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Agglomeration and Job Matching among College Graduates

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Abstract

We examine job matching as a potential source of urban agglomeration economies. Focusing on college graduates, we construct two direct measures of job matching based on how well an individual's job corresponds to his or her college education. Consistent with matching-based theories of urban agglomeration, we find evidence that larger and thicker local labor markets increase both the likelihood and quality of a job match for college graduates. We then assess the extent to which better job matching of college-educated workers increases individual-level wages and thereby contributes to the urban wage premium. We find that college graduates with better job matches do indeed earn higher wages on average, though the contribution of such job matching to aggregate urban productivity appears to be relatively modest.

Key words: agglomeration, labor market matching, productivity, underemployment, urban wage premium

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I. INTRODUCTION

The agglomeration of economic activity provides significant productivity advantages to firms and workers. Estimates of the magnitude of such urban agglomeration economies suggest that doubling the size or density of an urban area is associated with a 2 to 8 percent increase in productivity.[1] Explanations of the underlying causes of these productivity benefits have evolved from Marshall's (1890) classic ideas about the sources of agglomeration related to input sharing, labor market pooling, and knowledge spillovers to Duranton and Puga's (2004) more formal exposition of these micro-foundations based on increasing returns arising from sharing, matching, and learning externalities. While the magnitude of urban agglomeration economies is well established, empirically identifying the underlying sources of these productivity benefits has proven to be more difficult. As a result, little is currently known about the importance of these micro-foundations.

In this paper, we study one potential source of urban agglomeration economies: better job matching. Economists have long believed that large and dense urban environments help facilitate matching between workers and firms. This is because more agglomerated local labor markets lower the costs associated with job search and provide a wider variety of job opportunities. As a result, workers in big cities are more likely to match their human capital to a job in which their skills are put to their most productive use. Indeed, the matching-based models of urban agglomeration that have been developed predict that more agglomerated local labor markets enhance productivity by

[1] Rosenthal and Strange (2004), Puga (2010), and Combes and Gobillon (2015) provide comprehensive reviews of the empirical evidence on urban agglomeration economies, while Melo, Graham, and Noland (2009) provide a meta-analysis of study characteristics affecting the magnitudes of existing estimates of agglomeration effects.

improving both the likelihood of matching and increasing the quality of these matches (Helsley and Strange, 1990; Sato, 2001; Berliant, Reed, and Wang, 2006).

Recently, a small body of literature has begun to provide evidence consistent with matching-based theories of urban agglomeration. These empirical studies have found that larger and thicker urban labor markets enhance worker productivity by allowing for a greater specialization of professional activities (Baumgardner, 1988; Garicano and Hubbard, 2007); helping to solve dual-career problems (Costa and Kahn, 2000); improving matching between workers and firms (Andersson, Burgess, and Lane, 2007; Andini et al., 2013); enhancing the efficiency of job search (Yankow, 2009; Di Addario, 2011), and reducing labor market churn (Wheeler, 2008; Bleakley and Lin, 2012). While this work has improved our understanding of the benefits of urban agglomeration, the empirical evidence surrounding job matching as a source of urban agglomeration economies remains, so far, largely indirect in nature.

By indirect, we mean that most existing studies do not explicitly look at the nature of job matches, but rather infer that better job matching has occurred based on a secondary observation. A recent example of this approach is Bleakley and Lin (2012), who find that workers change occupations and industries less frequently in more densely populated areas, and attribute this outcome to enhanced job matching facilitated by dense urban environments. A more direct approach would compare the amount and types of skills a worker possesses relative to the job performed to determine the extent of a job match, and examine how matches vary across the urban spectrum. No doubt, taking such a direct approach has been hampered by difficulties associated with defining what constitutes a match and limitations posed by available data that make it difficult to measure the human capital possessed by workers and compare this to the skills necessary to perform the job a worker holds.

To close this gap in the existing literature, we utilize newly available data to construct two measures of job matching for college graduates based on how well their job corresponds to their college education. As such, we build from the broader labor economics literatures analyzing the match between an individual's education and job (see, e.g., Hersch, 1991; Robst, 2007), as well as the role of job search and occupational choice in forming job matches (see, e.g., Miller, 1984; Neal, 1999; Shimer, 2007). Job search and matching has also proven to be important in the process of human capital accumulation (see, e.g., Bowlus and Liu, 2013). However, these broader literatures have largely ignored how local labor market conditions influence the job matching process.

Our first matching measure, which we refer to as a *College Degree Match*, determines whether a college graduate is working in an occupation that requires a college degree. Our second measure, which we refer to as a *College Major Match*, gauges the quality of a job match by determining how well an individual's college major corresponds to that person's occupation. Thus, by utilizing both measures, we are able to analyze how the likelihood and quality of job matching among college graduates varies across the urban spectrum.

Our main empirical analysis examines the extent to which larger and denser urban environments facilitate job matching among college graduates. We estimate probit models of the determinants of job matching for college graduates located in metropolitan areas. Consistent with matching-based theories of agglomeration, we find evidence that larger and thicker local labor markets help college graduates find better jobs by increasing both the likelihood and quality of a match. Although the marginal effects we estimate are small, the difference in match probability between large and small-to-medium metropolitan areas or between dense and sparse metropolitan areas is economically important.

The estimation approach used for this analysis addresses a number of challenging identification issues that may arise in estimating the relationship between job matching and urban agglomeration. Perhaps most fundamentally, biases may result if either the workers or job opportunities in large and dense urban areas are systematically more or less conducive to job matching. Indeed, recent research indicates that it is important to account for worker characteristics and metropolitan area composition effects in studies of the effects of urban agglomeration (Combes et al., 2008, 2010; Abel, Dey, and Gabe, 2012). As such, we include a wide array of worker characteristics, including each individual's college major, and account for differences in the economic structure and performance of metropolitan areas in all of our models. In addition, to allay concerns about more traditional urban agglomeration endogeneity issues, such as simultaneity or omitted variables, we show that our results are robust to standard instrumental variables estimation.

As an extension to our main empirical analysis, we then assess the extent to which better job matching of college graduates increases individual-level wages and thereby contributes to the urban wage premium. We find that college graduates, on average, earn a significant wage premium when working in a job related to their college education. Further, we provide evidence that supports the idea that better job matching contributes to the urban wage premium. Thus, these results provide direct evidence that better job matching is a source of urban agglomeration economies, though the contribution of job matching to aggregate urban productivity appears to be relatively modest.

