Wage Premia in Employment Clusters: Agglomeration or Worker Heterogeneity?

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Abstract

This paper tests whether the correlation between wages and the spatial concentration of employment can be explained by unobserved worker productivity differences. Residential location is used as a proxy for a worker's unobserved productivity, and average workplace commute times are used to test whether location based productivity differences are compensated away by longer commutes. Analyses using the 2000 Census find that the agglomeration estimates are robust to comparisons within residential location and that the estimates do not persist after controlling for commutes suggesting that the productivity differences across locations are due to agglomeration rather than productivity differences across individuals.

Introduction

The strong correlation between wages and the concentration of economic activity has often been cited as evidence of agglomeration economies, but this correlation may also arise because highly productive workers prefer locations with high levels of economic activity. In this paper, a standard wage model is used to test for agglomeration economies except that a worker's residential location is used as a proxy for their unobservable productivity under the premise that workers sort across residential locations based in part on their permanent incomes or innate labor market productivity. Further, in a locational equilibrium, identical workers should receive equal compensation, and therefore similar workers facing the same housing prices should receive the same wage net of commuting costs. The conceptual experiment is to compare two observationally equivalent individuals who reside in the same location and work in locations with different levels of agglomeration. Does the individual that works in the high agglomeration location earn a higher wage suggesting higher productivity at that work location, and if so does he or she also have a sufficiently longer commute so that the two workers receive the same real wage suggesting that the workers indeed have similar, innate labor market productivity?

Cities are the primary location of economic activity throughout the world. A key explanation for the existence of cities is that the concentration of economic activity enhances the efficiency of economic production, in other words, agglomeration economies. A huge literature exists on testing for the existence of and uncovering the magnitude and nature of agglomeration economies. These studies use a wide variety of approaches including examining productivity (Ciccone and Hall, 1996; Henderson, 2003), employment (Glaeser, Kallal, Scheinkman, and Shleifer, 1992; Henderson, Kuncoro, and Turner, 1995), establishment births and relocations (Carlton, 1983; Duranton and Puga, 2001; Rosenthal and Strange, 2003), co-agglomeration of industries (Ellison and Glaeser, 1997; Dumais, Ellison, and Glaeser, 2002), product innovation (Audretsch and Feldman, 1996; Feldman and Audretsch, 1999), and land rents (Rauch, 1993; Dekle and Eaton, 1999).[1]

An increasingly important approach for studying agglomeration is to examine wage differences across work locations. A central feature of most models of agglomeration economies is that agglomeration raises productivity. Since firms pay workers the value of their marginal production in competitive labor markets, a natural test for agglomeration economies is whether firms pay a wage premium in areas with concentrated economic activity. Glaeser and Mare (2001), Wheeler (2001), Combes, Duranton, and Gobillon (2004), Fu (2007), Rosenthal and Strange (2006), Yankow (2006) and DiAddario and Potacchini (2005) all find that wages are higher in large labor markets with high concentrations of employment. Many of these studies also find a positive link between wages and the human capital level associated with an employment concentration.[2]

A classic question in this literature is whether the concentration of employment causes higher productivity and therefore higher wages or whether high quality workers have simply sorted into areas with higher concentrations of employment. Glaeser and Mare (2001), Wheeler (2001), Combes, Duranton, and Gobillon (2004) and Yankow (2006) find evidence of an urban wage premium using longitudinal data where they can control for heterogeneity using worker fixed effects (although worker fixed effects do explain a substantial portion of the raw correlation between employment concentration and wages). These studies typically find evidence that wages grow faster in larger urban areas, potentially due to faster accumulation of human

[1] See Audretsch and Feldman (2004), Duranton and Puga (2004), Moretti (2004), and Rosenthal and Strange (2004) for detailed discussions of the literature on agglomeration economies and production externalities within cities.
[2] Other studies, Wheaton and Lewis (2002), Combes, Duranton, and Gobillon (2004), and Fu (2007), find evidence that wages increase with concentrations of employment in an individual's own occupation or industry.

capital.[3] The obvious limitation of this approach is that the effect of agglomeration on wages is identified by the subset of people who move from one metropolitan or labor market area to another.[4]

Our paper proposes a new strategy that avoids relying on movers by drawing explicitly on several well establish features of urban economies. First, a worker's residential location is used as a proxy for his or her unobservable productivity attributes. Specifically, the paper estimates wage premia across work locations located in the same metropolitan area and examines whether these work location wage premia are robust to the inclusion of residential location fixed effects. This research design draws on the commonly accepted premise that individuals sort over residential location based on tastes, which are partially unobservable and correlated with worker productivity. For example, workers with higher productivity know that they can expect a higher lifetime income, and therefore these workers are likely to have a greater willingness to pay for neighborhood amenities. Workers residing in similar quality locations should have similar levels of productivity, and after controlling for residential location those workers should earn similar wages unless their respective employment locations create productivity differences between the workers.[5] This strategy is similar to Dale and Kruger's (2004) paper on higher education where they condition on the set of schools to which students applied and were either accepted or

[3] The most compelling evidence behind the human capital accumulation story is provided by Glaeser and Mare (2001) who find that workers who migrate away from large metropolitan areas retain their earnings gains.

[4] In a cross-sectional study, DiAddario and Potacchini (2005) argue that they have identified causal effects of agglomeration on wages because there is almost no migration, i.e. sorting, across the labor markets covered in their sample of workers in Italy. The paper provides strong evidence that workers in large labor markets in Italy are more productive, but it is unclear whether this higher productivity arises from agglomeration economies or other unobservables, such as across market differences in the quality of the education system or attitudes towards work.

[5] Rosenthal and Strange (2006) also examine agglomeration effects on wages within metropolitan areas, but their primary focus is on the attenuation of these economies over space. They address concerns about the endogeneity of work location by comparing the effects of employment concentrations on wages across concentric rings of employment at different distances from a worker's place of work. They also include fixed effects for all metropolitan area-occupation combinations and instrument for the level of agglomeration in a location using geographical features of the land on which the employment activity is located.

rejected, and among students with similar choices and outcomes on this margin the selection into a specific school is assumed to be exogenous to quality of that school.

Further, equilibrium in an urban economy requires that equivalent workers should obtain the same level of utility even if they live or work in different locations. After controlling for commuting time differences, workers residing in the same neighborhood should be indifferent between jobs in different locations even if one of those locations creates agglomeration economies leading to higher productivity and higher nominal wages. Rational workers will sort into locations with higher wages until congestion raises commuting time eroding the real value of the high nominal wage. In equilibrium, wage differences across locations must be entirely compensated by longer commutes (Timothy and Wheaton 2001),[6] and unexplained location wage premia should not persist in models that control for both residential location and commute time unless those premia were created by unobserved productivity differences between workers. Specifically, the inclusion of commute time in the wage equation provides us with a test for the relationship between workplace agglomeration and real or net of commute wages, and a zero estimate on workplace agglomeration in a model of real wages is consistent with no conditional correlation between workplace agglomeration and worker unobserved productivity. While this compensation logic has been applied extensively in the quality of life literature (Roback 1982, Gyouko, 1999, Albouy 2008, 2009) and is applied by Davis, Fisher, and Whited (2009) to study agglomeration wage premia across metropolitan areas, the logic has not been exploited in models examining agglomeration economies within metropolitan areas even though presumably mobility

[6] Timothy and Wheaton (2001) examine the capitalization of commutes into wages within urban labor markets Some earlier studies of urban wage gradients include Ihlanfeldt and Young (1994), Ihlanfeldt (1992), McMillen and Singell (1992), and Madden (1985).

should be higher and transaction costs lower when considering equilibrium wages within metropolitan areas.

We draw a sample of individuals residing in mid-sized to large metropolitan areas from the Public Use Microdata Sample (PUMS) of the 2000 U.S. Decennial Census and estimate the relationship between the concentration of employment in their workplace Public Use Microdata Area (PUMA) and their nominal wage rate, controlling for a standard set of individual level controls including occupation, industry, and metropolitan area fixed effects. We find agglomeration effects that are comparable in size to the effects identified by Rosenthal and Strange (2006) using a similar sample also drawn from the 2000 PUMS, as well as evidence that the wages are higher in locations with more educated workers, again similar to Rosenthal and Strange (2006).[7] We find that these estimated agglomeration effects increase in magnitude after controlling for unobserved worker productivity differences using residential location fixed effects potentially because low skill individuals reside in central cities near agglomerated work locations. Further, the inclusion of a commute time control eliminates any relationship between the agglomeration variable and wages. Wages net of commuting costs do not appear to vary systematically over space suggesting that the estimated agglomeration effect on nominal or firm wages is not due to unobserved differences in worker productivity. Similar findings arise for human capital externalities using an extended model that includes a control for the education level of workers.

