age 55-65	0.226	0.094
Less than high school	0.402	0.104
High school diploma	0.327	0.306
Some college	0.134	0.510
Bachelor's degree or greater	0.137	0.080
	(mean and std. dev.)	
Age	44.34	40.22
	(11.26)	(9.87)
Educational attainment, years	11.38	13.36
	(3.28)	(2.53)

Notes: As indicated, entries reflect either the mean and standard deviation of the row variable, or the share of population in the row category. Samples are the 1970 Public-Use Microdata Sample (PUMS), and the Displaced Worker Supplements (DWS) to the Current Population Survey, 1994, 1996, 1998, 2000, 2002. PUMS sample includes all workers age 25 to 65; DWS sample includes all workers age 25 to 65 who were displaced from their jobs within the 3 years of the survey date. Individual-level statistics calculated on population where either occupation or industry, or both, are identified in both periods. Metropolitan-level statistics calculated on population in the labor force, age 25 to 65, at the time of the survey. DWS estimates come from the full CPS sample. PUMS sample sizes: occupation-identified sample, 516,854; industry-identified sample, 518,801; both occupation- and industry-identified sample, 509,643; number of metropolitan areas and county groups, 328. DWS sample size: main sample, 11,211; number of metropolitan areas, 191.

Table 2: Occupation and industry switching, 1970 PUMS

	(1)	(2)	(3)	(4)	(5)
Log density (/100)	-0.637 ***	-0.623 ***	-0.623 ***	-0.542 ***	-0.541 ***
	(0.160)	(0.144)	(0.140)	(0.103)	(0.104)
Male	-	0.031 ***	0.029 ***	0.032 ***	0.030 ***
		(0.002)	(0.002)	(0.002)	(0.002)
Black	-	-0.009 **	-0.011 ***	-0.011 ***	-0.012 ***
		(0.004)	(0.004)	(0.004)	(0.004)
Hispanic	-	-0.011 ***	-0.011 ***	-0.012 ***	-0.011 ***
		(0.003)	(0.003)	(0.003)	(0.003)
Married	-	-0.014 ***	-0.014 ***	-0.014 ***	-0.014 ***
		(0.003)	(0.003)	(0.002)	(0.002)
Citizen	-	-0.051 ***	-0.048 ***	-0.048 ***	-0.046 ***
		(0.010)	(0.009)	(0.011)	(0.011)
Educational attainment	-	0.006 ***	-	0.006 ***	-
		(0.000)		(0.000)	
Age group dummies	-	X	-	X	-
Potential experience terms and education group dummies	-	-	X	-	X
Region dummies	-	-	-	X	X
Share of population with college degree	-	-	-	0.266 ***	0.268 ***
				(0.085)	(0.086)
Share of population with some college	-	-	-	0.258 ***	0.248 ***
				(0.071)	(0.070)
Share of population with HS diploma	-	-	-	0.057 *	0.067 **
				(0.033)	(0.033)
Share of population working in manufacturing industry	-	-	-	0.075 ***	0.075 ***
				(0.017)	(0.017)
Share of population working in professional occupational	-	-	-	-0.228 **	-0.233 **
				(0.090)	(0.091)
Adjusted R-squared	0.169	0.194	0.197	0.2	0.197

Notes: Each column displays the results from a separate regression. The dependent variable is an indicator variable if there is a change in detailed occupation or industry group between 1964 and 1969. Standard errors, adjusted for clustering on metropolitan area/county group, are reported in parentheses. Coefficients that are statistically significant at the 90% level of confidence are marked with a $*$; at the 95% level, a $**$; and at the 99% level, a ***. All regressions include a constant and fixed effects for lagged detailed industry $\times$ occupation. Number of observations is 509,643. Number of clusters is 328.

Table 3: Alternative Aggregations of Occupation and Industry, 1970 PUMS

	Industry change			
Occupation change	No change	Major Group	Minor Group	Detailed Group
No change	-	-0.548	-0.753	-0.826
	-	(0.096)	(0.105)	(0.106)
Major Group	-0.741	-0.740	-0.764	-0.754
	(0.086)	(0.102)	(0.106)	(0.106)
Minor group	-0.820	-0.788	-0.762	-0.694
	(0.092)	(0.101)	(0.103)	(0.105)
Detailed Group	-0.656	-0.602	-0.581	-0.542
	(0.104)	(0.104)	(0.105)	(0.104)

Notes: Each entry represents a separate regression. Cells contain estimates for the coefficient on log density (/100). Dependent variable is occupation change or industry change between 1964 and 1969, at the aggregation level indicated by row and column headings. Standard errors, adjusted for clustering on metropolitan area/county group, are reported in parentheses. Number of observations of occupation-changing, 516,854; industry-changing, 518,801, both occupation- and industry-changing, 509,643. Regressions include covariates as specified in column (5) of Table 2. All coefficients in the table are statistically significant at the 99% level of confidence.

