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# Agglomeration and Job Matching among College Graduates

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Richard Deitz

Staff Report No. 587  
December 2012



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## **Agglomeration and Job Matching among College Graduates**

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### **Abstract**

We study one potential source of urban agglomeration economies: better job matching. 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 help college graduates find better jobs by increasing both the likelihood and quality of a match. 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. While we find that college graduates with better job matches do indeed earn higher wages on average, 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

## 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.<sup>1</sup> 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

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<sup>1</sup> Rosenthal and Strange (2004) and Puga (2010) 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.

developed predict that more agglomerated local labor markets enhance productivity by 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); facilitating more assortative matching between workers and firms (Andersson, Burgess, and Lane, 2007); improving 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 occupation and industry 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 also extend the existing labor economics literature analyzing the match between an individual's education and job (see, e.g., Hersch, 1991; Robst, 2007), which has largely ignored how local labor market conditions influence the job matching process. Our first 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. To do so, 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 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 individual-level characteristics, including choice of college major, and account for differences in the economic structure and performance of metropolitan areas in all of our models. In addition, to address potential endogeneity issues, we develop an instrumental variables approach that relies on historical counts of major professional sports franchises to predict differences in agglomeration across metropolitan areas. Not only is this instrumental variable a strong predictor of the current size and density of metropolitan areas, it is plausible that any effect it may have on the likelihood of local job matching operates only *through* the agglomerative forces that may exist in large and dense urban environments. As such, our analysis allows for a causal interpretation that larger and thicker urban labor markets help college graduates find better jobs by increasing the probability of finding a match.

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 non-military labor force and located in metropolitan areas since this geography is a good proxy for local labor markets.<sup>2</sup> The full sample contains nearly 360,000 observations representing more than 36 million college graduates.<sup>3</sup>

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

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<sup>2</sup> The metropolitan areas used in our analysis are a subset of those developed by the Office of Management and Budget (OMB) for federal statistical purposes, which represent geographic areas consisting of a large population nucleus and adjacent communities with a high degree of economic and social integration.

<sup>3</sup> We apply the nationally representative ACS sample weights in all of our analysis.



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 job-related requirements.<sup>4</sup> 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 50 percent or more of the respondents working in that occupation indicated that at least a Bachelor’s degree was necessary to perform the job. We then merged these data on educational requirements for each occupation to individual workers and their actual occupations from the ACS. An individual matches (i.e., College Degree Match=1) if they are working in an occupation that requires a college degree. Unemployed workers, by definition, are a non-match.<sup>5</sup> As shown in Figure 1, we find that about two-thirds of the college graduates in our sample work in a job that requires a college degree.

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<sup>4</sup> 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).

<sup>5</sup> 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 based on the full sample.

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 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.<sup>6</sup> 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 (i.e., College Major Match=1) if they were working in an occupation that is related to their reported degree major.<sup>7</sup> 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

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

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

possesses a graduate degree. Thus, 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, we omit individuals with a graduate degree from our analysis that utilizes this measure of job matching. Figure 1 indicates that about 27 percent of undergraduate degree holders in our sample are working in a job that is directly related to their college major.

Table 1 provides some examples of how we classify each type of job match for four different college graduates with a Communications major. The first person works as a “Public Relations Manager,” an occupation that both requires a college degree and is directly related to a Communications major. Therefore, we consider this individual’s occupation and college education to match along both measures of job matching. The second and third individuals shown in Table 1 work as a “Medical and Health Services Manager” and “Securities, Commodities, and Financial Services Sales Agent,” respectively. While both occupations require a college degree, neither job is directly related to the training provided by a Communications major. We consider these individuals to match based on our first measure of job matching, but not our second. Finally, the college graduate shown at the bottom of Table 1 works as a “Retail Salesperson,” an occupation that does not require a college degree and is not directly connected to a Communications major. Thus, we do not consider this individual’s occupation to match their college education for either measure of job matching.