The two obvious weaknesses of this approach are that residential location at the level measured may provide an imperfect control for unobserved worker quality and that workers may

[7] The influence of the presence of educated workers on wages is discussed in the context of human capital externalities. However, this paper does not make any explicit attempt to test the various competing hypotheses concerning the underlying causes of agglomeration economies. See Ellison, Glaeser, and Kerr (2007) for recent work on this question.

sort over commute time based on their unobservables creating a correlation between commutes and worker productivity.[8] In terms of concerns about imperfect neighborhood controls, we verify that the estimated coefficients on education variables are attenuated by the inclusion of the residential controls exactly as is expected if the residential controls are successfully capturing worker productivity unobservables. Further, the findings are robust to models that restrict our sample to large metropolitan areas where the larger number of residential PUMA's provide better controls for neighborhood and models that expand residential controls both to allow for individual heterogeneity based on when individuals moved into a neighborhood and tenure status (Ortalo-Mange and Rady, 2006) and to allow for different submarkets based on the housing stock.

Concerning the commute time model, we directly test whether workers sort across commutes based on observable measures of human capital. We find that the conditional correlation between average workplace commute time and worker education is very near to zero. After controlling for other model variables, workers are not sorting across commutes based on observable measures of human capital, which is at least supportive of a maintained assumptions that workers are not sorting over commutes based on unobservable ability.[9] In addition, we estimate a model dropping all individual covariates in order to increase the variation in wages associated with unobserved productivity, and our results are very robust. Finally, we estimate separate models across regions, worker education, transportation modes, and race/ethnicity subgroups. If the influence of commute time on estimates of agglomeration economies arose due

[8] The systematic selection of workers across commutes based on income or wage rate is well established in urban economics, see LeRoy and Sonstelie (1983) and Glaeser, Kahn, and Rappaport (2008).
[9] Altonji, Elder, and Tabor (2005) suggest that the degree of selection on observables may provide a good indication of the potential selection on and bias from unobservables. Further, given the anticipated strong correlation between education and ability, sorting over commutes based on ability would likely show up as a correlation between commutes and education.

to correlation with unobservables, we would expect very unstable estimates on the commute time variables across these various samples, but the estimated coefficients are quite robust suggesting that the estimates capture a fundamental relationship in urban economies.

The approach pursued in this paper can be viewed as a complement to the longitudinal studies of agglomeration economies discussed above. The longitudinal studies usually focus on small research oriented panels of a few thousand workers and are only identified by workers that migrate between labor markets. In this paper, we apply our approach to a large cross-sectional sample and estimate the effect of concentrated employment using a broad population of workers residing in large and mid-sized U.S. metropolitan areas. Even after conditioning on residential location, we find estimates of agglomeration economies and human capital externalities that are comparable in magnitude to traditional estimates. Further, the failure to find any empirical relationship between agglomeration and net of commute wages suggests that the agglomeration estimates are not biased by unobserved worker productivity.

The paper is organized as follows. The next section presents our conceptual framework and empirical methodology. The third and fourth sections describe the data and the findings, and the fifth section concludes.

Methodology

The basic empirical model is quite similar to models investigated in previous wage studies of agglomeration economies where it is assumed that firms pay workers their marginal revenue product and so differences in nominal wages capture the returns to higher productivity arising from agglomeration. The logarithm of individual *i*'s wage (y_{ij}) in location *j* is

$$y_{ij} = \beta X_i + \gamma Z_j + \alpha_i + \varepsilon_{ij} \quad (1)$$

where X_i is a function of individual observable attributes, Z_j is employment concentration in the employment location j, α_i is an individual specific random effect that captures heterogeneity in labor market productivity, but is uncorrelated with X_i, and ε_{ij} is a random error that allows an individual's current earnings or wage to differ from their permanent income or earnings capacity. If individuals sort over employment locations based on their expected wage $(\beta X_i+\alpha_i)$, or tastes that are correlated with productivity, the unobserved component of productivity α_i will be correlated with Z_j or

$$E[Z_j, \alpha_i] \neq 0$$

biasing estimates of γ.

Residential Location as a Proxy for Worker Unobservables

Our proposed solution to this problem is based on the simple idea that individuals sort into residential locations based on their unobservables, and therefore one can minimize unobservable differences between workers by comparing individuals who reside in the same location. The properties of models of residential sorting with taste unobservables have been well established in models by Epple and Platt (1998), Epple and Sieg (1999), and Bayer and Ross (2006). Specifically, these models imply perfect stratification so that if individuals sort across residential locations based solely on a common measure of location quality (W_k) and their demand for location quality, then each residential location k will contain workers in a continuous interval of location quality demand.

If we assume demand depends on permanent income based on a worker's innate productivity $(\beta X_i+\alpha_i)$, worker productivity will be monotonic in location quality, or in other words locations can be ordered so that if

$$W_k < W_{k+1}$$

for location k then

$$\phi_k < \beta X_i + \alpha_i < \phi_{k+1}$$

for all individuals i residing in location k where ϕ_k is assumed to be less than ϕ_{k+1} for any k. If there are a large number of residential choices then

$$\phi_k \approx \beta X_i + \alpha_i \qquad (2)$$

and consistent estimates of γ can be obtained by substituting equation (2) into equation (1) and estimating the following equation

$$y_{ijk} = \delta_k + \gamma Z_j + \varepsilon_{ij}\, , \qquad (3)$$

where δ_k is the fixed effect for residential location k. In this specification, workers in the same residential location are assumed to have identical productivity, and so unexplained wage differences across workers in the same residential location must reflect aspects of the job, such as agglomeration economies, rather than worker unobservables.

However, the use of residential location controls will not produce consistent estimates if the number of residential neighborhoods in each metropolitan area is limited, if the sample only allocates households to a small number of broad, spatial regions, or if sorting is imperfect. Further, sorting will be imperfect if household preferences for location quality differ from the household members' labor market productivity or if households differ in the definition of location quality. Naturally, all of these situations are likely to arise in practice, and the empirical model must be extended to account for an imperfect correlation between ϕ_k and $\beta X_i + \alpha_i$.

If ϕ_k differs from the productivity of an individual residing in k by a random error (μ_{ik}) that is uncorrelated with $\beta X_i + \alpha_i$ or

$$\phi_k = \beta X_i + \alpha_i + \mu_{ik}\, , \qquad (4)$$

then a classic measurement error bias arises. Specifically, μ_{ik} is part of the fixed effect, and since it is not part of the model in equation (1) it becomes imbedded in the error term in equation (3). This problem is easily observed by substituting equation (4) into equation (1), which yields

$$y_{ijk} = \delta_k + \gamma Z_j + (\varepsilon_{ij} - \mu_{ik})\,. \tag{5}$$

The estimated values of δ_k are attenuated towards zero due to the negative correlation between the fixed effect and the unobservable.

This creates a standard bias in γ where the downward bias in the estimated fixed effects causes a bias in γ as well because $\beta X_i+\alpha_i$ and therefore the fixed effects δ_k are correlated with Z_j due to workers sorting across residential locations. Since the attenuated fixed effect estimates provide only a partial control for $\beta X_i+\alpha_i$, the estimates can be improved by directly including X_i in the location fixed effect model specification

$$y_{ijk} = \tilde{\beta} X_i + \tilde{\delta}_k + \gamma Z_j + (\tilde{\varepsilon}_{ij} - \tilde{\mu}_{ik})\,, \tag{6}$$

where tilde's have been added to signify the specification change.

Based on equation (4), the inclusion of $\beta X_i+\alpha_i$ into the model would perfectly control for μ_{ik} (and in fact would also eliminate any need for location fixed effects) while the inclusion of X_i provides only a partial control. The reader should note that the omission of α_i from the model along with the inclusion of the residential location fixed effects in equation (6) is likely to lead to attenuation bias in the estimate of β. Two individuals with different X_i's residing in the same neighborhood or community are likely to have different α's; otherwise, they would have had different preferences and chosen different neighborhoods. This selection process into neighborhoods creates a negative correlation between X_i and α_i within any residential location (Gabriel and Rosenthal, 1999; Bayer and Ross, 2006) attenuating the estimated coefficients on the human capital variables. This bias, however, is an advantage, rather than a problem, for obtaining consistent estimates of γ. The estimates of β adjust to optimally absorb variation in α_i biasing β, and by absorbing more of the variation in α_i the bias in β further mitigates bias in the estimates of agglomeration economies from unobserved productivity attributes.