Table 4: Occupation and Industry Switching, Correction for Sorting

	State of Residence		State of Birth			
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Estimates from Two-Stage Least Squares					
Log density (/100)	-1.439 ***	-0.917 *	-1.545 ***	-1.226	-1.317 ***	0.337
	(0.183)	(0.530)	(0.198)	(0.894)	(0.216)	(0.661)
Metropolitan area controls	-	X	-	X	-	X
	Panel B. First-Stage Results					
Log state density	0.771 ***	0.369 ***	0.566 ***	0.202 ***		
	(0.140)	(0.100)	(0.111)	(0.041)		
Log state density, 1880					0.469 ***	0.214 ***
					(0.106)	(0.100)

Notes: Each column displays the results from a separate regression. The dependent variable is an indicator variable if there is a change in detailed occupation or industry group between 1964 and 1969. Standard errors, adjusted for clustering on state (of residence or birth, as appropriate), are reported in parentheses. Coefficients that are statistically significant at the 90% level of confidence are marked with a $*$; at the 95% level, a $**$; and at the 99% level, a ***. All regressions include lagged detailed industry $\times$ occupation dummies. Log density (/100) at the state level is used as an instrument for density at the metro-area/county-group level. Density for the state of residence is used in columns 1–2, while density from the state of birth is used in columns 3–6. Population density in 1880 for the state of birth is used as the excluded instrument in columns 5–6, following Ciccone and Hall (1996). Number of observations is 421,750 for the state-of-residence regressions and 459,411 for the state-of-birth regressions. The former sample is smaller because state of residence is censored for some due to privacy concerns. State of birth is not observed for non-natives, hence citizenship status is dropped from those regressions.

Table 5: Alternative Measures of Density, 1970 PUMS

		(1)	(2)	(3)	(4)	(5)
		Panel A. Using alternative measures of density				
		Entire sample	*Decomposed by region*			
			Northeast	Midwest	South	West
	Density measure					
1	Log density, metro area	-0.782 ***	-0.881 ***	-1.049 ***	-0.125	-0.515
		(0.141)	(0.202)	(0.283)	(0.167)	(0.369)
2	Log density, county group	-0.707 ***	-0.697 ***	-1.136 ***	-0.085	-0.711 ***
		(0.081)	(0.131)	(0.167)	(0.180)	(0.239)
3	Log density, county	-0.758 ***	-0.707 ***	-1.234 ***	-0.181	-0.874 ***
		(0.086)	(0.137)	(0.189)	(0.187)	(0.231)
4	Log density, tract	-0.637 ***	-0.571 ***	-0.801 ***	-0.409 ***	-0.267
		(0.116)	(0.129)	(0.202)	(0.151)	(0.266)
		Panel B. Alternative measures of density as IV				
			Alternative density measure used as instrument			
		Baseline	Tract	County	Cty. grp.	All
			B.1. Estimates from Two-Stage Least Squares			
	Log density (/100)	-0.541 ***	-1.577 ***	-1.307 ***	-1.531 ***	-1.210 ***
		(0.104)	(0.121)	(0.088)	(0.104)	(0.086)
				B.2. First-Stage Results		
	Alternative density measure		0.485 ***	0.563 ***	0.514 ***	-
			(0.001)	(0.001)	(0.001)	
		Panel C. Include employment share of worker's industry/occupation				
	Log density (/100)	-0.541 ***	-0.650 ***	-0.744 ***	-0.810 ***	
		(0.104)	(0.107)	(0.116)	(0.001)	
	Log employment share, 3-digit occupation		-2.743 ***		-2.017 ***	
			(0.297)		(0.257)	
	Log employment share, 3-digit industry			-3.998 ***	-3.599 ***	
				(0.157)	(0.141)	

Notes: Each cell displays the results from a separate regression. Cells contain estimates for the coefficient on log density (/100). The dependent variable is the change in detailed occupation or industry group between 1964 and 1969. All regressions contain log density, individual, and aggregate controls, as in column 5 of table 2. Standard errors, adjusted for clustering on metropolitan area/county group, are reported below in parentheses. Coefficients that are statistically significant at the 90% level of confidence are marked with a $*$; at the 95% level, a $**$; and at the 99% level, a ***. Panel A presents OLS results using alternative measures of density. Row 1 uses log density calculated at the county group level, except in metropolitan areas, where it is calculated at the metropolitan area level. Row 2 uses log density calculated at the county group level, except in metropolitan areas, where it is calculated as a weighted average of component county-group densities. Row 3 uses log density calculated at the county group level, as a weighted average of component county densities. Row 4 uses log density calculated at the county group level, as a weighted average of component census tract densities. Panel B contains results in which the density measures above are then used as instruments for measurement error of the metro-level density. Instrument sets are indicated in the column headings. In Panel B.1, the last column uses the three previous density measures as instruments. Panel B.2 displays the first-stage results for the just-identified equations. In Panel C, the second and third variables are, respectively, the log of own three-digit occupation or industry employment as a share of total metropolitan employment (computed from the PUMS data).