### 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  $\text{MATCH}_{ijk}$  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:

$$\text{Prob}(\text{MATCH}_{ijk} = 1) = \Phi(\alpha A_{jk} + \beta \mathbf{X}_{ijk} + \delta \mathbf{M}_{ijk} + \mu \mathbf{Z}_{jk} + \sigma_k) \quad (1)$$

where  $A_{jk}$  is a variable measuring the agglomeration of a metropolitan area;  $\mathbf{X}_{ijk}$  is a vector of individual-level characteristics;  $\mathbf{M}_{ijk}$  is a vector of dummy variables denoting an individual's degree major;  $\mathbf{Z}_{jk}$  is a vector of other metropolitan area-level variables to control for differences in the characteristics of metropolitan areas;  $\sigma_k$  is a spatial fixed effect; and  $\alpha$ ,  $\beta$ ,  $\delta$ , and  $\mu$  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,  $A_{jk}$ , 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,<sup>8</sup> although both measures are still

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<sup>8</sup> 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.

used in the empirical agglomeration literature. We consider both population size and employment density in alternative models.<sup>9</sup>

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 that is 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 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

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<sup>9</sup> The correlation between these measures of urban agglomeration is 0.74, while the Spearman rank correlation is 0.62.

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 composition effects in studies of the effects of urban agglomeration (Combes et al., 2008, 2010; Abel, Dey, and Gabe, 2012).

To address these fundamental identification issues, our probit models include a wide range of individual level characteristics in  $\mathbf{X}_{ijk}$  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  $\mathbf{M}_{ijk}$  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. Moreover, inclusion of these variables enables us to account for any differences in the match probability across degree fields. For example, individuals with a degree in a major that offers occupation-specific training, like Accounting or Engineering, may be 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.

To account for potential 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  $\mathbf{Z}_{jk}$ . 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,  $\sigma_k$ , 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 the potential endogeneity of urban agglomeration. 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, which reduces their associated level of significance, 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 marginal effects. As such, our estimates can be interpreted as the percentage point change in the probability of a job match when all other variables in the model are evaluated at their mean level. We begin by discussing the baseline results of our analysis of the determinants of a College Degree Match, and then proceed to describe the baseline results of our analysis of the determinants of a College Major Match.

##### *i. College Degree Match*

Table 2 presents the probit marginal effects from our initial 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 0.23 percentage points as metropolitan area population increases by 1 million people or as metropolitan area employment density increases by 100 employees per square mile. Relative to the average College Degree Match rate of 62 percent, these estimated marginal effects represent a 0.4 percent increase in the likelihood of matching.

To put these results in perspective, Figure 2 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., 10<sup>th</sup>-25<sup>th</sup> percentiles) to extremely large and dense metropolitan areas (e.g., 95<sup>th</sup> percentile and above).<sup>10</sup> Panel (a) of Figure 2 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

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<sup>10</sup> 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 10<sup>th</sup> and 50<sup>th</sup> percentiles, those with 3.25 million people would be at the 95<sup>th</sup> percentile, while a metropolitan area at the 99.9<sup>th</sup> 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 (10<sup>th</sup>-50<sup>th</sup> percentiles), 464 workers per square mile (95<sup>th</sup> percentile), and 1,321 workers per square mile (99.9<sup>th</sup> percentile).



(75<sup>th</sup> percentile for population, 50<sup>th</sup> percentile for density); Medford, OR (50<sup>th</sup>, 10<sup>th</sup>); or Abilene, TX (10<sup>th</sup>, 25<sup>th</sup>).<sup>11</sup> 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.

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 26 percentage points. In addition, married individuals and those with children are more likely to match, while males, older individuals, 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 not statistically significant.

#### *ii. College Major Match*

Columns (3) and (4) of Table 2 presents the probit marginal effects from our initial 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 0.16 percentage points as

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<sup>11</sup> For example, Figure 2 (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 50<sup>th</sup> percentile to the 99.9<sup>th</sup> percentile—a difference of 5.5 percent. Similarly, the probability of a college graduate working in a job requiring a college degree increases from 61.3 percent to 63.8 percent when the employment density of a metropolitan area increases from the 50<sup>th</sup> percentile to the 99.9<sup>th</sup> percentile—a difference of 4.1 percent.

metropolitan area population increases by 1 million people and by about 0.28 percentage points as metropolitan area employment density increases by 100 employees per square mile. Relative to the average College Major Match rate of 27 percent, these increases represent a 0.6 to 1.0 percent increase in the likelihood of matching.

Panel (b) of Figure 2 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.<sup>12</sup> 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,

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<sup>12</sup> For example, Figure 2 (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 50<sup>th</sup> percentile to the 99.9<sup>th</sup> 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 50<sup>th</sup> percentile to the 99.9<sup>th</sup> percentile—a difference of 11.7 percent.