Further, the potential for attenuation bias in the human capital coefficient estimates provides a useful metric for assessing whether the residential location fixed effects successfully capture variation associated with individual unobserved productivity. Specifically, the estimated coefficients on human capital variables in the residential fixed effects model can be compared to the estimates from a simple regression model without fixed effects. If the magnitude of the estimates attenuate when residential location fixed effects are added, then one can conclude that workers are systematically sorting across residential locations and the residential fixed effects have captured variance associated wtih unobserved productivity attributes.

Testing for Evidence of a Correlation between Worker Unobservables and Agglomeration

Our second strategy for testing whether the estimated value of γ is biased by unobserved differences in worker productivity draws upon the concept of a locational equilibrium. A locational equilibrium requires that no workers desire to change either their residential or employment locations. As discussed earlier, observationally equivalent workers residing in the same location should earn the same wages net of commute or the same real wage unless some workers have higher productivity based on unobservables. Specifically, the inclusion of commute time and residential location fixed effects into a model of wages over space provides us with a test for whether real wages vary systematically across workplaces. Under the assumption that the urban economy is in a locational equilibrium, we must attribute any systematic differences in wages net of commuting costs to the sorting of individuals across work locations based on individual productivity unobservables. A finding of no systematic relationship between real wages and agglomeration is consistent with a zero correlation between unobserved differences in worker productivity and agglomeration and therefore consistent with unbiased estimates of agglomeration economies in the model of nominal wages..

Formally, locational equilibrium requires that

$$U(y_j, P_k, V_{jk}) = U(y_{j'}, P_k, V_{j'k}), \tag{7}$$

where U is the indirect utility function of a type of individuals who reside in location k and are observed in both employment locations j and j', P_k is the price of per unit of housing services in location k, and V_{jk} is the commuting time or cost between locations k and j. Fujita and Ogawa (1982) and Ogawa and Fujita (1980) consider a simple model of the urban economy with production externalities (agglomeration economies) and commuting where work hours and land consumption are fixed. In this model, the equilibrium condition in equation (7) requires that wages net of commuting costs must be the same across all employment locations j conditional on a worker's residential location. Specifically,

$$U(y_j - \eta V_{jk}, P_k) = U(y_{j'} - \eta V_{j'k}, P_k) \quad or \quad y_j - \eta V_{jk} = y_{j'} - \eta V_{j'k} \tag{8}$$

over all work locations j and j' where η is the per mile or minute commuting costs.[10] The reader should note that wages net of commute costs or real wages in this context are constant across workplace locations even though agglomeration economies exist as reflected by nominal wage differences across work locations.

[10] They refer to their model as non-monocentric because employment concentrations arise endogenously. See Ross (1996) and Ross and Yinger (1995) for examples of the same locational equilibrium condition in a traditional monocentric urban model with an exogenous city center. In those papers, housing demand is endogenous, and the locational equilibrium condition in equation (8) still arises. In fact, this equation will hold and commute time is monetized in any model where either leisure does not enter preferences or total work hours including commute time are fixed.

Building on the logic of this model, we include a control for commute time into the residential location fixed effects model of wages. The inclusion of commute time shifts the wage equation from a model of firm wages or worker productivity as a function of work location to a model of workers' effective wage rate, which is used to examine whether wage differences across locations are compensated by differences in commute times.[11] If y_j is the wage premia offered in location *j* relative to wages in some baseline employment location, this wage premia can be expressed as an individual's wage minus the individual's inherent productivity independent of employment location. In other words, observable human capital levels (βX_i) can be incorporated into equation (8) to yield

$$y_{ij} - \beta X_i - \alpha_i - \eta V_{jk} - \varepsilon_{ij} = y_{ij'} - \beta X_i - \alpha_i - \eta V_{j'k} - \varepsilon_{ij'} \qquad (9)$$

Differencing by residential location yields a residential fixed effect wage model that does not include the agglomeration variable, and in the following estimation equation

$$y_{ij} = \hat{\beta} X_i + \eta V_{jk} + \hat{\delta}_k + \hat{\gamma} Z_j + \hat{\varepsilon}_{ij} \qquad (10)$$

the locational equilibrium condition implies that the true estimate of $\hat{\gamma}$ should be zero if the urban economy is in a locational equilibrium and $\hat{\beta} X_i + \hat{\delta}_k$ accurately captures $\beta X_i + \alpha_i$.

Unobserved differences in worker productivity that are correlated with Z_j and have not been captured by the residential location fixed effects would still remain in $\hat{\varepsilon}_{ij}$. If estimates of agglomeration economies arose due to unobserved productivity differences, the wage differences across space related to the ability of a firm's workers should not be compensated for by commute time differences, and the estimated relationship between the agglomeration variable and wages

[11] Gabriel and Rosenthal (1996) and Petitte and Ross (1999) applied similar logic to empirically study the welfare impacts of residential segregation by testing whether African-Americans had longer commutes after including residential location fixed effects, and in the case of Petitte and Ross (1999) also including employment location fixed effects, as controls for housing price and wage differentials that might compensate for longer commutes.

should remain after including a control for commute time. On the other hand, if the estimated value of γ based on equation (10) is near zero, the inclusion of residential location fixed effects must have eliminated any correlation between Z_j and the unobservables, and accordingly the estimates of agglomeration economies in equation (6) are unlikely to contain bias arising from omitted productivity attributes.

Sample and Data

The models in this paper are estimated using the 5% Public Use Microdata Sample (PUMS) from the 2000 U.S. Decennial Census. The sample provides substantially more geographic detail on work location than the PUMS from previous censuses. A subsample of prime-age (30-59 years of age), full time (usual hours worked per week 35 or greater), male workers is drawn for the 33 Consolidated Metropolitan and Metropolitan Statistical areas that have one million or more residents and at least three workplace Public Use Microdata Areas (PUMA's).[12] These restrictions lead to a sample of 831,046 workers.

The dependent variable, logarithm of wage rate, is based on a wage that is calculated by dividing an individual's 1999 labor market earnings by the product of number of weeks worked in 1999 and usual number of hours worked per week in 1999. The wage rate model includes a standard set of labor market controls including variables capturing age, race/ethnicity, educational attainment, marital status, number of children in household, immigration status, as well as industry, occupation,[13] and metropolitan area fixed effects. Finally, the model includes controls for share of college-educated employees in a worker's industry or occupation at the

[12] This sample is comparable to the sample of Rosenthal and Strange (2006) except that we explicitly restrict ourselves to considering residents of mid-sized and large metropolitan areas, where the workers' employment locations can be identified below the metropolitan area level. Rosenthal and Strange (2006) also consider smaller samples where more precise information on employment location within the metropolitan area is available, and their results are robust in those subsamples.
[13] Workers are classified into 20 major occupation codes and 15 major industry codes.

metropolitan level.[14] The mean and standard errors for these variables are shown in Table 1 separately for the college educated and non-college educated subsamples.

We consider two alternative specifications to capture employment concentration: the number of workers employed at the PUMA and the PUMA employment density.[15] The control for commute time is based on the average commute time[16] for all full time workers employed at a workplace PUMA.[17] Additional specifications are estimated that control for the fraction of workers in the workplace PUMA who have a college degree,[18] are in the same occupation as the worker, and are in the same industry as the worker. All standard errors are clustered by workplace PUMA.

[14] These controls are similar in spirit to a control used by Glaeser and Mare (2001) for occupation education levels nationally. Obviously, the industry, occupation, and metropolitan area fixed effects even when combined with the metropolitan area industry and occupation education controls do not absorb as much variation as the MSA-occupation cell fixed effects used by Rosenthal and Strange (2006). Given our focus on models that control for the large number of residential PUMA fixed effects, it is not feasible to simultaneously include this large array of MSA-occupation fixed effects. However, the models without residential fixed effects have been re-estimated with MSA-occupation fixed effects and results were similar. Further, models including MSA-occupation fixed effects were estimated for some subsamples based on a small number of very large MSA's, where residential fixed effects could be included directly in the model rather than first differenced. Again, results were similar.

[15] The agglomeration variables are constructed using all full time workers not just the prime-age, male workers as in the regression sample.

[16] In principle, the model should include a control for the commute of the marginal worker, but such information is not typically available. Timothy and Wheaton (1991) and Small (1992) describe the circumstances under which average commute times will be a sufficient statistic for marginal commute times, and Small (1992) provides empirical and simulation evidence suggesting that average commutes are a good proxy for marginal commutes.