Table 6: Sensitivity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Level of aggregation (digits)															
Occupation	0	0	0	1	1	1	1	2	2	2	2	3	3	3	3
Industry	1	2	3	0	1	2	3	0	1	2	3	0	1	2	3
Panel A: Estimates Using Ordinary Least Squares															
Additional controls:															
None	-0.545	-0.750	-0.823	-0.740	-0.737	-0.761	-0.752	-0.818	-0.785	-0.759	-0.691	-0.654	-0.599	-0.579	-0.539
	(0.096)	(0.105)	(0.106)	(0.086)	(0.102)	(0.106)	(0.106)	(0.092)	(0.101)	(0.103)	(0.105)	(0.104)	(0.104)	(0.105)	(0.104)
Demographics	-0.604	-0.766	-0.823	-0.681	-0.729	-0.740	-0.729	-0.757	-0.764	-0.733	-0.674	-0.639	-0.599	-0.587	-0.572
	(0.091)	(0.094)	(0.100)	(0.087)	(0.101)	(0.104)	(0.110)	(0.093)	(0.102)	(0.102)	(0.109)	(0.106)	(0.106)	(0.107)	(0.111)
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Employment and Income	-0.553	-0.781	-0.882	-0.793	-0.806	-0.852	-0.861	-0.883	-0.837	-0.836	-0.819	-0.663	-0.636	-0.644	-0.629
	(0.100)	(0.109)	(0.115)	(0.104)	(0.121)	(0.126)	(0.127)	(0.118)	(0.127)	(0.128)	(0.130)	(0.118)	(0.120)	(0.118)	(0.120)
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Climate	-0.627	-0.789	-0.849	-0.781	-0.783	-0.774	-0.760	-0.830	-0.809	-0.758	-0.697	-0.648	-0.592	-0.564	-0.530
	(0.101)	(0.113)	(0.115)	(0.097)	(0.113)	(0.120)	(0.122)	(0.108)	(0.116)	(0.120)	(0.124)	(0.122)	(0.123)	(0.127)	(0.126)
	{0.150}	{0.200}	{0.300}	{0.120}	{0.070}	{0.110}	{0.200}	{0.350}	{0.160}	{0.130}	{0.160}	{0.190}	{0.080}	{0.050}	{0.040}
All of the above	-0.477	-0.552	-0.630	-0.578	-0.573	-0.542	-0.558	-0.612	-0.562	-0.499	-0.516	-0.426	-0.374	-0.370	-0.391
	(0.114)	(0.121)	(0.119)	(0.114)	(0.132)	(0.137)	(0.139)	(0.122)	(0.133)	(0.133)	(0.140)	(0.139)	(0.140)	(0.142)	(0.142)
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Panel B: Estimates Using Two-Stage Least Squares (Alternative Density Concepts as Instruments for Measurement Error)															
Additional controls:															
None	-0.714	-1.061	-1.286	-1.205	-1.290	-1.344	-1.391	-1.432	-1.426	-1.400	-1.365	-1.158	-1.159	-1.139	-1.121
	(0.086)	(0.094)	(0.101)	(0.094)	(0.103)	(0.106)	(0.109)	(0.100)	(0.106)	(0.108)	(0.111)	(0.104)	(0.107)	(0.109)	(0.112)
All of the above	-0.963	-1.163	-1.304	-1.013	-1.215	-1.180	-1.150	-1.294	-1.302	-1.167	-1.158	-0.809	-0.860	-0.834	-0.903
	(0.161)	(0.175)	(0.187)	(0.175)	(0.192)	(0.196)	(0.201)	(0.186)	(0.197)	(0.200)	(0.204)	(0.193)	(0.199)	(0.201)	(0.206)
	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}	{0.000}
Panel C: Additional Specification Checks															
Sample or dependent variable:															
Drop movers	-0.567	-0.779	-0.856	-0.841	-0.804	-0.831	-0.776	-0.853	-0.815	-0.806	-0.708	-0.681	-0.613	-0.592	-0.536
	(0.087)	(0.095)	(0.098)	(0.085)	(0.096)	(0.104)	(0.103)	(0.089)	(0.095)	(0.100)	(0.104)	(0.103)	(0.106)	(0.105)	(0.108)
Drop observations with allocated data	-0.567	-0.738	-0.814	-0.697	-0.704	-0.730	-0.733	-0.781	-0.759	-0.738	-0.673	-0.627	-0.574	-0.558	-0.519
	(0.093)	(0.102)	(0.103)	(0.081)	(0.099)	(0.104)	(0.104)	(0.090)	(0.100)	(0.102)	(0.104)	(0.104)	(0.103)	(0.104)	(0.105)
Predict censoring on LHS	-0.019	-0.021	-0.019	-0.020	-0.021	-0.020	-0.019	-0.020	-0.020	-0.020	-0.017	-0.020	-0.020	-0.020	-0.019
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)