II. MEASURING JOB MATCHING AMONG COLLEGE GRADUATES

The primary dataset used in our analysis is the 2010 American Community Survey (ACS), a nationally representative 1 percent sample of the U.S. population (Ruggles et al., 2010). These data include a variety of economic and demographic information for individuals, including a person's occupation, wage, and level of education. Of particular use for our purposes, the ACS recently began to include detailed information on an individual's undergraduate degree major. Given our focus on college graduates, we limit our sample to working-age individuals (i.e., aged 16 to 64) with at least a Bachelor's degree who are in the civilian labor force, and located in metropolitan areas, since this geography is a good proxy for local labor markets. The full sample contains nearly 360,000 observations representing more than 36 million college graduates.[2]

We combine these micro data with other sources of information to develop two measures of job matching among college graduates. Our first measure, which we refer to as a *College Degree Match*, utilizes data from the U.S. Department of Labor's Occupational Information Network (O*NET) to determine whether a college graduate is working in an occupation that requires a college degree. The O*NET system contains occupation-level data for hundreds of detailed occupations, collected via interviews of incumbent workers and input from professional occupational analysts, on a wide array of

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[2] We apply the nationally representative ACS sample weights in all of our analysis.

job-related requirements.[3] We use the following question from the O*NET Education and Training Questionnaire to determine whether an occupation requires a college degree: "If someone were being hired to perform this job, indicate the level of education that would be *required*?" (emphasis added). Respondents can then select from the following twelve education levels: "Less than a High School Diploma, High School Diploma, Post-Secondary Certificate, Some College Courses, Associate's Degree, Bachelor's Degree, Post-Baccalaureate Certificate, Master's Degree, Post-Master's Certificate, First Professional Degree, Doctoral Degree, and Post-Doctoral Training." We considered a college education to be a requirement for a given occupation if more than 50 percent of the respondents working in that occupation indicated that at least a Bachelor's degree was necessary to perform the job.[4] We then merged these data on educational requirements for each occupation to individual workers and their actual occupations from the ACS. An individual matches if they are working in an occupation that requires a college degree. Unemployed workers, by definition, are a non-match.[5] We find that about 62 percent of the college graduates in our sample work in a job that requires a college degree.

Our second measure of job matching, which we refer to as a *College Major Match*, gauges the quality of a job match by determining if an individual's college major

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[3] We use O*NET Version 15 for our analysis, see http://www.onetcenter.org/ for more information. The O*NET database is discussed in detail by Peterson et al. (2001).

[4] We selected this threshold because it indicates that the majority of respondents believe that at least a Bachelor's degree is required to perform a given job. In practice, however, few occupations are clustered around the 50 percent threshold. For most occupations, respondents either overwhelmingly believe that a Bachelor's degree is required for the job or not. Nonetheless, we performed sensitivity analysis using both a 40 percent and 60 percent threshold. While the share of graduates with a College Degree Match increases or decreases slightly using these alternative thresholds, the main job matching results presented in the paper are not sensitive to our choice of threshold.

[5] We also analyzed a restricted sample consisting of only employed individuals. While eliminating unemployed individuals increased the raw match rates somewhat, our empirical results were nearly identical to those presented in the paper that use the full sample.

is related to the job that person is performing. The ACS recently began to identify an individual's undergraduate college major, classifying them into one of 171 detailed degree fields. Our strategy to estimate a College Major Match is to determine whether a person's major is related to the occupation in which they are currently working. We determine whether such a connection exists using an occupational crosswalk provided by the Department of Education's National Center for Education Statistics (NCES) that links degree majors listed in the Classification of Instructional Programs (CIP 2000) to occupations in the Standard Occupational Classification (SOC) system.[6] This linking of degree majors to occupations is not mutually exclusive as many majors feed into multiple occupations. With this bridge between occupations and majors serving as a foundation, we then match the occupation and major information provided in the crosswalk with the occupation and detailed degree major classifications available in the ACS. Since the CIP classification of degree majors does not correspond on a one-for-one basis to the ACS classification of degree majors, we matched majors from the two classification systems as closely as possible.

We consider a college graduate to match along this dimension if they were working in an occupation that is related to their reported degree major.[7] A limitation of this approach is that the degree major information provided in the ACS corresponds to an individual's *undergraduate* field of study, even if a person possesses a graduate degree. In the case of a person with a graduate degree, only the undergraduate field of study is identified. Since we cannot appropriately determine a field of study match in these cases,

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6 See http://nces.ed.gov/pubs2002/cip2000/ for more information.

7 The ACS allows individuals to list up to two detailed degree majors when completing the survey. We allow individuals to match if either of their listed degree majors corresponds to their occupation.

we omit individuals with a graduate degree from our analysis that utilizes this measure of job matching. We find that about 27 percent of undergraduate degree holders are working in a job that is directly related to their college major.[8]

To provide a better sense of our matching classification, Table 1 provides several examples of jobs that match to a selected group of majors, together with matching rates for each major. Take, for example, graduates with a Computer Science major. A person who works as a Software Developer, an occupation that both requires a college degree and is directly related to the major, would be considered both a College Degree Match and a College Major Match. On the other hand, a person who works as an Advertising Manager, an occupation that requires a college degree but is not directly related to a Computer Science major, would have a College Degree Match, but not a College Major Match. Finally, a person who works as a Customer Service Representative, an occupation that does not require a college degree and is not directly related to a Computer Science major, would not be considered a match for either measure. In looking at the match rates for the universe of Computer Science majors in our data, we see that about 73 percent of these majors work in jobs that require a college degree, while 33 percent work in jobs directly related to their major.

Job match rates vary considerably across majors. For example, though about two-thirds of all college graduates are working in a job that requires a Bachelor's degree, 80 percent of those with a Computer Engineering degree but only 44 percent of those with a Studio Arts degree are doing so. Similarly, while about one-fourth of all college graduates appear to be working in a job directly related to their major, more than half of

[8] In the analysis that follows, we continue to refer to this group as "college graduates" even though the sample contains only undergraduate degree holders.

those with an Accounting or Elementary Education degree but almost no one with a History or Liberal Arts degree are doing so.

While our job matching strategy and matching rates tend to follow expectations, using the published crosswalk to match college majors to related occupations for the College Major Match has its limitations, as the matching scheme tends to be quite strict. For example, though it could be argued that someone working as an Insurance Underwriter uses some of the skills provided by a Finance degree to do their job, the occupational crosswalk does not link this occupation and college major. A similar argument might be made for someone with a Mathematics degree who is working as a Budget Analyst. This type of issue becomes even more apparent with majors that tend to be general, rather than narrowly focused. For instance, while the College Major Match rate is 53 percent for Accounting majors, it is just 1 percent for Liberal Arts majors. On one hand, this may seem appropriate since Liberal Arts majors arguably possess skills that are directly relevant to very few occupations. However, such majors probably have some skills specific to a number of jobs that are not picked up by our measure.

Overall, these biases in the crosswalk most likely understate the true extent of matching a job to one's major. However, our focus is on modeling patterns of variation in the probability of matching, primarily with respect to differences across space. Further, our regression analysis will control for college major when estimating the relationship between urban agglomeration and job matching. This allows us to pick up the correlates to differences in the probability of matching *within* majors, reducing concerns about biases in our matching measures.

III. AGGLOMERATION AND JOB MATCHING

To what extent do more agglomerated urban environments facilitate job matching? To address this question, we estimate regressions that model the determinants of job matching for college graduates, including the size and density of the metropolitan areas in which these individuals are located.