[17] Since the models are identified based on within residential PUMA variation, the workplace PUMA commute time implicitly controls for commute times between PUMA of residence and PUMA of work without the measurement error inherent in estimating average commute times between every PUMA to PUMA commute combination. In principle, the appropriate way to handle measurement error in PUMA to PUMA commute time is to instrument for PUMA to PUMA commute time with workplace PUMA commutes rather than simply including workplace commutes directly in the wage model. The IV estimates controlling for PUMA to PUMA commute time are very similar in magnitude (slightly smaller) to the estimates presented here and discussed in this paper, and obviously the estimated coefficients on the agglomeration variables are unaffected by such a specification change.

[18] Rosenthal and Strange (2006) control separately for the number of college educated and non-college educated workers. They find that the number of college educated workers increases wages while the number of non-college educated workers reduces wages. While this result is fairly robust, the number of college and non-college workers in a workplace PUMA have correlations above 0.97 even after conditioning on metropolitan area or residential PUMA. Further, we have identified at least one specification where we observe a sign reversal so that wages fall with the number of college educated. When we estimate models that are directly comparable to Rosenthal and Strange (2006), the estimated effect sizes for our model are fairly similar in magnitude to their estimates for a five mile radius circle.

Results

Table 2 presents the results for a baseline model of agglomeration economies in wages using both controls for total employment and employment density. The estimates on the control variables are quite standard and stable across the two specifications considered. Based on our model, adding 100,000 workers to a workplace PUMA is associated with a 0.49 percent increase in wages while an increase in employment density of 1000 workers per square kilometer is associated with a 0.62 percent increase in wages.

Panel 1 of Table 3 contains the estimates for the baseline model, as well as the models that include residential location fixed effects and include both residential fixed effects and commute time. In the residential location fixed effect model, the positive relationship between agglomeration and wages is robust to the inclusion of these controls, which should increase the similarity of individuals over which the effect of agglomeration economies is identified. In fact, the agglomeration effect appears to increase in magnitude from 0.0049 to 0.0081 for the total employment model. These findings are consistent with low ability workers sorting into dense concentrations of employment, potentially because in the United States the poor live close to the city center where employment tends to be concentrated (Glaeser, Kahn, and Rappaport, 2008). While workers may sort across employment locations based on productivity, this type of sorting is quite likely dominated by the fact that within a labor market workers sort into work locations that are near to where they live.

We examine the estimates on the education variables in the wage equations. As discussed earlier, if the residential location fixed effects provide effective controls for individual productivity unobservables due to residential sorting, the coefficient estimates on human capital should be biased towards zero by the inclusion of residential location fixed effects. We find such evidence of attenuation bias for both models. In the total employment model, the inclusion of residential fixed effects reduces the estimates on above masters level, masters degree, four year college degree, associate degree, and high school diploma from 0.703, 0.577, 0.455, 0.271, and 0.206 to 0.635, 0.520, 0.408, 0.240, and 0.183, respectively, a reduction of about 10 percent in all coefficients.[19]

The next column in panel 1 of Table 3 contains the estimates for the model containing residential location fixed effects and workplace PUMA average commute time. As hypothesized, the inclusion of commute time as a control completely eliminates any relationship between the agglomeration variables and wages, and the magnitude of the estimated coefficients fall by more than a factor of ten. The estimated agglomeration effects are completely compensated for by longer commutes, as we would expect if the observed wage differences that drive the estimated agglomeration effects are based upon a comparison of intrinsically similar workers in terms of innate productivity.

Further, the inclusion of commute time does not cause any attenuation in the estimated coefficients on the human capital variables. For the total employment specification with residential location and commute time controls, the estimates are 0.632, 0.516, 0.405, 0.238, 0.182, which are nearly identical to the estimates from a model with just residential location controls. The lack of attenuation bias with the inclusion of commute time is not consistent with the concern that workers sort over commute time. In fact, after conditioning on all other model controls, the correlation between commute time and worker education level is about 0.03.[20] As

[19] Attenuation of estimates in the employment density model is virtually identical to attenuation in the total employment model.

[20] Workplace commute time, a dummy variable for high school degree or higher, and a dummy variable for four year college degree or higher are regressed on the PUMA fixed effects model in table 3 except that the education dummy variables and the agglomeration variables are excluded from the model. The correlations of workplace commute time residual with the residuals of the high school and college attainment dummies are 0.021 and 0.033.

suggested by Altonji, Elder, and Tabor (2005) in the context of Catholic schools, the conditional correlation between a control and observable measures of ability likely provides some indication of the conditional correlation between that control and unobserved ability, and in our data we find a conditional correlation of zero between average workplace commutes and education, our observable measure of human capital.

Further, in Panel 2, we examine the effect of increasing the bias from unobserved ability by restricting the number of individual controls. Specifically, we re-estimate the models in Panel 1 dropping all individual covariates including the education, age and family structure variables, which correlate very strongly with labor market outcomes. Naturally, the R-squares of the estimated models fall substantially with the omission of these measures of human capital. The OLS estimates of agglomeration economies decline from 0.0049 to 0.0024 for total employment, which is consistent with our earlier conclusion that low ability workers sort into residential locations near dense concentrations of employment. The fixed effects estimates increase somewhat from 0.0081 to 0.0097 for total employment, which is a relatively small increase given the omission of so much information relevant to labor market outcomes. As before, the inclusion of a commute time control results in estimates of agglomeration economies that are near zero.

On the other hand, in Panel 3, we examine the effect of restricting the sample to a more homogeneous population of single, male workers. This population of workers are less likely to have their residential location decision influenced by marital and family obligations. The pattern of estimates is very similar with the OLS agglomeration estimates of 0.0048, residential fixed effects estimates of 0.0064, and fixed effects and commute time control estimates of 0.0011 for total employment. Agglomeration effects increase in magnitude after including residential location controls and disappear once a control for commutes has been included. It is worth noting that the decline in estimated agglomeration effects for the sample of single, male workers is not driven by marital status. Rather, single male workers are younger and have less education on average than married males, and our estimated agglomeration effect appears to increase with an individual's level of human capital.[21]

Finally, the magnitude of the within metropolitan area estimates of agglomeration economies are quite reasonable. The within metropolitan estimates are comparable in magnitude to simple OLS estimates arising from comparisons across metropolitan areas.[22] Specifically, we find that a one standard deviation increase in metropolitan wide employment or employment density increases log wages by 0.0481 and 0.0707, respectively. Meanwhile, using the PUMA fixed effects estimates, a one standard deviation in workplace PUMA total employment or density leads to an increase in log wages of 0.0323 and 0.0468. In addition, in panel 2 of Table 4, we examine a wage model that controls for the logarithm of the agglomeration variables converting the estimated effects to elasticities. The pattern of estimates in panel 2 is nearly identical to the pattern for the baseline estimates shown in panel 1 of table 4, and the estimates imply that a doubling of agglomeration economies is associated with a 2.8 to 3.4 percent increase in wages.[23]

Next, turning to the estimates on the commute time variable itself, the coefficient estimate is statistically significant and positive as expected in a compensation model. After controlling for residential location, workers with the longest commutes also earn the highest wages, which is required if urban economies are in a locational equilibrium. In order to assess

[21] Agglomeration estimates by education level are presented in Table 9 and show larger agglomeration effects for college educated. In addition, we estimated models for single workers by education level finding similar results that agglomeration economies increase with education levels for both single and married males.
[22] We estimate the same wage model controlling for metropolitan total employment or the metropolitan wide employment density, as well as regional fixed effects to replace the residential PUMA fixed effects.
[23] All other estimates in the paper involve employment and density levels rather than logs in order to be comparable to other recent work that uses the Census microdata to study agglomeration economies.

the magnitude of these estimates, we shift to an instrumental variables framework in which we control for an individual's time spent commuting as a share of average daily work time including commuting time (two way commute time divided by the sum of commute time and one-fifth of average hours worked per week) and use the average commute time for the workplace PUMA as an instrument.[24] This specification uses the exact same source of variation to identify the compensation of commutes, but uses the share time spent commuting in order to scale the effect and estimate compensation as a fraction of the wage rate. For example, if commuting increases the work day by one percent then wages for time spent at work would need to increase by one percent in order to just compensate the worker for the time spent commuting at the wage rate.