Notes: Each cell displays the results from a separate regression. Standard errors, adjusted for clustering on metro area or county group, are reported in parentheses. All regressions include the controls listed for Table 2, Column (5), plus lagged industry × occupation dummies at the level of aggregation indicated in the column headings. For all but the bottom row, the dependent variable is an indicator variable if there is a change in occupation/industry between 1964 and 1969 at the indicated level of aggregatation, and coefficients are statistically significant at the 99% level or better. The additional aggregate controls are defined in Appendix A.2. In the first row of Panel C, "movers" are observations with different states of residence in 1964 and 1969. The final row of Panel C ("Predict censoring on LHS") uses a binary dependent variable that takes on a value of 1 when occupation or industry is observed in 1969 and 0 otherwise, and none of the estimated coefficients are statistically different from zero at conventional confidence levels. (In all cases, the sample is conditioned on occupation or industry observed in 1964.)

Table 7: Occupation/industry switching among Displaced Workers, 1994-2002

	Industry change		
Occupation change	No change	Major Group	Detailed Group
	Panel A. All Displaced Workers		
No change	-	-0.709	-1.971 **
	-	(0.770)	(0.941)
Major Group	-1.811 **	-1.222 *	-2.197 ***
	(0.830)	(0.733)	(0.853)
Detailed Group	-1.741 **	-1.485 **	-1.608
	(0.848)	(0.748)	(1.033)
	Panel B. Plant Closing Sample		
Occupation change	No change	Major Group	Detailed Group
No change	-	-0.324	-2.308 *
	-	(1.130)	(1.329)
Major Group	-2.428 *	-2.323 *	-2.463 *
	(1.326)	(1.226)	(1.514)
Detailed Group	-3.321 **	-2.383 *	-1.962
	(1.408)	(1.356)	(2.286)

Notes: This table reports regression results using data from the CPS Displaced Worker Supplement, 1994-2002. Each entry displays the results from a separate regression. Cells contain estimates for the coefficient on log density (/100). The dependent variable is occupation change or industry change after being displaced from a job, at the aggregation level indicated by row and column headings. Standard errors, adjusted for clustering on metropolitan area/county group, are reported below in parentheses. Coefficients that are statistically significant at the 90% level of confidence are marked with a ∗; at the 95% level, a ∗∗; and at the 99% level, a ***. Panel A includes all workers who were displaced from their jobs; Panel B includes only workers displaced by plant closings. Panel A: Number of observations of occupation-changing, 11,259; industry-changing, 11,274; both occupation- and industry-changing, 11,211 Panel B: Number of observations of occupation-changing, 4,106; industry-changing, 4,116; both occupation- and industry-changing, 4,089. Regressions include covariates as specified in column (5) of Table 2.

Table 8: Density, Occupation/Industry Switching, and Employer Changes

	(1)		(2)		(3)	
Worker controls	-		X		X	
Metropolitan controls	-		-		X	
Panel A. Job Change as Dependent Variable						
Log density (/100)	-1.478	***	-1.559	***	-1.105	***
	(0.267)		(0.259)		(0.297)	
Panel B. Control for Job Change						
Log density (/100)	-0.715	**	-0.731	**	-0.652	***
	(0.322)		(0.300)		(0.202)	
Job change	0.434	***	0.423	***	0.386	***
	(0.007)		(0.007)		(0.008)	

Notes: This table reports regression results using data from the CPS Job-Tenure Supplement, 1994-2002. Each panel/column displays the results from a separate regression. Standard errors, adjusted for clustering on metropolitan area/county group, are reported below in parentheses. Coefficients that are statistically significant at the 90% level of confidence are marked with a $*$; at the 95% level, a $**$; and at the 99% level, a $***$. The dependent variables are the following indicators: in Panel A, a change of 3-digit occupation or change; in Panel B, a change in employer. Regressions include covariates as specified in columns (1), (3), and (5) of Table 2, respectively.

Appendix A: Data Sources and Construction

This section provides detailed descriptions of data and methods used in the analysis of occupation and industry switching.