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 from our initial probit estimation is that differences in the agglomeration of metropolitan areas are not randomly assigned across space, making causal inference difficult. Indeed, job 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,  $\sigma_k$ , 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 assess the direction and magnitude of this potential concern, we re-estimate our probit models using an instrument for the agglomeration variables.

Implementing an instrumental variables approach requires that we identify a variable that is correlated with our measures of urban agglomeration (i.e., relevant) but not directly related to the likelihood of job matching across metropolitan areas (i.e., exogenous). We propose using a new variable to instrument for our measures of urban agglomeration that satisfies these conditions: the number of major professional sports franchises supported by a metropolitan area in 1970. Because operating a major

professional sports franchise requires large fixed investments to build stadiums or arenas, professional sports teams historically located in places where these costs could be most easily recovered by attracting a large fan base to attend games in person throughout the season. Indeed, a leading explanation for the existence of cities is the presence of indivisibilities in the provision of shared facilities such as these. As such, historical counts of the number of professional sports teams hosted by a metropolitan area should be a strong predictor of the current size and density of a metropolitan area. Thus, our key identifying assumption is that any relationship between this variable and the likelihood of local job matching operates only through the agglomerative forces that may exist in large and dense urban environments.

To determine whether a metropolitan area hosted a professional sports franchise in 1970, we limit our attention to the four major sports leagues in the United States: Major League Baseball (MLB), the National Football League (NFL), the National Basketball Association (NBA), and the National Hockey League (NHL).<sup>13</sup> As part of our instrumental variables strategy, we collect this information from an earlier time period to ensure that the location of professional sports franchises is independent of the likelihood of local job matching today. We selected the year 1970 because gate receipts were still the dominant source of league revenues during this time and it is the earliest year available that allows us to include franchises that were added during the significant expansions of the NBA and NHL during the 1960s, as well as the franchises that joined the NFL as part of the AFL-NFL merger in 1970.

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<sup>13</sup> Metropolitan area professional sports franchise data were collected from [baseball-reference.com](http://baseball-reference.com), [nfl.com](http://nfl.com), [nba.com](http://nba.com), and [nhl.com](http://nhl.com) using information on historical standings for the 1970 season.

Another advantage of focusing on these four major sports leagues is that they target a national audience. As such, it is in the interest of each sports league to coordinate the location decisions of individual franchises in an effort to promote a broad geographic coverage across the United States. In 1970, for example, metropolitan areas as geographically diverse as Atlanta, GA; Boston, MA; Buffalo, NY; Dallas, TX; Detroit, MI; Green Bay, WI; Kansas City, MO; Portland, OR; and San Diego, CA each hosted at least one professional sports franchise—cities whose economic fortunes varied considerably at the beginning of the 21<sup>st</sup> century. Moreover, a number of large and highly productive metropolitan areas today, such as Austin, TX; Charlotte, NC; Orlando, FL; and San Jose, CA did not host a professional sports franchise in 1970. Thus, it is quite plausible that the only influence our proposed instrumental variable may have on the likelihood of local job matching operates only through the agglomerative forces that may exist in large and dense urban environments.

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. As expected, our proposed instrument is a positive and statistically significant predictor of both measures of urban agglomeration, alone explaining 20 to 30 percent of the variation in population size and employment density observed across U.S. metropolitan areas.

The top portion of the table reports the 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 marginal effects of increasing population size or employment density more than

double 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 0.49 percentage points as metropolitan area population increases by 1 million people and by 0.77 percentage points as metropolitan area employment density increases by 100 employees per square mile. The corresponding estimates for College Major Matching—shown in Columns (3) and (4)—are 0.36 percentage points as population size increases and 0.57 percentage points as employment density increases.