The estimates for the total employment and employment density models in the first column of table 5 are 2.0806 and 2.1824 suggesting that time spent commuting is compensated at approximately double the wage rate, which is consistent with Timothy and Wheaton (2001) who found compensation rates of between 1.6 and 3.0 times the wage rate.[25] Further, Small (1992) estimates that on average the monetary cost of commuting is both proportional to and similar in magnitude to an individual's wage suggesting a compensation rate of two if people also value their time spent commuting at the wage rate.[26] Further, the next two columns present estimates that restrict the coefficient on commute time share to 1.5 and 1.0, respectively. The estimates on the agglomeration variables rise and are about half the size of the Table 3 estimates

[24] The first stage includes all control variables in the log wage equation except for the agglomeration variable so that the entire effect of agglomeration is captured directly by the estimated coefficient on the agglomeration variable. Note that models in which the agglomeration variable is included in the first stage yield nearly identical results.
[25] These estimates are consistent with a back of the envelop calculation using the estimates from Panel 1 of Table 3. Specifically, a one minute increase in one way commute time leads to approximately 0.9 percent increase in wages. With an eight hour day, a two minute increase in round trip commutes represents 0.42 percent increase in the length of the workday. The 0.9 percent point estimate is then a little more than double what would be expected if time spent commuting was compensated at the market wage.
[26] The literature on commute times historically finds that time costs of commutes are valued at approximately half the wage (Small, 1992). However, more recent estimates from Small, Winston, and Yan (2005) and Brownstone and Small (2005) find evidence that commuting time is valued at about 90% of the wage.

when the commute time share coefficient is restricted to 1.0. These quite conservative estimates suggest that at a minimum half of the estimated agglomeration economies can be compensated away and so cannot be due to unobserved productivity differences across individuals.

Improving the Residential Location Controls

The residential location controls used in this paper are clearly limited by the location information available in the PUMS's. Specifically, residential location is only provided down to a geographic area containing 100,000 or more residents. As we focus on larger, denser Metropolitan Statistical Areas, however, these areas will be divided into more residential PUMA's, which presumably allows for more across residential PUMA sorting.[27] Specifically, we examine three subsamples where the 1999 metropolitan population must exceed two, three, and five million, respectively. The results are shown in Table 6, and the estimated effect of agglomeration is unchanged for these subsamples. The coefficient estimates on the human capital variables again exhibit an attenuation of approximately 10 percent across all subsamples from the inclusion of the residential location fixed effects.

In addition, we consider expanded fixed effect models that might better control for unobserved heterogeneity. Ortalo-Mange and Rady (2006) find substantial heterogeneity among homeowners within neighborhoods, but considerable homogeneity among renters and among homeowners who moved into the neighborhood at similar times. Presumably, renters and recent homeowners chose this neighborhood based on current prices and neighborhood amenities and therefore are very similar, while homeowners that moved to the neighborhood in earlier years chose this neighborhood based on different prices and amenity levels. Alternatively, one physical residential location might be divided into different submarkets based on the type of housing

[27] Rosenthal and Strange (2006) use a similar strategy in their paper focusing on dense employment areas where employment is spread over more workplace PUMA's.

stock. For example, an individual who resides in a small loft in an apartment building may be very different from someone who selected a large single family dwelling in the same residential location even if the two individuals have similar levels of observable human capital.

In order to address these concerns, we develop residential location fixed effects by tenure in residence and by housing stock categories. For the tenure of residence fixed effect model, a full set of PUMA fixed effects are created for each of the following categories: renters, owners who have been residing in the neighborhood for less than one year, owners who have been residing in the neighborhood between one and five years, and owners who have been residing in the neighborhood for more than five years. For the housing stock model, PUMA fixed effects are created for each of seven housing stock categories: mobile home, multifamily 1 bedroom or less, multifamily 2 bedroom, multifamily 3 bedroom or more, single family 2 or less bedrooms, single family 3 bedrooms, and single family 4 ore more bedrooms. The results are shown in Table 7, and the expansion of the residential fixed effects has little impact on the estimated agglomeration effect. Further, both sets of controls significantly improve the model, and the attenuation of the coefficient estimates on the human capital variables increases from 10 to between 15 and 20 percent.

Alternative Subsamples and Robust Commute Time Estimates

As discussed earlier, a key concern is that commute time may be correlated with the unobservable productivity variables that are potentially generating a spurious relationship between agglomeration variables and wages. In that case, commute time may act as a proxy for those unobservables, and the commute time model may be capturing the true relationship between nominal wages and employment concentration. As noted earlier, our best evidence on this issue is that the inclusion of commute does not cause any attenuation in the estimates on individual human capital variables, which would be expected if workers were sorting across commutes based on their unobserved productivity attributes. As discussed above, the conditional correlation between workplace commute and education is near zero, and there is no evidence of sorting on observable measures of human capital.

However, as an additional test, we examine the estimated coefficient on commutes across a variety of subsamples. If commute time acts as a proxy for individual productivity unobservables, we would not expect a robust relationship between commute time and wages across regions, population subgroups or mode choice. Rather, the estimated coefficient on commute in a wage equation would likely vary across subsamples based on how those groups sort within metropolitan areas. Sorting outcomes for particular groups are likely to vary based on the urban environment and the options faced by the individuals in those subsamples. On the other hand, if commute time captures a more fundamental relationship in urban economies, such as the existence of a locational equilibrium, the estimated coefficient on commute time should be fairly stable across these subsamples.

Table 8 presents estimates for a series of regional subsamples for the total employment specification. The first column presents results for the full sample with the subsequent columns containing the estimates for metropolitan areas in the Northeast, Midwest, South, and West regions. The commute time results are quite stable across the samples with estimates ranging from 0.0075 to 0.0099 over the four regions as compared to 0.0089 for the full sample. Similarly, estimates from the density model, which are not presented in a table, range from 0.0085 to 0.0119 over the four regions as compared to 0.0093 for the full sample. These findings suggest that commute time is capturing a relationship between wages and commutes that is fairly stable across different regions of the country, even though residential sorting and commuting patterns vary dramatically across those regions.

The qualitative findings concerning the coefficient estimate on total employment in Table 3 are replicated across all four regions. The estimated impact of agglomeration increases moderately after controlling for residential fixed effects and then falls to near zero after the inclusion of a control for commute time. The raw coefficient estimates on total employment exhibit substantial variation across regions, but in part this is due to different urban environments in each region. After standardizing the coefficients using the within metropolitan area standard deviation of total employment, the estimated agglomeration effects in the fixed effect models are closer in magnitude with values of 0.0318, 0.0616, 0.0316, 0.0226, and 0.0153 for the full sample, Northeast, Midwest, South, and West regions, respectively. In addition, while the raw estimates on employment density differ from the estimates for total employment, the standardized estimates for density have a nearly identical pattern across regions with estimates of 0.0313, 0.0565, 0.0291, 0.0193, and 0.0123 using the same samples.[28]

Table 9 presents a similar set of estimates for subsamples based on college education, transportation mode, and race/ethnicity. As in Table 7, the estimates on commute time are stable across the college educated, non-college educated workers, automobile commuters, mass transit commuters, and non-Hispanic white samples with estimates ranging between 0.0083 and 0.0116. The only exception to this finding is the minority sample, where the estimated relationship

[28] Note that the within metropolitan area standard deviations on total employment for the full sample, Northeast, Midwest, South, and West are 3.931, 3.993, 1.729, 2.160, and 6.311, and the standard deviations on employment density for the same samples are 3.484, 6.945, 0.394, 0.571, and 0.603. These lead to substantial variation in the raw estimates. For example, in the total employment estimates, the raw estimates for the Northeast, Midwest, and South regions are much larger than in the West, while in the employment density models the raw estimates for the Midwest and to some extent the South and West regions are larger than the estimates for the Northeast.

between commute time and wages of 0.0058 is substantially smaller than the estimates for any other samples considered.

This finding should not be surprising considering previous research concerning minority commutes and the spatial mismatch hypothesis. For example, Gabriel and Rosenthal (1996) and Petitte and Ross (1999) both find racial differences in commutes that cannot be compensated for by differences in housing prices and/or wages. Our findings are consistent with the notion that minorities are in a locational equilibrium when compared to each other, but are under compensated for their commutes when compared to the majority population. It is also notable that the effect of agglomeration economies on minority wages is less than half the effect on white wages. These results appear consistent with the idea that barriers faced by minorities or imperfections in the labor market that differentially affect minorities prevent minorities from being fully compensated for their commutes or capturing in wages the full surplus created by productivity differences across locations.