A.1 Base data and sample restrictions

The base data set, as noted in the text, is the 1970 Form 1 Metro sample from the Integrated Public Use Microdata Series (Ruggles et al., 2004). This is a 1% random sample of the entire U.S. population. Two features of the sample make the analysis possible. First, the sample identifies geographic information to the level of metropolitan area and county group. Second, it includes labor market information from both 1964 and 1969.

We restrict the sample to adults between the ages of 25 and 65. They must also have valid reported industry or occupation data for both 1964 and 1969. This restriction varies the size of the sample depending on the outcome variable: for example, if the outcome variable is a change in an individual's reported industry, then the relevant restriction is valid industry information for both 1964 and 1969.

In addition, we exclude Alaska and Hawaii from our analysis.

A.2 Geography

The smallest geographic units identified in the 1970 census are metropolitan area (identified for those living in metropolitan areas with populations greater than 100,000) and county group (identified for every individual).

For individuals living in identified metropolitan areas, we take that to be the individual's relevant labor market. Some exceptions exist here. We combine certain neighboring metropolitan areas according to census-defined 1990 consolidated metropolitan statistical areas (CMSAs), which group metropolitan areas in close proximity. Note that the CMSA concept did not exist in 1970; however, these areas formed unified labor markets. This procedure alters the following metropolitan areas (with absorbed MSAs in parantheses): Boston (Brockton), Chicago (Gary), Cleveland (Akron, Lorain), Dallas (Fort Worth), Los Angeles (Anaheim, Riverside-San Bernardino, Ventura), Miami (Fort Lauderdale), New York (Nassau-Suffolk, Bergen-Passaic, Jersey City, Newark), Philadelphia (Trenton, Wilmington), San Francisco (San Jose), and Seattle (Tacoma).

For individuals not living in identified metropolitan areas, we use county group information to identify their geographic location. County groups are analogous to the concept of Public Use Microdata Areas (PUMAs) introduced in the 1990 census and are identified for the entire population. County groups again consist of a central city and surrounding counties, with a minimum population of 250,000. In urban areas, these groups might identify small sub-areas within metropolitan areas. In rural areas, where metropolitan area is often not identified, county groups are much larger in area, frequently crossing state lines, but still usually centered on the largest urban center in the area. Maps of 1970 county groups are available at the IPUMS website (http://www.ipums.org/usa/volii/t1970maps.html).

Metropolitan and county-group aggregates are calculated based on data from the IPUMS. These aggregates are population, the share of total workers with a college degree, the share of total workers in the manufacturing sector, and the share of total workers in professional occupations.

Land area for metropolitan areas, used to calculate population density, is obtained from the Census Bureau's State and Metropolitan Area Data Book (1979).

Land area for county groups are obtained from The Historical United States County Boundary Files (HUSCO) (Earle et al. 1999). HUSCO contains land area data for every U.S. county in 1970. These data are matched with a county group composition (CGC) file available from the IPUMS website. The CGC matches counties to the county group to which they belong. After this matching, we sum area across counties to create land area data by county group. Future users of the CGC file should note that there are a number of minor errors in the county group composition table, including missing county codes and the misallocation of several Oklahoma counties to Maryland. Counties with missing county codes were matched based on county name and state; Oklahoma counties were carefully re-allocated using the maps available on the IPUMS website.

Additional regional controls are from the 1970 City and County Data Book (abbreviated as CCDB; source: ICPSR, 1984). We match county data to the hybrid metropolitan area-county group regions used in the analysis, taking weighted averages based on county population where appropriate. Demographic data taken from the CCDB includes white and black population shares, percent changes in population, the component of population change due to net migration, and working-age and 65+ population shares. Data on income/wealth and employment include low income shares, median income, rents, housing values, total bank deposits, and the percent change in manufacturing value added from 1963 to 1967. Climate data were constructed not from the CCDB, but from a geographic database (Oregon Climate Service, 2006) and consist of the following variables: average maximum temperature in July, the average minimum temperature in January, and the average dew point in July (a measure of humidity). We also include in the "climate" variables the share of total retail receipts to the recreation sectors (taken from the CCDB), as a control for consumption amenities. The population density (per square mile) in 1880 was computed from ICPSR (1984).

In section 4.2.2, we describe adjusting our density measure in a number of ways. Population-weighted averages of county group and county densities within our metropolitan area/county group hybrids use data from HUSCO and the CGC. Population-weighted averages of tract densities use data from the CensusCD (GeoLytics, 2001), a commercial product that contains tract population and tract shape files. We use the mapping tools provided on the CD to calculate tract area from these shape files. Then, we take population-weighted averages of tract densities within metropolitan areas and county groups. For the most part, only metropolitan areas were tracted in 1970. This adjustment affects only these areas.