Figure 3 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 analysis, similar to the figures discussed earlier. Given the increase in the size of the estimated marginal effects, our estimates imply that College Degree Matching is 11-15 percent more likely and College Major Matching is 20-26 percent more likely in a place like New York City than in metropolitan areas falling within the 10<sup>th</sup> to 75<sup>th</sup> percentile of population size or employment density.<sup>14</sup>

Specification tests reported at the bottom of Table 3 generally reject the null hypothesis of exogeneity for both measures of job matching and urban agglomeration. However, because of the inefficiency of instrumental variables analysis, most of our baseline probit estimates fall within the 95 percent confidence interval around their corresponding instrumental variables estimates. Thus, to the extent that the endogeneity

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<sup>14</sup> For example, Figure 3 (a) shows that the probability of a college graduate working in a job requiring a college degree increases from 60.0 percent to 67.1 percent when the population size of a metropolitan area increases from the 50<sup>th</sup> percentile to the 99.9<sup>th</sup> percentile—a difference of 11.8 percent. Similarly, Figure 3 (b) shows that the probability of a college graduate working in a job related to their college degree major increases from 25.7 percent to 32.0 percent when the employment density of a metropolitan area increases from the 50<sup>th</sup> percentile to the 99.9<sup>th</sup> percentile—a difference of 24.5 percent.

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.

#### 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 these questions.

##### 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:

$$\ln w_{ijk} = \alpha \ln A_{jk} + \beta \mathbf{X}_{ijk} + \delta \mathbf{M}_{ijk} + \mu \mathbf{Z}_{jk} + \sigma_k + \varepsilon_{ijk} \quad (2)$$

$$\ln w_{ijk} = \alpha' \ln A_{jk} + \phi \mathbf{MATCH}_{ijk} + \beta \mathbf{X}_{ijk} + \delta \mathbf{M}_{ijk} + \mu \mathbf{Z}_{jk} + \sigma_k + \nu_{ijk} \quad (3)$$

where  $w_{ijk}$  is an individual's hourly wage;  $A_{jk}$ ,  $\mathbf{X}_{ijk}$ ,  $\mathbf{M}_{ijk}$ ,  $\mathbf{Z}_{jk}$ , and  $\sigma_k$  are defined as before;  $\mathbf{MATCH}_{ijk}$  is a vector of our two college job matching measures;  $\alpha$ ,  $\alpha'$ ,  $\phi$ ,  $\beta$ ,  $\delta$ , and  $\mu$  are parameters to be estimated, and  $\varepsilon_{ijk}$  and  $\nu_{ijk}$  represent error terms.

We again consider both population size and employment density to capture differences in urban agglomeration across metropolitan areas,  $A_{jk}$ . However, we include these variables in logarithmic form in our wage models to obtain elasticity estimates,

allowing us to compare our estimates to prior work. The parameter  $\alpha$  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,  $\phi$  represents the wage premium associated with job matching independent of other forms of agglomeration and  $\alpha'$  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  $\alpha$  and  $\alpha'$ .

Given the focus of this part of our analysis and 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 that control for a wide array of individual, metropolitan area, and regional factors.<sup>15</sup> Specifically, we include a number of standard individual-level characteristics in our models, including potential experience and experience squared, 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. The metropolitan area industry and occupation share variables along with the unemployment rate and spatial fixed effects also help control for differences in local economic conditions and broader unobserved regional

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<sup>15</sup> 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).



factors. As before, we estimate and report robust standard errors that are 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 sign. 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 a college graduate working in a job that requires a college degree earns, on average, almost 25 percent more than those who do not match along this dimension.<sup>16</sup> 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 on our agglomeration variables decrease slightly, from 4.0 percent to 3.8 percent for

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<sup>16</sup> 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).

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. 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 suggest 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 degree major. Further, in an extension of this analysis, 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.

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 our analysis, 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 control more fully for differences in individual-level 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 Examples

Degree Major	Occupation	College Degree Match	College Major Match
Communications	Public Relations Manager	1	1
Communications	Medical and Health Services Manager	1	0
Communications	Securities, Commodities, and Financial Services Sales Agent	1	0
Communications	Retail Salesperson	0	0



