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Wage Premia in Employment Clusters: Agglomeration Economies or Worker Heterogeneity?

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Abstract

The correlation between wage premia and concentrations of firm activity may arise due to agglomeration economies or workers sorting by unobserved productivity. A worker's residential location is used as a proxy for their unobservable productivity attributes in order to test whether estimated work location wage premia are robust to the inclusion of these controls. Further, in a locational equilibrium, identical workers must receive equivalent compensation so that after controlling for residential location (housing prices) and commutes workers must be paid the same wages and only wage premia arising from unobserved productivity differences should remain unexplained. The models in this paper are estimated using a sample of male workers residing in 33 large metropolitan areas drawn from the 52000 U.S. Decennial Census. We find that wages are higher when an individual works in a location that has more workers or a greater density of workers. These agglomeration effects are robust to the inclusion of residential location controls and disappear with the inclusion of commute time suggesting that the effects are not caused by unobserved differences in worker productivity. Extended model specifications suggest that wages increase with the education level of nearby workers and the concentration of workers in an individual's own industry or occupation.

Journal of Economic Literature Classification: R13, R30, J24, J31

Keywords: Agglomeration, Wages, Sorting, Locational Equilibrium, Human Capital

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Wage Premia in Employment Clusters: Agglomeration Economies or Worker Heterogeneity?

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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 long literature exists on testing for the existence 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]

Another increasingly common approach for studying agglomeration is to study wages. A central feature of almost every model of agglomeration economies is that agglomeration raises productivity. Since workers are paid the value of their marginal production in competitive labor markets, a natural test for agglomeration economies is whether workers receive 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

[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.

with high concentrations of employment. 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. Many of these studies also find a positive link between wages and the human capital level associated with an employment concentration.

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 capital. 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. 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.[2]

Alternatively, Rosenthal and Strange (2006) address concerns about the endogeneity of location by looking within metropolitan areas, rather than across metropolitan areas, and

[2] 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. While the paper appears to provide strong evidence that workers in large labor markets in Italy are more productive, 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.

controlling for a host of fixed effects. While it may seem counter-intuitive to look within metropolitan areas because workplace sorting within a metropolitan area is more obviously endogenous than sorting across, Rosenthal and Strange (2006) exploit the additional variation arising from these comparisons to control for a variety of fixed effects that cannot be explicitly controlled for in studies that exploit across metropolitan variation. Most significantly, they include fixed effects for all metropolitan area-occupation combinations. Further, in examining the attenuation of agglomeration economies over space,[3] they implicitly control for a work location fixed effects within metropolitan area by differencing employment concentration effects between rings that are different distances from the center of each concentration.[4]

Our paper proposes a new strategy that avoids relying on mover's by drawing explicitly on the theoretical implications of standard models in urban economics. A worker's residential location is used as a proxy for their unobservable productivity attributes, and the paper examines whether the estimates of work location wage premia are robust to the inclusion of controls for residential location. 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, a worker with high productivity knows that they can expect a higher lifetime income, and therefore the worker is likely to have a greater willingness to pay for neighborhood amenities. Workers residing in similar quality locations

[3] Other studies that examine attenuation of agglomeration economies include Henderson and Arzaghi's (2005) study of the advertising industry, Duranton and Overman's (2002) study of industry localization, Fu's (In Press) study of wages, Rosenthal and Strange's (2003) study of establishment births, and Sivitanidou's (1997) study of commercial rents.

[4] Rosenthal and Strange (2005) also instrument for the level of agglomeration in a location using geographical features of the land on which the employment activity is located. This IV strategy seems less relevant than the use of fixed effects to addressing concerns about worker sorting across employment locations. The use of such instruments should break the correlation between observed employment concentration and unobserved features of the location, such as physical access, that may raise profits and lead to a concentration of employment, but does not necessarily break the correlation between location and worker unobservables since workers who sort into dense employment concentrations will necessarily live in areas where the geography supports such concentrations. See Bayer and Ross (2006) for discussion of a model with place and individual unobservables.

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 employees.