A.3 Occupation and Industry

The 1970 IPUMS contains information on individuals' occupation and industry in both 1964 and 1969. These occupations and industries are categorized using a three-digit scheme of the Census Bureau's own making. On its website, IPUMS lists detailed industry (http://www.ipums.org/usa/volii/97indus.html) and occupation (http://www.ipums.org/usa/volii/97occup.html) codes.

We generate two-digit and one-digit occupation and industry codes by using contemporaneous census classifications. One-digit occupational groups are (1) Professional and technical workers, (2) Managers and administrators, (3) Sales workers, (4) Clerical workers, (5) Craftsmen, (6) Operatives, (7) Laborers, (8) Farmers, (9) Service workers, and (10) Private household workers. One-digit industrial groups are (1) Agriculture, mining, and construction, (2) Manufacturing, (3) Transportation, communications, and other public utilities, (4) Wholesale and retail trade, (5) Finance, insurance, and real estate, (6) Entertainment, recreation, and professional services, and (7) Public administration. We use 38 two-digit occupations and 34 two-digit industries.

For 1969 occupation and industry, the universe consists of persons aged 14 and older who have worked in the past 10 years, and who are not in the armed forces or new workers. The 1964 information is reported for all persons aged 14 and older who were working at a job or business in 1964. Missing values for the 1969 data are coded as "N/A" or "Unemployed person, last worked in 1959 or earlier"; missing values for the 1964 data include the additional category "Occupation not recorded."

The 1970 IPUMS contains information on altered cases in a separate quality flag variable. Separate variables indicate whether the Census Bureau altered occupation, industry, lagged occupation, or lagged industry information. However, in all cases, the allocation method is unspecified. These data are used in Section 4.3 and Table 5.

Appendix B: Probit Estimates for Occupation/Industry Switching, 1970 PUMS

	Industry change			
Occupation change	No change	Major Group	Minor Group	Detailed Group
No change	-	-0.539	-0.785	-0.889
	-	(0.096)	(0.108)	(0.113)
Major Group	-0.762	-0.756	-0.805	-0.818
	(0.087)	(0.105)	(0.113)	(0.114)
Minor group	-0.848	-0.817	-0.807	-0.755
	(0.094)	(0.105)	(0.110)	(0.114)
Detailed Group	-0.791	-0.714	-0.702	-0.667
	(0.128)	(0.126)	(0.129)	(0.130)

Notes: Each entry reports the estimated marginal effects from a separate probit regression. Cells contain estimates for the coefficient on log density (/100). Dependent variable is occupation change or industry change between 1964 and 1969, at the aggregation level indicated by row and column headings. Standard errors, adjusted for clustering on metropolitan area/county group, are reported in parentheses. Number of observations of occupation-changing, 516,854; industry-changing, 518,801, both occupation- and industry-changing, 509,643. Regressions include covariates as specified in column (5) of Table 2. Estimating a model with occupation/industry fixed effects was computationally infeasible in several cases, so we instead de-meaned the independent variables prior to estimation and also include in the model the average switching rate by occupation/industry cell instead of fixed effects. (Results are quite similar to those from a fixed-effects model in the subset of cases in which fixed-effects estimation was feasible.) All coefficients in the table are statistically significant at the 99% level of confidence.

Appendix C: Add Controls for Unionization Rate, Displaced-Workers Sample, 1996-2002

	(1)	(2)	(3)
Worker controls	-	X	X
Metropolitan controls	-	-	X
Log density (/100)	-1.629 **	-1.543 **	-1.514 **
	(0.703)	(0.680)	(0.643)
MSA labor force % in unions	-0.274 ***	-0.258 ***	-0.176 **
	(0.070)	(0.067)	(0.072)

Notes: This table reports regression results using data from the CPS Displaced Worker Supplement, 1994-2002. Each entry displays the results from a separate regression. Cells contain estimates for the coefficient on log density (/100). The dependent variable is detailed occupation change after being displaced from a job, with controls for the aggregate unionization rate. Standard errors, adjusted for clustering on metropolitan area/county group, are reported below in parentheses. Coefficients that are statistically significant at the 90% level of confidence are marked with a $*$; at the 95% level, a $**$; and at the 99% level, a ***. Regressions include covariates as specified in columns (1), (3), and (5) of Table 2, respectively.