A. Estimation Approach

Because our measures of job matching are binary variables, we use a probit model to estimate the likelihood of job matching for college graduates. Letting MATCH_i represent a job match for individual *i* located in metropolitan area *j* that is contained within a larger region *k*, the probability that an individual's job matches their college education can be expressed as:

$$Prob\,(\text{MATCH}_i = 1) = \Phi\,(\alpha \text{A}_j + \boldsymbol{\beta}\mathbf{X}_i + \boldsymbol{\delta}\mathbf{M}_i + \boldsymbol{\mu}\mathbf{Z}_j + \sigma_k) \qquad (1)$$

where A_j is a variable measuring the agglomeration of the metropolitan area in which individual *i* is located; $\mathbf{X}_i$ is a vector of individual-level characteristics; $\mathbf{M}_i$ is a vector of dummy variables denoting an individual's degree major; $\mathbf{Z}_j$ is a vector of other metropolitan area-level variables to control for differences in the characteristics of metropolitan areas; σ_k is a spatial fixed effect; and α, $\boldsymbol{\beta}$, $\boldsymbol{\delta}$, and $\boldsymbol{\mu}$ are parameters to be estimated. $\Phi(\cdot)$ is a normal cumulative distribution function, and the estimated parameters are chosen to maximize the sum of the log likelihoods over all observations.

The explanatory variable of most interest in our model, A_j, captures differences in agglomeration across metropolitan areas. While early empirical studies of urban agglomeration tended to emphasize city size as the key agglomerative force, more recent work has gravitated toward measures of urban density, although both measures are still used in the empirical agglomeration literature.[9] We consider both population size and employment density in alternative models.[10]

Using alternative agglomeration measures is appealing for our purposes as each variable likely captures different aspects of the potential job matching benefits that arise from urban agglomeration. For example, to the extent that job matching is enhanced by the wider variety of jobs that result from a greater division of labor made possible in more agglomerated areas, population size may be the preferred measure. On the other hand, employment density may be the better choice if job matching is made easier because of the reduced search costs that may exist in more agglomerated areas. In practice, all of the potential job matching benefits of urban agglomeration are simultaneously at work, and since these variables are correlated, they likely capture similar though potentially somewhat different effects.

Our measure of metropolitan area population size comes from the 2010 U.S. Census, while our measure of metropolitan area employment density uses 2010 employment data from the Quarterly Census on Employment and Wages (QCEW) published by the U.S. Bureau of Labor Statistics coupled with corresponding land area information provided in the 2010 U.S. Census. We combine these metropolitan area agglomeration measures with individual level data from the 2010 ACS, matching these

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9 See Sveikauskas (1975) and Segal (1976) for early studies of urban agglomeration employing population size. Seminal work by Ciccone and Hall (1996) shifted the focus from population size to the density of economic activity to measure urban agglomeration.

10 The correlation between these measures of urban agglomeration is 0.74, while the Spearman rank correlation is 0.62. We also considered probit models using the logarithm of population size and employment density instead of the level. Results from these models were consistent with our baseline results.

data as closely as possible to the metropolitan area definitions provided in the ACS. Complete data are available for 264 metropolitan areas.

Estimating the relationship between job matching and urban agglomeration presents a number of empirical challenges. First, the estimated relationship between job matching and urban agglomeration would be biased if individuals with a systematically higher or lower likelihood of job matching are drawn to large or dense urban areas. In addition, a similar bias would arise if the type of economic activity that occurs in large or dense urban areas is either systematically more or less conducive to job matching. Indeed, recent research indicates that it is important to account for worker characteristics and metropolitan area composition effects in studies of the effects of urban agglomeration (Combes et al., 2008, 2010; Abel, Dey, and Gabe, 2012).

To address identification issues related to differences in worker characteristics, our probit models include a wide range of individual level characteristics that are expected to influence the likelihood of matching, such as age, sex, marital status, race, the presence of children, and, in our College Degree Match (but not College Major Match) estimation, whether the individual has a graduate degree. In addition, the vector $\mathbf{M}_i$ includes dummy variables for an individual's college major, which provides a more comprehensive way to control for differences in skill than has previously been available in cross-sectional studies of this nature.[11] Moreover, inclusion of these variables enables us to account for any differences in the match probability across degree fields. For

[11] Recent panel data studies have addressed this type of identification problem by exploiting the longitudinal dimension of the data and employing a worker fixed effect approach (Combes et al., 2008, 2010). With panel data unavailable for our study, we instead incorporate information on a wide array of worker characteristics, including each individual's college major, to reduce any biases stemming from differences in workers located across the urban spectrum.

example, as shown in Table 1, individuals with a degree in a major that offers occupation-specific training, like Accounting or Elementary Education, are more likely to match along either dimension than those with a degree in a major that provides a more general education, such as History or Liberal Arts.

One potential limitation of our empirical strategy, even when including these worker traits, is that there may be unobserved worker characteristics that are endogenous with respect to our measures of urban agglomeration. For example, people who value the amenities of big and dense places may tend to acquire or possess specialized skills, or choose majors, which are more likely or less likely to yield a match. However, by including fixed effects for college major, we are essentially able to identify differences in match probability *among* those with a particular major—say, an Accounting degree. Thus, any remaining concerns about identification are conditional on major choice, which should limit such concerns.

To account for potential metropolitan area composition effects and differences in local economic performance that may be captured by the agglomeration variables, we also include a number of metropolitan area level characteristics in $\mathbf{Z}_j$. These include industry shares based on the 15 major NAICS categories, occupational shares based on the 23 major SOC categories, and the local unemployment rate. Finally, inclusion of spatial fixed effects, σ_k, helps control for unobserved differences across larger regions.

We begin our analysis by estimating equation (1) separately for each measure of job matching and urban agglomeration. After establishing baseline results, we then re-estimate our probit models using an instrumental variables approach to investigate the direction and magnitude of biases that might arise from more traditional endogeneity issues that can occur in studies of urban agglomeration, such as simultaneity or omitted variables. In all of our analysis, we assume that individual error terms are independent across metropolitan areas but potentially correlated within metropolitan areas. Therefore, we estimate and report robust standard errors that are clustered at the metropolitan area level. Clustering at the metropolitan area level tends to increase the coefficient standard errors, but does not affect the coefficient estimates themselves.

B. Probit Estimation Results

Because of the difficulties in interpreting the raw coefficient estimates obtained via probit analysis, we instead present the corresponding average marginal effects. As such, our estimates can be interpreted as the average percentage point change in the probability of a job match. We begin by discussing the baseline results of our analysis of the determinants of a College Degree Match and College Major Match.

i. College Degree Match

Table 2 presents the probit marginal effects from our College Degree Match analysis. Results with population size as the measure of agglomeration are shown in Column (1), while results using employment density are shown in Column (2). Across both specifications, we find that college-educated individuals located in more agglomerated metropolitan areas have a higher probability of working in a job that requires a college degree, although the marginal effects are relatively small. In particular, an individual's probability of working in a job requiring a college degree increases by 0.21 percentage points as metropolitan area population increases by 1 million people or as metropolitan area employment density increases by 100 workers per square mile.

Relative to the average College Degree Match rate of 62 percent, these estimated marginal effects represent a 0.34 percent increase in the likelihood of matching.