The estimates of total employment are again consistent with the general results from Table 3. For all subsamples, the inclusion of residential location fixed effects leads to moderate increases in the estimated effect of agglomeration economies, and any estimated effect of agglomeration economies disappears when controls for commute time are included. The estimates for every subgroup are consistent with the existence of agglomeration economies that are underestimated in simple OLS estimation because low skill individuals tend to reside in central cities near employment concentrations, and there is no evidence of bias from omitted ability variables in the fixed effect estimates because all wage differentials are entirely compensated by differences in commuting time between employment locations. The estimated agglomeration effects in the residential location fixed effect models are very similar between the education level subsamples. On the other hand, the estimated agglomeration effects for the mass transit sample is much larger than for the automobile sample, which is likely due to the high concentration of mass transit users in the Northeast where agglomeration effects are largest.[29]

Finally, our finding of large agglomeration economies for college graduates is notable because it is consistent with recent work by Moretti (2009). Moretti (2009) finds that have been migrating to more agglomerated, higher cost metropolitan areas, and his evidence suggests that the reason behind this is a shift in the demand for labor in these areas, not stronger preference for large city amenities among college educated. Similarly, we find that agglomeration wage premium are higher for college educated individuals, and the college educated wage premium is not associated with unobserved ability because the premium is entirely compensated away by longer commutes.

Locational Equilibrium and Housing Submarkets

Another concern with using the locational equilibrium concept to test for agglomeration economies is the required assumption that individuals in the same residential location face the same price per unit of housing services. This assumption may not be reasonable because it is expensive and often prohibited by zoning to change the type of housing on specific parcels of land. As a result, the price per unit of housing services may vary considerably across different forms of housing in the same neighborhood due to differences between current demand and the historical supply of housing in this neighborhood. In order to address this concern, we re-estimate the commute time models allowing for residential fixed effects for each of the six categories of housing stock discussed earlier, as well as re-estimate the models with residential fixed effects using tenure and time of residence since owner-occupancy status may play a role in

[29] Northeast residents comprise more than half of the mass-transit subsample. The authors recognize that transportation mode choice is clearly endogenous to labor market earnings, and these models are estimated primarily to examine the stability of commute time coefficients across subsamples.

creating distinct housing submarkets. Specifically, in table 10, we present the same models presented in table 7 except that these models also include the control for commute time. In all models, the estimated effect of agglomeration is near zero when commute time is included, and the results are robust.

Extended Model Specifications

Panel 1 of Table 11 estimates models that also include a control for the workplace PUMA share of workers with a four year college education or higher. The extended model is still consistent with agglomeration economies associated with total employment or employment density. The education level of workers in the PUMA is also positively associated with wages, which is consistent with the standard human capital externalities explanation that often arises in this context (Rauch, 1993; Moretti, 2004; Rosenthal and Strange, 2006). As before, the inclusion of residential PUMA fixed effects increases the relative magnitude of the estimated agglomeration coefficients, and the findings are consistent with low productivity individuals sorting into locations with concentrated employment, possibly due to the centrality of their residential locations. On the other hand, the estimated effects of share college educated decline when residential fixed effects are included. These findings are consistent with the notion that high skill individuals sort into places with concentrations of highly educated workers. As in previously estimated models, the inclusion of commute time as a regressor leads to very large reductions in the magnitude of and statistical insignificance of the overall agglomeration effect and the effect associated with college educated workers.[30]

[30] We also examined models including controls for the share of workers in the worker's own occupation and share of workers in the worker's own industry. We find that wages also increase with the share of workers in a worker's own occupation and industry suggesting the existence of localization economies (Wheaton and Lewis, 2002; Combes, Duranton, and Gobillon, 2004; Fu, 2007). The inclusion of commute time, however, does not erode the magnitude of the estimates on the localization economy variables over industry and occupation. Unlike the employment concentration and education variables, the localization economy variables represent factors that vary

Panels 2 and 3 of Table 11 present estimates for model with no covariates for the full sample and for the baseline model for the subsample of single, male workers. All results are robust. For both sets of estimates, the effect of agglomeration economies strengthens and the effect of human capital externalities weaken somewhat after controlling for residential location fixed effects. Further, the estimated coefficient on the agglomeration variable falls to zero after including a control for average workplace commute time, suggesting no bias from omitted productivity attributes after controlling for residential location.

Summary and Conclusions

This paper estimates standard agglomeration models using a sample of 33 Metropolitan and Consolidated Metropolitan Statistical Areas from the Public Use Microdata Sample of the 2000 Decennial Census. The estimates for both total employment and employment density are consistent with a positive relationship between employment-based measures of agglomeration and firm wages. The inclusion of residential location controls intended to absorb worker heterogeneity actually leads to an increase in the estimated effects of agglomeration. These findings suggest that lower productivity workers sort into concentrations of employment possibly due to their more central residential locations. Estimates for the individual education variables attenuate when the residential controls are included, which is consistent with the residential controls capturing unobserved heterogeneity. The location controls are refined by focusing on samples of larger metropolitan areas where the location controls should provide more information and by including location controls that also contain information on housing submarkets with all specifications yielding robust estimates. Further, the magnitude of these

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across workers for the same workplace location. It seems unlikely that commute time could both penalize a worker in industry A with a long commute because a large concentration of employment in that worker's industry leads to high wages, and simultaneously compensate a worker in industry B because of low wages associated with little employment in that worker's industry.

estimates are sizable with standardized effects of about two thirds of the estimated cross-metropolitan wage premium for the same sample.

The inclusion of commute time dramatically reduces the overall agglomeration effect. This finding suggests that the observed nominal wage differences cannot represent differences in ability across workers because the wages net of commuting costs do not vary systematically across employment locations presumably leaving similar workers with similar levels of well being. In addition, concerns that workers may be sorting across commutes based on ability are mitigated by the findings that the inclusion of commute time does not cause any attenuation in the estimated coefficients on the education variables and that the conditional correlation between commutes and observable measures of human capital is near zero. Further, the estimated magnitude of compensation for commutes is consistent with the existing literature. Finally, we examine how the coefficient on commute time varies across different subgroups associated with region, education level, minority status, and transportation mode. Presumably, the spatial pattern of residential and workplace locations varies dramatically across these subgroups and should lead to different correlations between commutes and unobserved productivity attributes, and yet with the exception of minority status the coefficients on commutes and the qualitative results of the tests for agglomeration economies are very stable across these subgroups.

In addition, we consider a very challenging test for our estimation strategy where we omit all individual level covariates. This strategy substantially decreases the R-squares of our models and increases the variance attributable to unobserved worker ability. The agglomeration estimates from OLS fall by half as expected if low ability workers sort near to employment concentrations within metropolitan areas. The fixed effects estimates increase somewhat, but only by 15 to 20 percent, and the estimates are near zero after controlling for commute times, which is consistent with the fairly stable agglomeration economy estimates in the fixed effects models.

Finally, an extended specification is estimated that includes a variable intended to capture human capital externalities, share of workers with a four year college degree. As in the previous literature, we find that wages increase with the concentration of college-educated workers. These results persist when residential location fixed effects are included with the effect of overall employment increasing in magnitude as in previous models. On the other hand, the effect of human capital externalities fall with the inclusion of fixed effects, possibly because high productivity individuals are sorting across work locations based on education levels. Finally, the inclusion of commute time completely eliminates any estimated relationship between wages and either employment concentration and share college educated workers variable, further supporting our view that these effects cannot be the result of unobserved productivity attributes.

The results in this paper also have more general implications concerning the nature of urban economies. Only limited empirical evidence on urban wage gradients exists to support the idea that urban labor markets are in a locational equilibrium. This paper provides substantially more direct evidence by demonstrating that wage gradients can completely compensate for nominal wage differences within metropolitan areas. Further, if agglomeration economies eventually plateau and possibly decline on the margin at very high concentrations of employment, empirical estimates of agglomeration effects may understate the total importance of agglomeration in urban economies, especially in cities with relatively effective transportation systems, because in equilibrium workers should continue to crowd into the high employment concentration locations until marginal productivity declines sufficiently to assure equal wages net of commuting costs.