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	0.0023 *** (0.0008)	0.0023 ** (0.0010)	0.0016 *** (0.0006)	0.0028 *** (0.0009)
Male	-0.0137 *** (0.0027)	-0.0137 *** (0.0027)	0.0085 *** (0.0023)	0.0085 *** (0.0023)
Married	0.0612 *** (0.0023)	0.0612 *** (0.0023)	0.0265 *** (0.0026)	0.0265 *** (0.0026)
Age	-0.0007 *** (0.0002)	-0.0007 *** (0.0002)	-0.0021 *** (0.0001)	-0.0021 *** (0.0001)
Children	0.0259 *** (0.0029)	0.0259 *** (0.0029)	-0.0053 ** (0.0024)	-0.0053 ** (0.0024)
Graduate Degree	0.2609 *** (0.0034)	0.2609 *** (0.0034)	-- --	-- --
Black	-0.0501 *** (0.0042)	-0.0499 *** (0.0042)	-0.0410 *** (0.0035)	-0.0410 *** (0.0035)
American Indian	-0.0685 *** (0.0187)	-0.0683 *** (0.0187)	0.0026 (0.0188)	0.0030 (0.0188)
Asian	-0.0472 *** (0.0045)	-0.0474 *** (0.0045)	-0.0315 *** (0.0037)	-0.0320 *** (0.0038)
Other Race, Non-Hispanic	-0.0232 (0.0254)	-0.0231 (0.0254)	-0.0295 (0.0328)	-0.0297 (0.0328)
Metro Area Unemployment Rate	-0.0010 (0.0009)	-0.0006 (0.0009)	-0.0014 * (0.0009)	-0.0011 (0.0008)
Log Pseudo Likelihood	-21,582,167 ***	-21,582,656 ***	-10,826,718 ***	-10,826,358 ***
Pseudo R-squared	0.103	0.103	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 control for individual's major (171 detailed degree major variables), metro area industrial structure (15 major NAICS category share variables), metro area occupational structure (23 major SOC category share variables), and larger region (9 Census division variables); results for these control variables are not presented for brevity. Marginal effects for dummy variables represent discrete change from 0 to 1. Individuals with graduate degrees are not included in College Major Match estimation as available degree major information corresponds to their undergraduate degree.

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	0.0049 *** (0.0013)	0.0077 *** (0.0022)	0.0036 *** (0.0011)	0.0057 *** (0.0018)
Male	-0.0138 *** (0.0027)	-0.0138 *** (0.0027)	0.0085 *** (0.0023)	0.0085 *** (0.0023)
Married	0.0613 *** (0.0023)	0.0614 *** (0.0023)	0.0265 *** (0.0026)	0.0266 *** (0.0026)
Age	-0.0007 *** (0.0002)	-0.0007 *** (0.0002)	-0.0021 *** (0.0001)	-0.0021 *** (0.0001)
Children	0.0259 *** (0.0029)	0.0259 *** (0.0029)	-0.0053 ** (0.0024)	-0.0053 ** (0.0024)
Graduate Degree	0.2608 *** (0.0035)	0.2609 *** (0.0035)	-- --	-- --
Black	-0.0505 *** (0.0042)	-0.0503 *** (0.0042)	-0.0413 *** (0.0036)	-0.0412 *** (0.0036)
American Indian	-0.0685 *** (0.0187)	-0.0676 *** (0.0187)	0.0027 (0.0188)	0.0036 (0.0188)
Asian	-0.0481 *** (0.0045)	-0.0494 *** (0.0047)	-0.0322 *** (0.0038)	-0.0332 *** (0.0040)
Other Race, Non-Hispanic	-0.0239 (0.0254)	-0.0244 (0.0254)	-0.0300 (0.0328)	-0.0304 (0.0328)
Metro Area Unemployment Rate	-0.0016 * (0.0010)	-0.0007 (0.0010)	-0.0018 ** (0.0008)	-0.0012 (0.0009)
Log Pseudo Likelihood	-85,648,892 ***	-78,032,349 ***	-52,378,556 ***	-47,468,778 ***
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: # of Pro Sports Teams in 1970	0.931 *** (0.174)	0.597 *** (0.117)	0.937 *** (0.176)	0.597 *** (0.119)
Partial R-squared of Excluded Instrument	0.286	0.201	0.284	0.197
Wald Test of Exogeneity: $\chi^2(1)$	6.46 **	9.42 ***	5.31 **	3.29 *
(p-value)	0.011	0.002	0.021	0.070

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 control for individual's major (171 detailed degree major variables), metro area industrial structure (15 major NAICS category share variables), metro area occupational structure (23 major SOC category share variables), and larger region (9 Census division variables); results for these control variables are not presented for brevity. Marginal effects for dummy variables represent discrete change from 0 to 1. Individuals with graduate degrees are not included in College Major Match estimation as available degree major information corresponds to their undergraduate degree.