To put these results in perspective, Figure 1 provides a comparison of the predicted probability of working in a job requiring a college degree for each measure of agglomeration along urban spectrum. To allow for a comparison between population size and employment density, the *x*-axis is expressed in percentiles, ranging from small and sparse metropolitan areas (e.g., 10th-25th percentiles) to extremely large and dense metropolitan areas (e.g., 95th percentile and above).[12] Panel (a) of Figure 1 plots the predicted probability of College Degree Matching at different points along the urban spectrum. These estimates suggest that job matching is most likely in the largest and most crowded metropolitan areas, and that the pattern is similar for each measure of urban agglomeration. Specifically, our estimates imply that College Degree Matching is 4-6 percent more likely in a place like New York City than in places such as Syracuse, NY (75th percentile for population, 50th percentile for density); Medford, OR (50th, 10th); or Abilene, TX (10th, 25th).[13] Thus, while the marginal effects we estimate are small, the difference in match probability between large and small-to-medium sized metropolitan areas or between dense and sparse metropolitan areas is economically important.

12 It is well known that population and employment density are not evenly distributed across the urban spectrum. Metropolitan areas with 140,000 to 370,000 people would fall between the 10th and 50th percentiles, those with 3.25 million people would be at the 95th percentile, while a metropolitan area at the 99.9th percentile would have a population of about 16.5 million people. The corresponding figures for employment density are 39 to 109 workers per square mile (10th-50th percentiles), 464 workers per square mile (95th percentile), and 1,321 workers per square mile (99.9th percentile).

13 For example, Figure 1 (a) shows that the probability of a college graduate working in a job requiring a college degree increases from 61.1 percent to 64.5 percent when the population size of a metropolitan area increases from the 50th percentile to the 99.9th percentile—a difference of 5.6 percent. Similarly, the probability of a college graduate working in a job requiring a college degree increases from 61.3 percent to 63.9 percent when the employment density of a metropolitan area increases from the 50th percentile to the 99.9th percentile—a difference of 4.2 percent.

Turning to other estimates presented in Columns (1) and (2) of Table 2, across both model specifications, we find that having a graduate degree is a strong predictor of whether an individual is working in a job that requires a college degree, increasing the probability of College Degree Match by about 25 percentage points. In addition, older individuals and those who are married or with children are more likely to match, while males and non-whites are generally less likely to match. Holding other factors constant, it appears that individuals living in metropolitan areas with higher unemployment rates are less likely to match, although the estimated marginal effects of this variable are generally not statistically significant.

ii. College Major Match

Columns (3) and (4) of Table 2 presents the probit marginal effects from our College Major Match analysis, with the results organized as before. Again, across both specifications, we find that college-educated individuals located in more agglomerated metropolitan areas have a higher probability of working in a job related to their college degree major. In particular, an individual's probability of working in a job related to their college degree major increases by about 0.15 percentage points as metropolitan area population increases by 1 million people and by about 0.25 percentage points as metropolitan area employment density increases by 100 workers per square mile. Relative to the average College Major Match rate of 27 percent, these increases represent a 0.54 to 0.93 percent increase in the likelihood of matching.

Panel (b) of Figure 1 provides a comparison of the predicted probability of working in a job related to an individual's college degree major for each measure of agglomeration along the urban spectrum. Again, these estimates suggest that job matching is most likely in the largest and most crowded metropolitan areas, but the increase is greater for employment density than population size. Focusing on population size, our estimates imply that College Major Matching is about 9 percent more likely in a place like New York City than in places such as Syracuse, NY; Medford, OR; or Abilene, TX. However, our estimates for employment density imply that College Major Matching is about 12 percent more likely in a place like New York City than these other metropolitan areas.[14] Interestingly, while we find a positive relationship between agglomeration and both measures of job matching, living in a large or dense metropolitan area appears to increase the likelihood of College Major Matching more than it increases the likelihood of College Degree Matching.

Turning to the other results presented in Columns (3) and (4) of Table 2, across both model specifications, we find that males and married individuals are more likely to be working in a job related to their major, while older individuals, those with children, and non-whites are generally less likely to match. Again, individuals living in metropolitan areas with higher unemployment rates are generally less likely to be working in a job related to their major, although the estimated marginal effect of this variable is statistically significant in only one model specification.

C. Instrumental Variables Estimation

A concern that arises with our probit estimation is that differences in the agglomeration of metropolitan areas are not randomly assigned across space. Indeed, job

[14] For example, Figure 1 (b) shows that the probability of a college graduate working in a job related to their college degree major increases from 26.7 percent to 29.1 percent when the population size of a metropolitan area increases from the 50th percentile to the 99.9th percentile—a difference of 8.9 percent. Similarly, the probability of a college graduate working in a job related to their college degree major increases from 26.5 percent to 29.6 percent when the employment density of a metropolitan area increases from the 50th percentile to the 99.9th percentile—a difference of 11.7 percent.

matching and urban agglomeration may be endogenous if the possibility of better job matching increases the size or density of a metropolitan area by attracting firms or people to it. In addition, although our empirical model includes spatial fixed effects, σ_k, and controls for a wide range of individual characteristics and differences in the structure and economic performance across metropolitan areas, the presence of other unobserved factors that are correlated with the likelihood of job matching and metropolitan area size or density remains a possibility. If this is the case, our baseline probit estimates may be biased. To address these concerns, we re-estimate our models using an instrumental variables probit approach.

Implementing an instrumental variables approach requires identifying a variable that is correlated with urban agglomeration (i.e., relevant) but not directly related to the likelihood of job matching across metropolitan areas (i.e., satisfies the exclusion restriction). Since Ciccone and Hall (1996), it has been common to use historical measures to instrument for modern urban agglomeration. We follow this standard approach and use long lags of metropolitan area population and density from the early 1900s to instrument for contemporaneous population size and employment density, respectively. The key identifying assumption to this approach is that any relationship that exists between these instrumental variables and the likelihood of local job matching operates only *through* the agglomerative forces that may exist in large and dense urban environments. Given the fundamental changes that have occurred in the U.S. economy over the past century, this assumption seems plausible. Moreover, more recent research by Combes et al. (2010) has shown that historical instruments generally perform similarly to other instrumental variables approaches used in urban agglomeration studies. Thus, we believe using this approach will help us assess the extent to which endogeneity biases may exist in our baseline probit estimates.

Results from our instrumental variables probit analysis are provided in Table 3. The bottom panel of the table reports the coefficient estimate for our instrumental variable from the first stage regressions. Consistent with previous research, each historical instrument is a strong predictor of modern urban agglomeration, explaining well over 20 percent of the variation in population size and employment density observed across U.S. metropolitan areas.

The top portion of the table reports the average marginal effects from our instrumental variables regressions. In general, the pattern of results from these second-stage regressions is consistent with those obtained in our baseline probit estimation. However, the average marginal effects of increasing population size or employment density are somewhat higher when these variables are treated as endogenous. As shown in Columns (1) and (2), an individual's probability of working in a job requiring a college degree increases by 0.33 percentage points as metropolitan area population increases by 1 million people and by 0.35 percentage points as metropolitan area employment density increases by 100 workers per square mile. The corresponding estimates for College Major Matching—shown in Columns (3) and (4)—are 0.24 percentage points as population size increases and 0.44 percentage points as employment density increases.