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Table1: Variable Names, Means, and Standard Deviations		
Variable Name	Non-College	College Graduates
Dependent Variable		
Average hourly wage	20.121 (27.466)	36.602 (54.294)
Workplace PUMA Controls		
Total PUMA employment in 100,000's	3.902 (5.255)	4.200 (5.116)
PUMA Employment density in 1000's/square KM	0.984 (3.506)	1.568 (4.673)
Share of college educated workers in PUMA	0.353 (0.082)	0.387 (0.087)
Average commute time in PUMA in minutes	27.326(6.136)	28.877(6.854)
Metropolitan Area Controls		
Percent college educated in MSA and occupation	0.024 (0.033)	0.053 (0.043)
Percent college educated in MSA and industry	0.031 (0.027)	0.048 (0.033)
Individual Worker Controls		
Age of worker	42.528 (7.964)	43.061 (8.076)
Non-Hispanic white worker	0.746 (0.435)	0.830 (0.376)
African-American worker	0.125 (0.330)	0.061 (0.240)
Hispanic worker	0.078 (0.268)	0.011 (0.106)
Asian and Pacific Islander worker	0.044 (0.205)	0.094 (0.292)
High school degree	0.705 (0.456)	0.000 (0.000)
Associates degree	0.114 (0.318)	0.000 (0.000)
Four year college degree	0.000 (0.000)	0.600 (0.490)
Master degree	0.000 (0.000)	0.256 (0.436)
Degree beyond Masters	0.000 (0.000)	0.144 (0.351)
Worker single	0.278 (0.448)	0.227 (0.419)
Number of children in household	0.547 (0.498)	0.558 (0.497)
Born in the United States	0.795 (0.403)	0.816 (0.387)
Years in residence if not born in U.S.	3.376 (7.257)	2.777 (6.687)
Quality of spoken English	0.158 (0.364)	0.174 (0.379)
Sample size	519,530	311,516

Table 2: Baseline Model of Agglomeration Economies for Logarithm of the Wage Rate		
Independent Variables	Total Employment	Density
Total employment in 100,000's	0.0049 (2.95)	
Employment density in 1000's per square KM		0.0062 (11.28)
Percent college educated in MSA and occupation	0.9186 (3.37)	0.9173 (3.32)
Percent college educated in MSA and industry	1.7158 (6.38)	1.6726 (6.47)
Age of worker	0.0387 (33.89)	0.0387 (33.87)
Age of worker squared divided by 100	-0.0004 (25.83)	-0.0004 (25.82)
Non-Hispanic white worker	0.1512 (11.90)	0.1523 (11.65)
African-American worker	0.0184 (1.50)	0.0206 (1.63)
Hispanic worker	-0.0102 (0.94)	-0.0084 (0.76)
Asian and Pacific Islander worker	0.0582 (5.91)	0.0591 (5.91)
High school degree	0.2064 (26.03)	0.2061 (26.09)
Associates degree	0.2705 (29.49)	0.2703 (29.81)
Four year college degree	0.4549 (43.58)	0.4547 (44.49)
Master degree	0.5774 (49.41)	0.5771 (50.65)
Degree beyond Masters	0.7030 (69.81)	0.7027 (71.47)
Worker single	-0.1307 (56.22)	-0.1306 (56.07)
Number of children in household	0.0714 (33.97)	0.0716 (33.46)
Born in the United States	0.2782 (12.94)	0.2764 (12.74)
Years in residence if not born in U.S.	0.0080 (13.43)	0.0079 (13.38)
Quality of spoken English	-0.0224 (3.49)	-0.0222 (3.45)
R-square	0.2883	0.2885

Note: The dependent variable for all regressions is the logarithm of the estimated hourly wages, which is calculated as annual labor market earnings divided by the product of number of weeks worked and average hours worked per week. The key variable of interest is either the total number of full time workers in a workplace PUMA or the density of full time workers in a PUMA where full-time work is defined as worked an average of at least 35 hours per week. The sample of 831,046 observations contains male full-time workers aged 30 to 59 in the selected metropolitan areas. The models include metropolitan, one-digit industry, and one-digit occupation fixed effects, but those estimates are suppressed. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 3: Agglomeration Wage Models without and with Location Controls						
Variables	Total Employment			Density		
	OLS	Fixed Effects	Commute Time	OLS	Fixed Effects	Commute Time
Baseline Model Specification						
Employment	0.0049 (2.95)	0.0081 (3.99)	0.0007 (0.92)			
Density				0.0062 (11.28)	0.0090 (18.43)	-0.0002 (0.41)
Commute Time			0.0089 (18.41)			0.0093 (22.24)
R-Square	0.2883	0.3029	0.3045	0.2885	0.3031	0.3045
No Individual Level Covariates						
Employment	0.0024 (1.27)	0.0097 (4.32)	0.0012 (1.14)			
Density				0.0047 (6.71)	0.0104 (17.09)	-0.0007 (1.12)
Commute Time			0.0103 (17.48)			0.0112 (22.08)
R-Square	0.1986	0.2365	0.2385	0.1990	0.2366	0.2385
Sample of Single Men						
Employment	0.0048 (3.41)	0.0064 (4.56)	0.0011 (1.14)			
Density				0.0056 (12.31)	0.0069 (19.58)	-0.0003 (0.0036)
Commute Time			0.0070 (11.37)			0.0076 (13.34)
R-Square	0.2441	0.2564	0.2574	0.2442	0.2565	0.2574

Note: The OLS columns in the first panel contain the results from table 2, the fixed effect columns contain the results for the same model where metropolitan fixed effects are replaced by residential Public Use Microdata Area (PUMA) fixed effects, and the commute time columns contain the results for the residential PUMA fixed effect model after the inclusion of the average commute time for the individual's workplace PUMA. The second panel presents estimates for a specification where all individual worker covariates (as listed in Table 1) are excluded. The first two models use the same sample of 831,046 observations while the last model uses the subsample of single men with 215,375 observations. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 4: Agglomeration Wage Models without and with Location Controls						
Variables	Total Employment			Density		
	OLS	Fixed Effects	Commute Time	OLS	Fixed Effects	Commute Time
Baseline Model Specification						
Employment	0.0049 (2.95)	0.0081 (3.99)	0.0007 (0.92)			
Density				0.0062 (11.28)	0.0090 (18.43)	-0.0002 (0.41)
Commute Time			0.0089 (18.41)			0.0093 (22.24)
R-Square	0.2883	0.3029	0.3045	0.2885	0.3031	0.3045
Logarithm of Employment, Density, and Commute Time						
Employment	0.0247 (6.43)	0.0342 (6.32)	0.0037 (1.61)			
Density				0.0211 (9.68)	0.0288 (8.26)	0.0044 (2.34)
Commute Time			0.2705 (13.63)			0.2571 (11.01)
R-Square	0.2889	0.3033	0.3045	0.2892	0.3038	0.3045

Note: The first panel replicates the estimates presented in table 3. The second panel presents estimates for the same specification in the first panel except that the logarithm of total employment, employment density, and commute time are used as covariates. Both models use the same sample of 831,046 observations. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 5: Agglomeration Wage Models Instrumenting for Commute Time as Share of Work Day						
Variables	Total Employment			Density		
	Commute Time IV Estimation	Commute Coefficient 1.5	Commute Coefficient 1.0	Commute Time IV Estimation	Commute Coefficient 1.5	Commute Coefficient 1.0
Employment	0.0007 (0.92)	0.0028 (4.02)	0.0045 (4.13)			
Density				-0.0002 (0.41)	0.0027 (11.50)	0.0048 (17.47)
Commute Time	2.0806 (18.41)	1.5000	1.0000	2.1824 (22.24)	1.5000	1.0000
R-Square	0.3045	0.2993	0.3001	0.3045	0.2992	0.3001

Note: The first and fourth columns present two-stage least squares estimates for the residential PUMA fixed effects agglomerations models controlling for an individual's total commute time (both ways) as a share of their entire work day (average hours worked per week divided by five plus the total commute time) using the average commute time for the place of work PUMA (the same control variable used in Table 3) as an instrument. The next two columns present estimates based on predicted commute time share, but restricting the coefficient on commute time share to 1.5 and 1.0, respectively. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 6: Agglomeration Wage Models with Location Controls for Subsamples of Larger Metropolitan Areas				
Sample	Full Sample	MSA Pop > 2 Mill.	MSA Pop > 3 Mill.	MSA Pop > 5 Mill.
Employment Total Models				
Employment	0.0081 (3.99)	0.0079 (3.90)	0.0076 (3.80)	0.0073 (3.31)
R-Square	0.3029	0.3052	0.3085	0.3087
Sample Size	831,046	699,266	602,240	484,285
Employment Density Models				
Density	0.0090 (18.43)	0.0088 (18.82)	0.0087 (19.18)	0.0087 (19.49)
R-Square	0.3031	0.3055	0.3089	0.3094
Sample Size	831,046	699,266	602,240	484,285

Note: The full sample column contains the results from the fixed effects model in panel 1 of table 3. The other columns present results from smaller samples based on dropping all metropolitan areas with 1999 populations below a threshold. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 7: Agglomeration Wage Models with Expanded Residential Location Controls						
Variables	Total Employment			Density		
	Fixed Effects	Tenure based Fixed Effects	Housing Stock Fixed Effects	Fixed Effects	Tenure based Fixed Effects	Housing Stock Fixed Effects
Employment	0.0081 (3.99)	0.0075 (3.84)	0.0073(3.86)			
Density				0.0090 (18.43)	0.0086 (18.86)	0.0084(18.15)
R-Square	0.3029	0.3175	0.3241	0.3031	0.3177	0.3244
Sample size	831,046	828,887	809,286	831,046	828,887	809,286