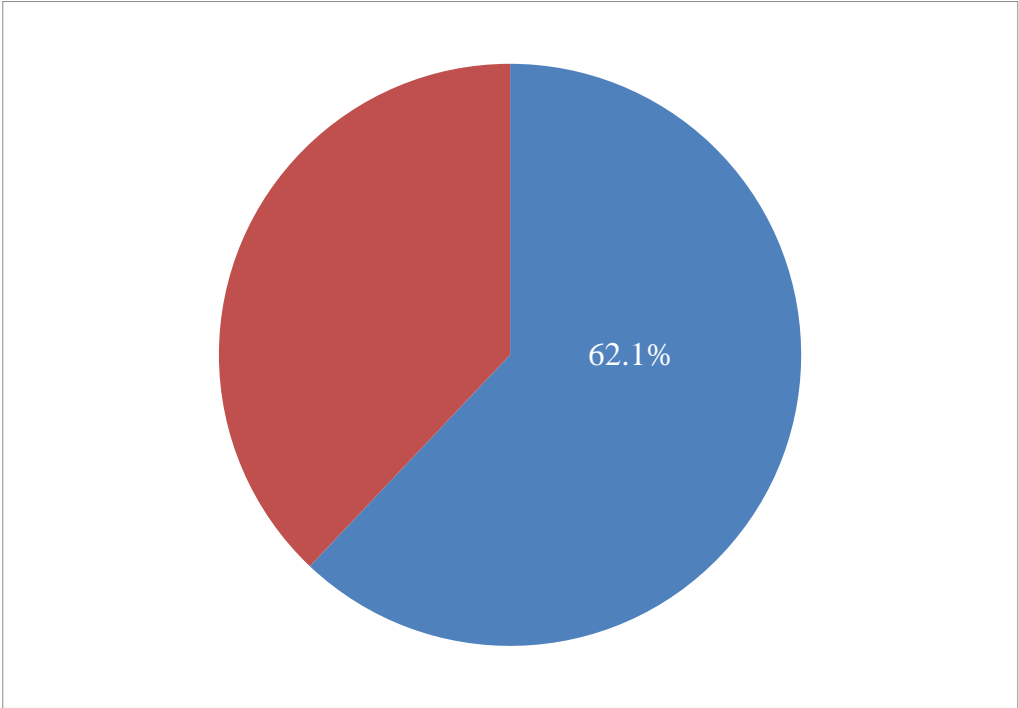
Table 4: Results from Urban Wage Regressions

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

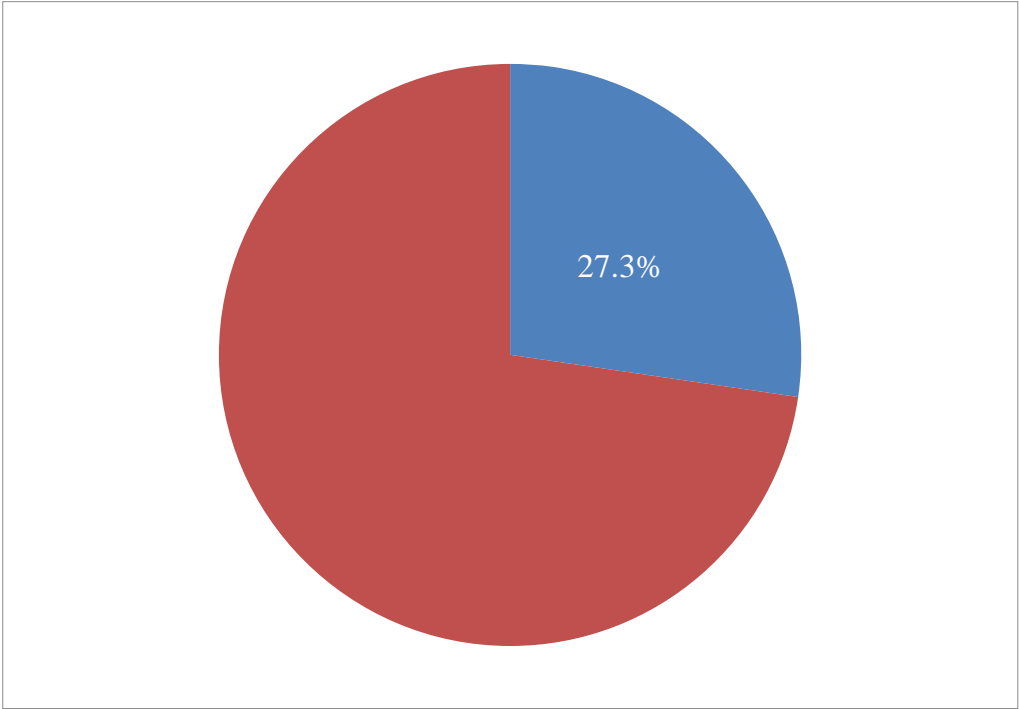
Note: Robust standard errors clustered at the metropolitan area level are reported in parentheses. \*\*\*, \*\*, and \* denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Agglomeration variables are entered in regressions in log form. Models also control for individual's major (171 detailed degree major variables), metro area industrial structure (15 major NAICS category share variables), metro area occupational structure (23 major SOC category share variables), and larger region (9 Census division variables); results for these control variables are not presented for brevity. Individuals with graduate degrees are not included in the estimation as available degree major information corresponds to their undergraduate degree.