Figure 2 provides a comparison along the urban spectrum of the predicted probability of working in a job related to an individual's college education for each measure job matching and urban agglomeration based on our instrumental variables probit analysis, similar to the figures discussed earlier. Given the increase in the size of the estimated marginal effects, our estimates imply that comparing a place like New York City to metropolitan areas falling within the 10th to 75th percentile of population size or employment density, College Degree Matching is 6 to 9 percent more likely, and College Major Matching is 14 to 22 percent more likely.[15]

When interpreting these results, it is important to note that because of the inefficiency introduced by an instrumental variables approach, our baseline probit estimates generally fall within one standard deviation of their corresponding instrumental variables estimates. Indeed, specification tests reported at the bottom of Table 3 fail to reject the null hypothesis of exogeneity for both measures of job matching and urban agglomeration. Thus, to the extent that the endogeneity of urban agglomeration biases our results, it appears our baseline probit estimates understate the job matching benefits that result from locating in larger and thicker urban environments.

Though one might expect using an instrumental variables approach would reduce point estimates in the presence of reverse causality, there are reasons to believe this result would not necessarily hold in this case. While some of the difference between our baseline and instrumental variables estimates may be due simply to measurement error, the prospect of better job matching in more agglomerated local labor markets may attract workers with skills, or firms with jobs, that are inherently more difficult to match. To the extent that this dynamic is at work, employing an instrumental variables approach can

[15] For example, Figure 2 (a) shows that the probability of a college graduate working in a job requiring a college degree increases from 60.5 percent to 65.8 percent when the population size of a metropolitan area increases from the 50th percentile to the 99.9th percentile—a difference of 8.8 percent. Similarly, Figure 2 (b) shows that the probability of a college graduate working in a job related to their college degree major increases from 25.9 percent to 31.3 percent when the employment density of a metropolitan area increases from the 50th percentile to the 99.9th percentile—a difference of 20.7 percent.

help control for this type of endogeneity, thereby increasing the estimated relationship between job matching and urban agglomeration.

IV. JOB MATCHING AND THE URBAN WAGE PREMIUM

To what extent does better job matching increase individual-level wages and contribute to the urban wage premium? Having established that large and dense urban environments do in fact facilitate job matching among college graduates, we next extend our analysis of job matching to address this question.

A. Estimation Approach

Our estimation approach involves comparing the results obtained from estimating a standard urban wage equation to those obtained when estimating an augmented version of the model that incorporates our measures of college job matching. Specifically, for individual *i* located in metropolitan area *j* that is contained within a larger region *k*, we estimate the following urban wage regressions:

$$\ln w_i = \alpha \ln A_j + \boldsymbol{\beta}\mathbf{X}_i + \boldsymbol{\delta}\mathbf{M}_i + \boldsymbol{\mu}\mathbf{Z}_j + \sigma_k + \varepsilon_i \quad (2)$$

$$\ln w_i = \alpha' \ln A_j + \boldsymbol{\phi}\mathbf{MATCH}_i + \boldsymbol{\beta}\mathbf{X}_i + \boldsymbol{\delta}\mathbf{M}_i + \boldsymbol{\mu}\mathbf{Z}_j + \sigma_k + \upsilon_i \quad (3)$$

where w_i is an individual's hourly wage; A_j, $\mathbf{X}_i$, $\mathbf{M}_i$, $\mathbf{Z}_j$, and σ_k are defined as before; $\mathbf{MATCH}_i$ is a vector of our two college job matching measures; α, α', $\boldsymbol{\phi}$, $\boldsymbol{\beta}$, $\boldsymbol{\delta}$, and $\boldsymbol{\mu}$ are parameters to be estimated, and ε_i and υ_i represent error terms.

We again consider both population size and employment density to capture differences in urban agglomeration across metropolitan areas, A_j. However, we include these variables in logarithmic form to obtain elasticity measures, allowing us to compare our estimates to prior work. The parameter α in equation (2) provides an estimate of the urban wage premium for college graduates arising from all sources of urban agglomeration economies. In equation (3), since job matching is included along with the agglomeration variable, ϕ represents the wage premium associated with job matching independent of other forms of agglomeration and α' represents the urban wage premium arising from all other sources of urban agglomeration economies excluding job matching. Thus, the contribution of job matching to aggregate urban productivity can be inferred by comparing α and α'.

Given the difficulties associated with identifying a set of instruments to address the range of potential endogeneity issues that may arise in wage estimation of this nature, we limit our attention to OLS models.[16] However, as with our previous analysis, we are able to control for a wide array of worker, metropolitan area, and regional factors. Specifically, we include a number of standard individual-level characteristics in our models, including potential experience, marital status, the presence of children, sex, and race in our wage models. As with our previous analysis, we are also able to control for an individual's college degree major and the composition of local labor markets in an effort to address concerns related to potential biases arising from differences in worker characteristics.[17] The metropolitan area industry and occupation share variables along with the unemployment rate and spatial fixed effects also help control for differences in

[16] A recent meta-analysis of urban productivity studies concludes that accounting for the potential endogeneity of urban agglomeration typically does not yield noticeable changes in the magnitude of estimated aggregate agglomeration effects (Melo, Graham, and Noland, 2009).

[17] Altonji, Blom, and Meghir (2012) and Altonji, Kahn, and Speer (2014) demonstrate that wages, and labor market outcomes more generally, vary considerably across individuals with different college majors.

local economic conditions and broader unobserved regional factors. As before, we estimate and report robust standard errors clustered at the metropolitan area level.

We utilize both measures of job matching in these regressions, since working in a job that requires a degree may influence wages independently of working in a job that utilizes one's major. Due to data limitations mentioned previously, we focus our attention on college graduates without a graduate degree as the degree major information provided in the ACS corresponds to an individual's undergraduate field of study only. In addition, we restrict our sample to those college graduates who are working full time (i.e., at least 35 hours per week for 40 or more weeks per year) and are estimated to earn between $5.00 and $400.00 per hour. These adjustments reduce our sample to about 162,000 observations representing nearly 17 million college graduates.

B. Results

Table 4 reports the results of our urban wage regressions, with Columns (1) and (2) showing the results using population size to measure agglomeration and Columns (3) and (4) showing the results using employment density. Overall, the baseline empirical models reported in Columns (1) and (3) perform reasonably well, explaining nearly 25 percent of the variation in the log of hourly wages of college graduates. In addition, the coefficients on the explanatory variables are statistically significant and of expected signs. For example, across all models, we find that college graduates who are male, married, white, have children, or have more potential experience tend to earn higher wages.

Focusing on the agglomeration variables in our baseline models reported in Columns (1) and (3), we find that a doubling of population size is associated with a 4.0

percent increase in wages, while a doubling of employment density is associated with a 3.9 percent increase in wages. Though our results are for college undergraduate degree holders only, these estimates fit squarely in the well-established range of 2.0 to 8.0 percent found by most studies measuring the magnitude of urban agglomeration economies, and are toward the upper end of the 2.0 to 4.0 percent range found by recent work that accounts more fully for potential sorting and composition effects (Rosenthal and Strange, 2004; Combes et al., 2008, 2010; Abel, Dey, and Gabe, 2012).