Appendix D: Decompositions by Major Occupation Five Years Ago

	(0)	(1)	(2)	(3)
		Specifications:		
Subsample:	Dependent Variable Mean:	Log Density Only	Individual Controls	Aggregate Controls
Professional and	0.333	-0.220	-0.467 ***	-0.489 ***
technical workers	(0.471)	(0.157)	(0.147)	(0.184)
Managers and	0.352	-0.097	-0.106	-0.074
administrators	(0.478)	(0.200)	(0.184)	(0.243)
Sales workers	0.856	-0.330 ***	-0.319 ***	-0.288 ***
	(0.351)	(0.080)	(0.076)	(0.105)
Clerical and	0.445	-0.642 ***	-0.535 ***	-0.335 *
kindred workers	(0.497)	(0.158)	(0.114)	(0.192)
Craftsmen	0.348	-0.679 ***	-0.651 ***	-0.392 **
	(0.476)	(0.174)	(0.163)	(0.194)
Operatives	0.408	-1.350 ***	-0.609 ***	-0.743 ***
	(0.491)	(0.199)	(0.215)	(0.223)
Laborers	0.466	-1.531 ***	-1.308 ***	-1.293 ***
	(0.499)	(0.219)	(0.193)	(0.269)
Farmers	0.326	4.002 ***	3.696 ***	2.435 ***
	(0.469)	(0.515)	(0.462)	(0.730)
Service workers	0.351	-1.562 ***	-1.733 ***	-1.610 ***
	(0.477)	(0.362)	(0.343)	(0.290)
Private Household	0.280	-0.359	-0.363	-0.648
Workers	(0.449)	(0.302)	(0.306)	(0.547)

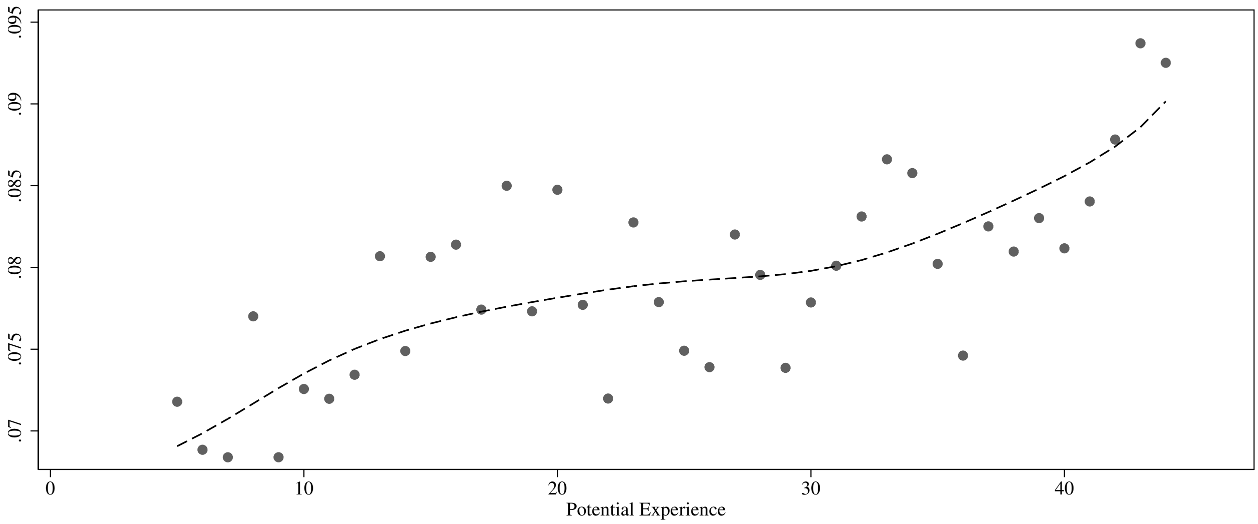
Notes: Each cell is a separate regression. Cells contain estimates for the coefficient on log density (/100). Coefficients that are statistically significant at the 90% level of confidence are marked with a †; at the 95% level, a ∗; and at the 99% level, a ∗∗. Standard errors, adjusted for clustering on metropolitan area/county group, are reported in parentheses. The dependent variable is the change in detailed occupation or industry group. Column 0 contains the dependent variable mean (plus standard deviation in parentheses) for each category. Column 1 contains regressions with log density and lagged industry and occupation dummies, as in column 1 of Table 2. Column 2 contains regressions with log density and individual controls, as in column 3 of Table 2. Column 3 contains regressions with log density, individual, and aggregate controls, as in column 5 of Table 2.