Figure 1: Job Matching Rates

(a) College Degree Match



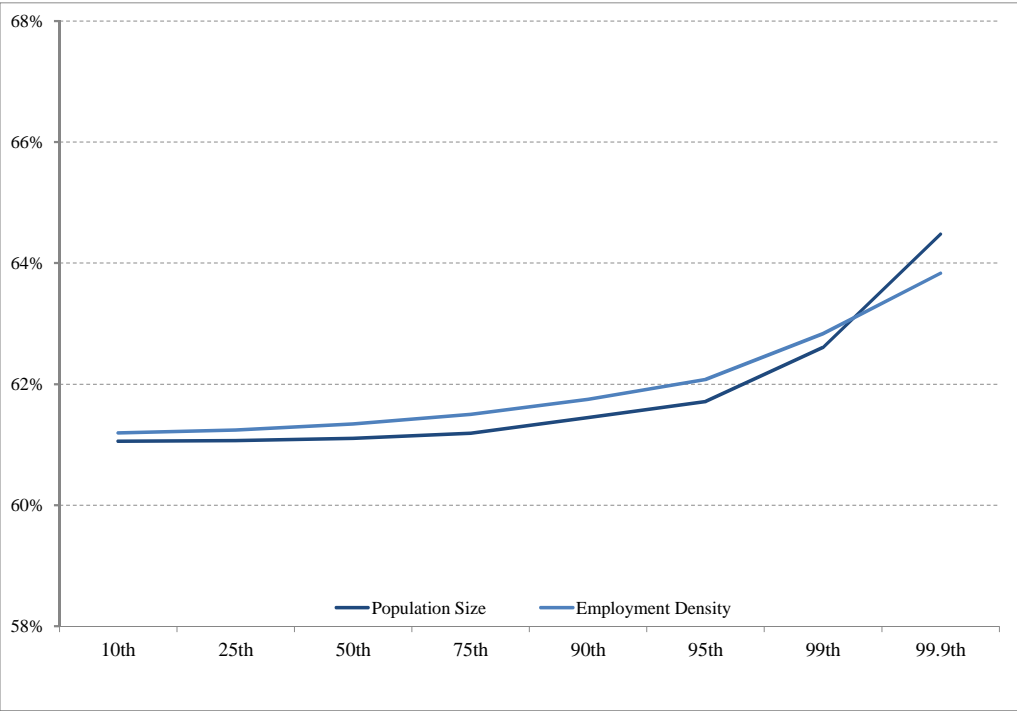
(b) College Major Match



Note: Individuals with graduate degrees are not included in College Major Match calculation as available degree major information corresponds to their undergraduate degree.