Results when our job matching measures are included in these models are reported in Columns (2) and (4) of Table 4. Doing so increases the explanatory power of our urban wage models, indicating that job matching is an important determinant of individual wages. Holding other factors constant, we find that college graduates working in a job that requires a college degree earn, on average, almost 25 percent more than those who do not match along this dimension.[18] In addition, we find that those college graduates who work in a job closely related to their college degree major earn, on average, an additional 5 percent more than those who do not, which in principle is on top of the wage premium for a College Degree Match. Thus, consistent with theories emphasizing the productivity benefits of better job matching, college graduates earn a significant wage premium when they are able to find jobs that more closely align with their college education.

How much does better job matching contribute to aggregate urban productivity? When our job matching measures are included in our wage regressions, the coefficients

[18] By comparison, recent estimates of the conventional college wage premium suggest that workers with a college degree earn twice as much as high-school educated workers (Acemoglu and Autor, 2011).

on our agglomeration variables decrease slightly, from 4.0 percent to 3.8 percent for population size and from 3.9 percent to 3.6 percent for employment density. This pattern of results suggests that better job matching among college graduates accounts for about 5 to 8 percent of the urban wage premium.[19] While this finding is consistent with the idea that better job matching of skilled workers in large and dense urban environments is a source of urban agglomeration economies, it appears the contribution of such job matching to aggregate urban productivity is relatively modest.

V. CONCLUSIONS

Matching-based theories of urban agglomeration predict that more agglomerated local labor markets enhance productivity by improving the likelihood of matching and increasing the quality of these matches (Helsley and Strange, 1990; Sato, 2001; Berliant, Reed, and Wang, 2006). Consistent with these ideas, we show that college graduates in larger and thicker local labor markets are more likely to work in a job that both requires a college degree and is related to their college major. Further, we find that, on average, college graduates earn a significant wage premium when their jobs are more closely tied to their college education and that better job matching of this sort contributes to the urban wage premium. Thus, taken together, our results provide direct evidence that better job matching of skilled workers in large and dense urban environments acts as a source of urban agglomeration economies, although the contribution of such job matching to aggregate urban productivity appears to be relatively modest.

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19 As a robustness check, we also estimated urban wage regressions omitting the metropolitan area-level controls, $\mathbf{Z}_j$. Doing so increases the magnitude of the estimated agglomeration effect to between 6.6 percent and 8.7 percent, and reduces the contribution of better job matching to the urban wage premium to between 2 and 3 percent.

When interpreting our results, it is important to recognize that formal education, although important, is only one aspect of job matching. While narrowing our focus to the amount and type of education required to perform a job has allowed us to overcome limitations in the existing empirical agglomeration literature by providing direct measures of job matching, we have surely missed other, more subtle, dimensions of the matching process. In addition, while our analysis is based on several hundred occupational categories, even these detailed categories do not fully capture differences in the specific jobs people perform, and the college degree majors we are able to consider is limited by the categories currently available.

Another limitation of this work, shared by nearly all existing studies of urban agglomeration and individual wage determination, is that we cannot fully account for potential unobserved heterogeneity arising from the spatial sorting of firms and individuals across space. While the use of detailed information on college degree majors allows us to more fully control for differences in worker skills across metropolitan areas than has previously been available in cross-sectional studies of this nature, there are sure to be differences in the skills and abilities of people with the same major. Along these lines, differences in an individual's grades or the quality and reputation of the higher education institution they attended may well contribute to their success in finding a job that matches their college education. However, given the data currently available, we are unable to account for such differences. Nonetheless, we believe this work takes an important step forward by providing direct evidence that urban agglomeration fosters better job matching among college graduates.

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Table 1: Job Matching for Selected College Majors

College Major	Example of Occupation with College Degree and College Major Match	Example of Occupation with College Degree Match Only	Example of Occupation with No Match	College Degree Match Rate	College Major Match Rate
Accounting	Accountant	Computer Systems Analyst	Cashier	68.3%	53.3%
Architecture	Architect	Marketing and Sales Manager	Painter	64.6%	42.0%
Business Management	Financial Manager	Meeting and Event Planner	Concierge	48.7%	39.1%
Chemistry	Chemist	Database Administrator	Insurance Sales Agent	74.0%	18.6%
Computer Engineering	Computer Hardware Engineer	Management Analyst	Electronics Assembler	80.1%	34.1%
Computer Science	Software Developer	Advertising Manager	Customer Service Representative	72.8%	32.7%
Elementary Education	Elementary School Teacher	Health Services Manager	Waiter	77.1%	52.9%
Finance	Personal Financial Advisor	Insurance Underwriter	Real Estate Broker	60.6%	38.0%
History	Curator	Financial Services Sales Agent	Security Guard	59.8%	2.7%
Journalism	Editor	Social Worker	Cook	57.0%	20.5%
Liberal Arts	Postsecondary Teacher	Human Resource Worker	Claims Adjuster	51.1%	1.3%
Mathematics	Actuary	Budget Analyst	Machinist	72.3%	5.8%
Mechanical Engineering	Mechanical Engineer	Purchasing Manager	Electrician	72.9%	18.3%
Philosophy and Religious Studies	Clergy	Counselor	Taxi Driver	63.5%	5.2%
Studio Arts	Designer	Training and Development Manager	Administrative Assistant	44.4%	20.4%
Total, All Majors	--	--	--	62.1%	27.3%

Note: Individuals with graduate degrees are not included in College Major Match Rate calculation.

Table 2: Probit Marginal Effects from Job Matching Regressions

	College Degree Match		College Major Match	
	(1)	(2)	(3)	(4)
	Pop Size	Emp Density	Pop Size	Emp Density
Agglomeration	0.0021 ***	0.0021 **	0.0015 ***	0.0025 ***
	(0.0007)	(0.0010)	(0.0006)	(0.0008)
Male	-0.0118 ***	-0.0118 ***	0.0076 ***	0.0076 ***
	(0.0024)	(0.0024)	(0.0020)	(0.0020)
Married	0.0531 ***	0.0531 ***	0.0238 ***	0.0238 ***
	(0.0021)	(0.0021)	(0.0023)	(0.0023)
Age	0.0137 ***	0.0137 ***	-0.0020 **	-0.0020 **
	(0.0006)	(0.0006)	(0.0008)	(0.0008)
Age-squared	-0.0002 ***	-0.0002 ***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children	0.0070 ***	0.0070 ***	-0.0047 **	-0.0047 **
	(0.0025)	(0.0025)	(0.0024)	(0.0024)
Graduate Degree	0.2480 ***	0.2480 ***	--	--
	(0.0032)	(0.0032)	--	--
Black	-0.0469 ***	-0.0468 ***	-0.0385 ***	-0.0385 ***
	(0.0037)	(0.0037)	(0.0035)	(0.0035)
American Indian	-0.0625 ***	-0.0622 ***	0.0023	0.0027
	(0.0163)	(0.0162)	(0.0167)	(0.0167)
Asian	-0.0423 ***	-0.0424 ***	-0.0292 ***	-0.0298 ***
	(0.0040)	(0.0040)	(0.0036)	(0.0036)
Other Race, Non-Hispanic	-0.0198	-0.0197	-0.0276	-0.0277
	(0.0227)	(0.0227)	(0.0321)	(0.0321)
Metro Area Unemployment Rate	-0.0010	-0.0006	-0.0013 *	-0.0010
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Log Pseudo Likelihood	-21,548,854 ***	-21,549,333 ***	-10,826,717 ***	-10,826,357 ***
Pseudo R-squared	0.104	0.104	0.212	0.212
N	358,640	358,640	225,708	225,708
Weighted N	36,240,022	36,240,022	23,412,572	23,412,572