Note: The fixed effect column contains the fixed effects results presented in panel 1 of table 3, the tenure based fixed effects column contains the estimates from a model that includes a unique fixed effect for each of four tenure categories in each residential PUMA, and the housing stock fixed effects column contains estimates from a model that includes a unique fixed effect for each housing stock category in each residential PUMA. The four tenure categories are renter, owner in residence less than one year, owner in residence between one and five years, and owner in residence more than five years. The seven housing stock categories are mobile home, multifamily 1 bedroom or less, multifamily 2 bedroom, multifamily 3 bedroom or more, single family 2 or less bedrooms, single family 3 bedrooms, and single family 4 ore more bedrooms. Observations are dropped if information on tenure or housing structure, respectively, is missing. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 8: Agglomeration Wage Models by Region for Total Employment					
Region	Full Sample	Northeast	Midwest	South	West
OLS					
Employment – Raw	0.0049 (2.95)	0.0095 (15.89)	0.0091 (3.91)	0.0120 (4.74)	0.0015 (1.77)
Employment – Stnd	0.0191	0.0376	0.0197	0.0208	0.0093
R-Square	0.2883	0.2848	0.2628	0.3095	0.2987
Fixed Effect					
Employment – Raw	0.0081 (3.99)	0.0156 (26.48)	0.0146 (5.37)	0.0131 (7.30)	0.0024 (2.56)
Employment – Stnd	0.0318	0.0616	0.0316	0.0226	0.0153
R-Square	0.3029	0.3023	0.2767	0.3198	0.3148
Commute Time					
Employment – Raw	0.0007 (0.92)	-0.0005 (0.034)	-0.0019 (0.82)	0.0029 (2.08)	0.0007 (0.76)
Employment – Stnd	0.0028	-0.0019	-0.0041	0.0050	0.0044
Commute Time	0.0089 (18.41)	0.0090 (10.89)	0.0099 (10.05)	0.0087 (10.66)	0.0075 (6.41)
R-Square	0.3045	0.3033	0.2777	0.3204	0.3153
Sample Size	831,046	211,991	198,309	221,043	199,703

Note: The first column labeled Full Sample presents the results from panel 1 in table 3, and the following columns present estimates for subsamples associated with census regions. The top panel presents the OLS results for all subsamples using the total employment specification, the second panel presents the results including residential location fixed effects, and the third panel presents the results including both residential location fixed effects and commute time. Standardized coefficients shown below the raw coefficient estimates are based on the within metropolitan area standard deviation of the total employment variable measured at the workplace PUMA. The standard deviations are 3.931, 3.993, 1.729, 2.160, and 6.311 for the full sample, Northeast, Midwest, South, and West, respectively. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 9: Agglomeration Wage Models by Subsample for Total Employment						
Subsample	No Four Year Degree	Four Year Degree	Automobile	Mass Transit	Non-Hispanic White	Minority
			OLS			
Employment–Raw	0.0029 (2.33)	0.0083 (3.99)	0.0048 (3.11)	0.0113 (7.16)	0.0096 (4.68)	-0.0001 (0.09)
Employment–Stnd	0.0115	0.0319	0.0179	0.0503	0.0333	-0.0005
R-Square	0.2110	0.1723	0.2808	0.4091	0.2476	0.2857
			Fixed Effects			
Employment–Raw	0.0072 (4.19)	0.0092 (3.92)	0.0068 (4.31)	0.0128 (10.46)	0.0108 (4.62)	0.0041 (2.94)
Employment–Stnd	0.0285	0.0354	0.0253	0.0569	0.0374	0.0201
R-Square	0.2257	0.1954	0.2944	0.4370	0.2623	0.3018
			Commute Time			
Employment–Raw	0.0002 (0.20)	0.0012 (1.73)	0.0008 (1.13)	-0.0026 (1.18)	0.0011 (1.67)	0.0004 (0.40)
Employment–Stnd	0.0008	0.0046	0.0030	-0.0116	0.0038	0.0020
Commute Time	0.0094 (17.42)	0.0083 (16.02)	0.0092 (18.41)	0.0116 (7.86)	0.0098 (21.61)	0.0058 (8.12)
R-Square	0.2278	0.1967	0.2959	0.4382	0.2642	0.3025
Sample Size	519,530	311,516	730,631	58,563	600,226	230,820

Note: Each column presents estimates for a specific subsample. The top panel presents the results for all subsamples using the total employment specification, the second panel presents the results including residential location fixed effects, and the third panel presents the results including both residential location fixed effects and commute time. Standardized coefficients shown below the raw coefficient estimates. The within metropolitan area standard deviations for the no four year degree, four year degree, automobile using, mass transit using, non-Hispanic white, and minority subsamples are 3.843, 3.961, 3.712, 4.473, 3.464 and 4.894, respectively. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 10: Agglomeration Wage Models with Commute Time and Expanded Residential Location Controls						
Variables	Total Employment			Density		
	Fixed Effects	Tenure based Fixed Effects	Housing Stock Fixed Effects	Fixed Effects	Tenure based Fixed Effects	Housing Stock Fixed Effects
Employment	0.0007 (0.92)	0.0005 (0.67)	0.0005 (0.69)			
Density				-0.0002 (-0.41)	0.00005 (0.11)	0.00028 (0.64)
Commute Time	0.0089 (18.41)	0.0085(19.31)	0.0082(18.12)	0.0093 (22.24)	0.0087(22.1)	0.0083(21.09)
R-Square	0.3045	0.3189	0.3254	0.3045	0.3189	0.3254
Sample size	831,046	828,887	809,286	831,046	828,887	809,286

Note: The fixed effect column contains the results presented in panel 1 of table 3 for the model containing commute time, the tenure based fixed effects column contains the estimates from a model that includes a unique fixed effect for each of four tenure categories in each residential PUMA, and the housing stock fixed effects column contains estimates from a model that includes a unique fixed effect for each housing stock category in each residential PUMA. The four tenure categories are renter, owner in residence less than one year, owner in residence between one and five years, and owner in residence more than five years. The seven housing stock categories are mobile home, multifamily 1 bedroom or less, multifamily 2 bedroom, multifamily 3 bedroom or more, single family 2 or less bedrooms, single family 3 bedrooms, and single family 4 or more bedrooms. Observations are dropped if information on tenure or housing structure, respectively, is missing. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 11: Agglomeration and Human Capital Externality Wage Models without and with Location Controls						
Variables	Total Employment			Density		
	OLS	Fixed Effects	Commute Time	OLS	Fixed Effects	Commute Time
Baseline Model Specification						
Employment	0.0017 (1.79)	0.0059 (3.73)	0.0007 (0.90)			
Density				0.0029 (8.55)	0.0067 (14.19)	-0.0001 (0.30)
Share with College	0.5149 (14.24)	0.3468 (9.97)	0.0398 (1.09)	0.4941 (13.90)	0.3076 (8.16)	0.0388 (1.07)
Commute Time			0.0088 (14.65)			0.0092 (15.96)
R-Square	0.2894	0.3029	0.3039	0.2895	0.3030	0.3035
No Individual Level Covariates						
Employment	-0.0013 (1.75)	0.0069 (4.14)	0.0012 (1.18)			
Density				0.0009 (1.64)	0.0074 (13.52)	-0.0006 (1.17)
Share with College	0.5506 (12.64)	0.3966 (9.88)	0.0554 (1.29)	0.5018 (11.56)	0.3656 (8.39)	0.0531 (1.25)
Commute Time			0.0098 (14.52)			0.0107 (15.62)
R-Square	0.2000	0.2364	0.2378	0.2000	0.2365	0.2378
Sample of Single Men						
Employment	0.0024 (2.79)	0.0044 (4.49)	0.0011 (1.16)			
Density				0.0029 (7.38)	0.0046 (9.45)	-0.0003 (0.40)
Share with College	0.4060 (10.28)	0.3129 (8.70)	0.0857 (2.16)	0.3975 (10.01)	0.2909 (8.23)	0.0844 (2.15)
Commute Time			0.0064 (8.77)			0.0071 (9.84)
R-Square	0.2446	0.2663	0.2668	0.2446	0.2663	0.2668

Note: The table presents results for the specifications in table 3 after including a control for the share of workers in the workplace PUMA who have a four year college degree or above. The first and third panels contain results for the baseline specification and the second panel presents results for the no covariate model. The models in the first two panels use the same sample of 831,046 observations, and the third panel uses the subsample of single men with 215,375 observations. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.