Appendix E: Decompositions by Major Industry Five Years Ago

Subsample:	(0) Dependent Variable Mean:	(1) Specifications: Log Density Only	(2) Individual Controls	(3) Aggregate Controls
Agriculture, mining	0.389	0.367	0.232	-0.063
construction	(0.488)	(0.251)	(0.240)	(0.227)
Manufacturing	0.424	-0.985 ***	-0.432 ***	-0.318 *
	(0.494)	(0.140)	(0.136)	(0.192)
Transportation,	0.353	-0.838 ***	-0.831 ***	-0.535 **
Comm., Utilities	(0.478)	(0.175)	(0.152)	(0.244)
Wholesale and	0.562	-0.799 ***	-0.755 ***	-0.966 ***
retail trade	(0.496)	(0.219)	(0.170)	(0.163)
Finance, Insurance,	0.399	-1.418 ***	-1.446 ***	-0.897 ***
Real Estate	(0.490)	(0.312)	(0.248)	(0.314)
Services	0.343	-0.429 **	-0.663 ***	-0.683 ***
	(0.475)	(0.169)	(0.161)	(0.147)
Public	0.329	-0.829 ***	-0.992 ***	-0.862 ***
administration	(0.470)	(0.200)	(0.196)	(0.270)

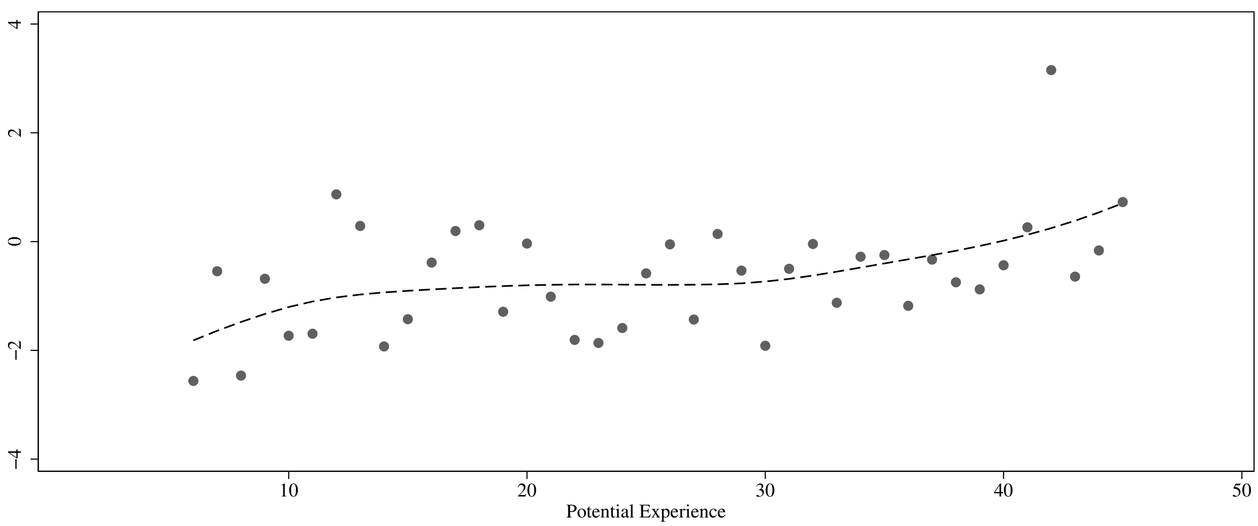
Notes: Each cell is a separate regression. Cells contain estimates for the coefficient on log density (/100). Coefficients that are statistically significant at the 90% level of confidence are marked with a †; at the 95% level, a $*$; and at the 99% level, a $**$. Standard errors, adjusted for clustering on metropolitan area/county group, are reported in parentheses. The dependent variable is the change in detailed occupation or industry group. Column 0 contains the dependent variable mean (plus standard deviation in parentheses) for each category. Column 1 contains regressions with log density and lagged industry and occupation dummies, as in column 1 of Table 2. Column 2 contains regressions with log density and individual controls, as in column 3 of Table 2. Column 3 contains regressions with log density, individual, and aggregate controls, as in column 5 of Table 2.

Appendix F: Effect of Density on Log Hourly Wage, by Potential Labor-Market Experience



Notes: Each point displays the results from a separate regression whose dependent variable is the log hourly wage. The y axis measures the density coefficient from these regressions. The x axis is years of potential experience in the labor market. All regressions include dummies for gender, race, marital status, citizenship, and years of education. The solid line is a smoothed version of the estimated coefficients, produced using Stata's "lowess" procedure. The data are drawn from the 1970 census, and the sample and variables are constructed as described in Appendix A.

Appendix G: Effect of Density on Job Changing, by Potential Labor-Market Experience



Notes: Each point displays the results from a separate regression whose dependent variable is an indicator variable for having changed employer in the past year. The y axis measures the density coefficient from these regressions. The x axis is years of potential experience in the labor market. All regressions include dummies for gender, race, marital status, citizenship, and years of education. The solid line is a smoothed version of the estimated coefficients, produced using Stata's "lowess" procedure. The data are drawn from the 1990s Job Tenure Supplements of the CPS, and the sample and variables are constructed as described in Appendix A.