Note: Robust standard errors, clustered at the metropolitan area level, are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Models also include the following controls (coefficients not reported for brevity): individual's major (171 degree fields); metro area industrial and occupational structure (employment shares in 15 NAICS categories and 23 SOC categories); and Census division. Marginal effects for dummy variables represent discrete change from 0 to 1. Individuals with graduate degrees are excluded from College Major Match regressions.

Table 3: IV Probit Marginal Effects from Job Matching Regressions

	College Degree Match		College Major Match	
	(1)	(2)	(3)	(4)
	Pop Size	Emp Density	Pop Size	Emp Density
Agglomeration	0.0033 **	0.0035 **	0.0024 *	0.0044 ***
	(0.0013)	(0.0019)	(0.0013)	(0.0017)
Male	-0.0119 ***	-0.0118 ***	0.0076 ***	0.0076 ***
	(0.0024)	(0.0024)	(0.0020)	(0.0020)
Married	0.0531 ***	0.0531 ***	0.0239 ***	0.0239 ***
	(0.0021)	(0.0021)	(0.0023)	(0.0023)
Age	0.0138 ***	0.0138 ***	-0.0020 **	-0.0020 ***
	(0.0006)	(0.0006)	(0.0008)	(0.0008)
Age-squared	-0.0002 ***	-0.0002 ***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children	0.0070 ***	0.0070 ***	-0.0047 **	-0.0047 **
	(0.0025)	(0.0025)	(0.0024)	(0.0024)
Graduate Degree	0.2479 ***	0.2480 ***	--	--
	(0.0032)	(0.0032)	--	--
Black	-0.0471 ***	-0.0469 ***	-0.0387 ***	-0.0387 ***
	(0.0037)	(0.0037)	(0.0035)	(0.0035)
American Indian	-0.0625 ***	-0.0620 ***	0.0024	0.0030
	(0.0162)	(0.0163)	(0.0167)	(0.0166)
Asian	-0.0426 ***	-0.0429 ***	-0.0296 ***	-0.0306 ***
	(0.0040)	(0.0040)	(0.0036)	(0.0038)
Other Race, Non-Hispanic	-0.0201	-0.0200	-0.0278	-0.0282
	(0.0227)	(0.0227)	(0.0321)	(0.0322)
Metro Area Unemployment Rate	-0.0013	-0.0006	-0.0015 **	-0.0010
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Log Pseudo Likelihood	-86,629,487 ***	-77,718,971 ***	-53,016,194 ***	-47,213,016 ***
N	358,640	358,640	225,708	225,708
Weighted N	36,240,022	36,240,022	23,412,572	23,412,572
First Stage IV Results				
IV: ln Pop 1920/ln Density 1920	1.370 ***	1.000 ***	1.364 ***	0.999 ***
	(0.173)	(0.140)	(0.172)	(0.138)
Partial R-squared of Excluded Instrument	0.245	0.213	0.244	0.215
Wald Test of Exogeneity: $\chi^2(1)$	1.30	0.86	0.71	1.79
(*p* -value)	0.254	0.355	0.400	0.181

Note: Robust standard errors, clustered at the metropolitan area level, are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Models also include the following controls (coefficients not reported for brevity): individual's major (171 degree fields); metro area industrial and occupational structure (employment shares in 15 NAICS categories and 23 SOC categories); and Census division. Marginal effects for dummy variables represent discrete change from 0 to 1. Individuals with graduate degrees are excluded from College Major Match regressions.

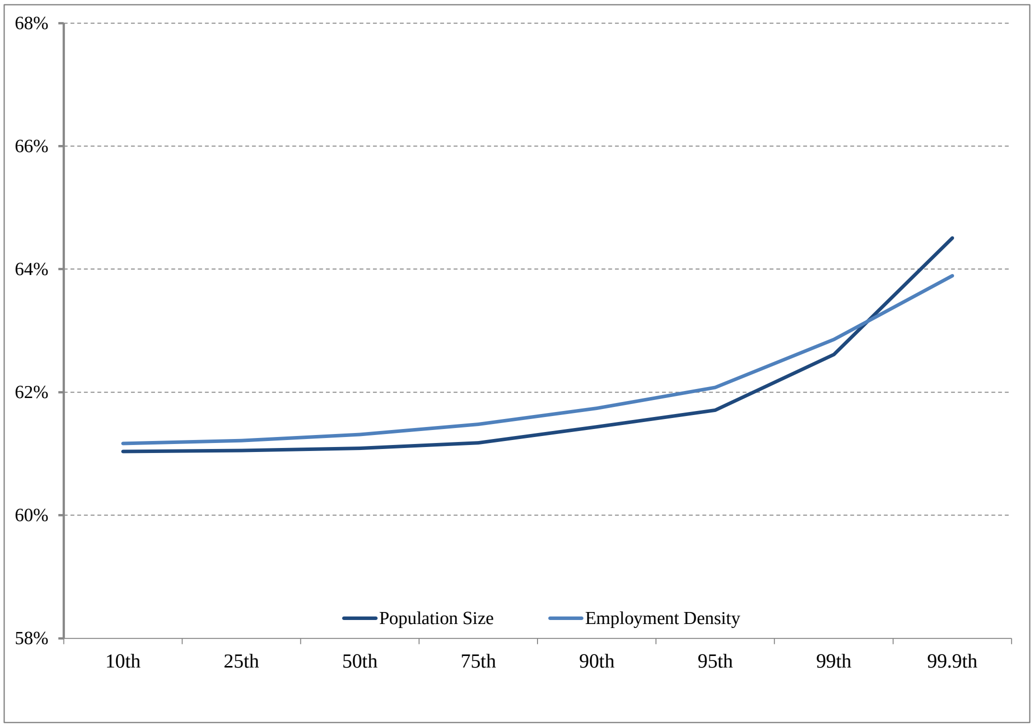
Table 4: Results from Urban Wage Regressions