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

(a) College Degree Match



(b) College Major Match

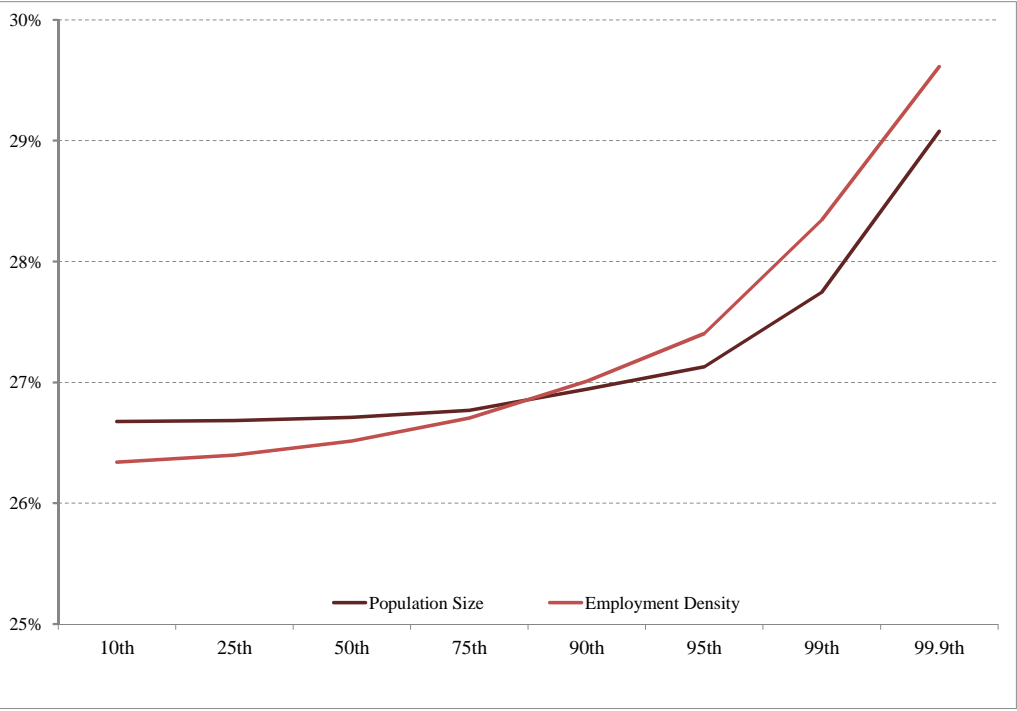
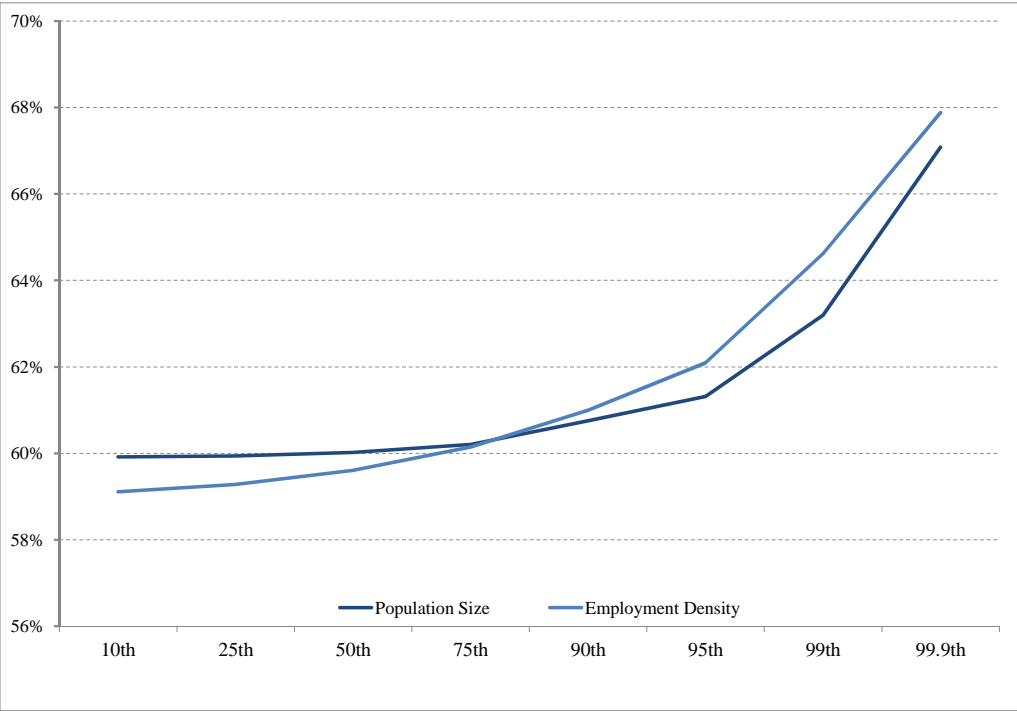


Figure 3: Predicted Probability of Job Matching Across the Urban Spectrum (IV Probit)

(a) College Degree Match



(b) College Major Match