	Population Size		Employment Density	
	(1)	(2)	(3)	(4)
	Baseline	Job Matching	Baseline	Job Matching
ln Agglomeration	0.040 ***	0.038 ***	0.039 ***	0.036 ***
	(0.006)	(0.006)	(0.009)	(0.009)
College Degree Match	--	0.244 ***	--	0.244 ***
	--	(0.011)	--	(0.011)
College Major Match	--	0.054 ***	--	0.053 ***
	--	(0.005)	--	(0.005)
Male	0.147 ***	0.155 ***	0.148 ***	0.155 ***
	(0.004)	(0.005)	(0.005)	(0.005)
Married	0.106 ***	0.095 ***	0.105 ***	0.094 ***
	(0.004)	(0.004)	(0.004)	(0.004)
Potential Experience	0.043 ***	0.043 ***	0.043 ***	0.043 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Potential Experience-squared	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Children	0.031 ***	-0.029 ***	0.031 ***	-0.029 ***
	(0.004)	(0.004)	(0.004)	(0.004)
Black	-0.152 ***	-0.141 ***	-0.151 ***	-0.139 ***
	(0.009)	(0.008)	(0.009)	(0.009)
American Indian	-0.106 ***	-0.099 ***	-0.101 ***	-0.095 ***
	(0.026)	(0.025)	(0.025)	(0.025)
Asian	-0.164 ***	-0.149 ***	-0.164 ***	-0.149 ***
	(0.010)	(0.009)	(0.010)	(0.010)
Other Race, Non-Hispanic	-0.258 ***	-0.249 ***	-0.257 ***	-0.249 ***
	(0.033)	(0.030)	(0.033)	(0.030)
Metro Area Unemployment Rate	0.002	0.002	0.007 ***	0.006 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Adjusted R-squared	0.243	0.285	0.243	0.284
N	162,454	162,454	162,454	162,454
Weighted N	16,868,373	16,868,373	16,868,373	16,868,373

Note: Robust standard errors, clustered at the metropolitan area level, are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Models also include the following controls (coefficients not reported for brevity): individual's major (171 degree fields); metro area industrial and occupational structure (employment shares in 15 NAICS categories and 23 SOC categories); and Census division. Individuals with graduate degrees are excluded from the analysis.

Figure 1: Predicted Probability of Job Matching Across the Urban Spectrum (Probit)

(a) College Degree Match



(b) College Major Match

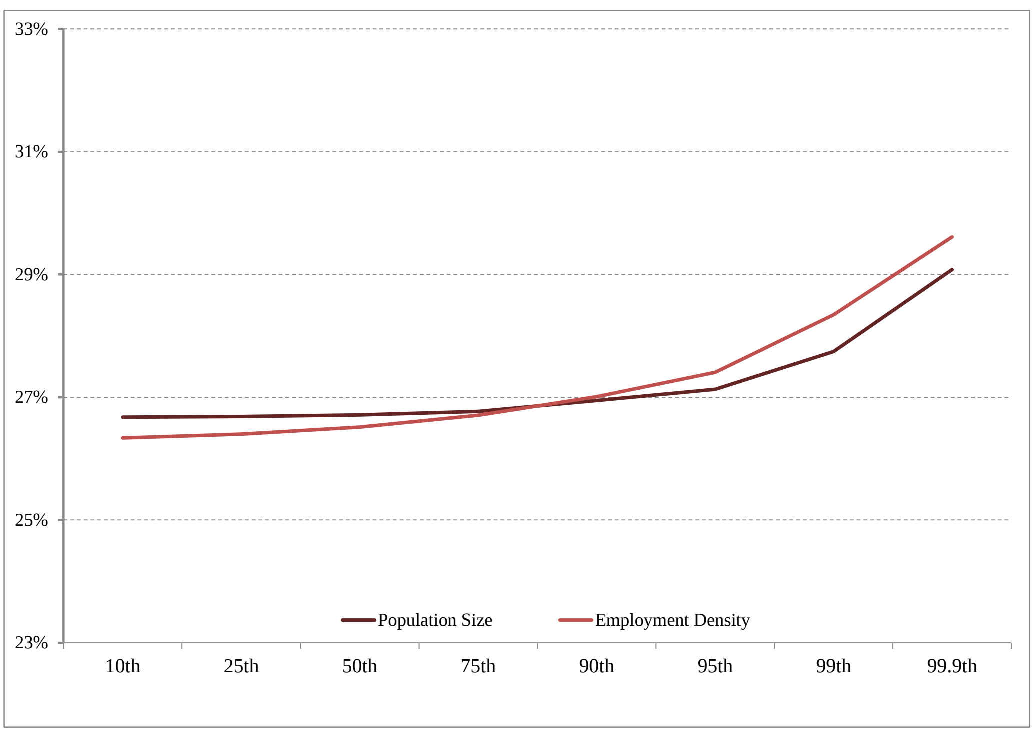
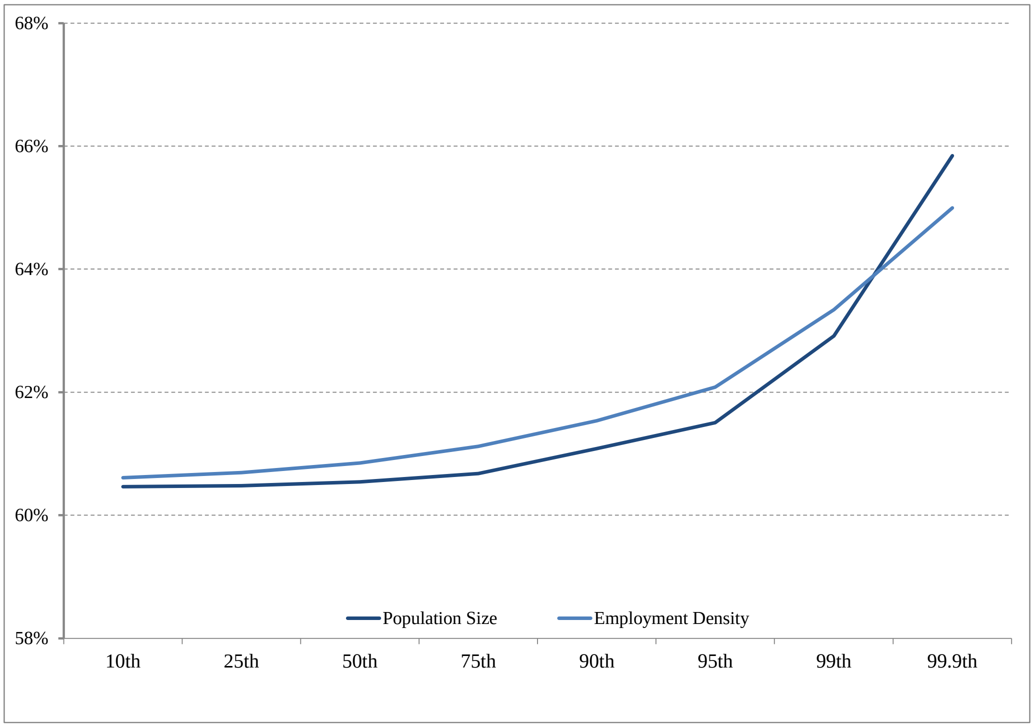


Figure 2: Predicted Probability of Job Matching Across the Urban Spectrum (IV Probit)

(a) College Degree Match



(b) College Major Match