Further, urban economic theory suggests that in a locational equilibrium equivalent workers should obtain the same level of utility. After controlling for commuting time differences, workers should be indifferent between jobs in different locations even if one of those locations creates agglomeration economies leading to higher productivity and higher wages. Rational workers will sort into locations with higher wages until either production diseconomies lower marginal productivity and wages or congestion raises commuting times and costs. In equilibrium, wage differences across locations must be entirely compensated for by more time consuming commutes, and unexplained location wage premia should not persist in models that control for both residential location and commute time unless that evidence was created by unobserved productivity differences between workers.

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 database, microdata from the U.S. Census, and estimate the effect of concentrated employment using a broad population of workers residing in large and mid-sized U.S. metropolitan areas. In order to implement our identification strategy, we focus on employment concentrations within metropolitan areas. As with Rosenthal and Strange (2006), the focus on within metropolitan variation allows us to difference away variation that is likely correlated with both individual unobservables and employment location, except that our specific tests of agglomeration economies are motivated explicitly by commonly accepted principles concerning how urban economies operate.

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 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).[5] We find that these estimated effects persist even after controlling for unobserved worker productivity differences using residential location fixed effects. Further, the inclusion of a commute time control eliminates any relationship between the agglomeration variable and wages, suggesting that the earlier estimates detected the effect of agglomeration variables rather than unobserved differences in worker productivity. Finally, our standardized agglomeration economy estimates are comparable in magnitude to the agglomeration effects estimated across metropolitan areas.

The two obvious weaknesses of this approach are that residential location at the level measured may provide a poor control for unobserved worker quality and that workers may sort over commute time may based on their unobservables creating a correlation between commutes and worker productivity.[6] In terms of concerns about imperfect neighborhood controls, we verify

[5] 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.

[6] 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 (2000).

that the estimated coefficients on education variables are attenuated by the inclusion of the residential controls exactly as is expected if the residential controls capture worker productivity unobservables. Further, the findings are robust to models that restrict our sample to large metropolitan areas where residential PUMA's provide better controls for neighborhood and models that expand controls to allow for 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 type of housing stock. On the other hand, the inclusion of commute time does not cause any attenuation in the education coefficients while attenuation bias would be expected if workers in the same residential location systematically sorted over commute times. In addition, we estimate separate models across region, worker education, transportation mode, and race/ethnicity subgroups. If the influence of commute time on estimates of agglomeration economies arises due 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 across samples suggesting that the estimates capture a fundamental relationship in urban economies.

The paper is organized as follows. The next section presents the theoretical basis for our empirical methodology. The third section describes the data and results, and the fourth section concludes.

Methodology

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

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

where X_i a function of individual observable attributes, Z_j is employment concentration in the employment location (Z_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. If individuals sort over employment locations based on their expected wage, permanent income or tastes that are correlated with productivity, the unobserved component of productivity will be correlated with Z_j or

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

biasing estimates of γ.

Our proposed solution to this problem arises from simple models of residential location sorting based on unobservables (Epple and Platt, 1998; Epple and Sieg, 1999; 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 labor market expectations then each residential location k will contain workers in a continuous interval of labor market expectations. Accordingly, 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.

$$y_{ijk} = \delta_k + \gamma Z_j + \varepsilon_{ij} \tag{3}$$

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

$$\phi_k = \beta X_i + \alpha_i + \mu_{ik} \tag{4}$$

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 employment 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 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, but 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.

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 worker desires to change either their residential or employment location. This equilibrium condition implies 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 individual who resides in location k is observed in both employment location j and j', and P_k is the price of per unit of housing services in location 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 V_{jk} is the commuting time or distance and t is the per mile or minute commuting costs.[7] The reader should note that wages net of commute costs are constant across workplace locations even though agglomeration economies exist.

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 worker productivity as a function of work location to a model of workers' net wage, which is used to examine whether wage differences across location are compensated by differences in commute times.[8] If y_j is the wage premia offered in location j

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[7] 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 if either leisure does not enter preferences or total work hours including commute time are fixed.

[8] 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, and in the case of Petitte and Ross (1999) also including employment location, as controls for housing price and wage differentials that might compensate for longer commutes.

relative to wages in some baseline employment location, this wage premia can be expressed as an individual’s wage minus the individual inherent productivity independent of employment location. In other words, individual human capital levels 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 $\beta X_i + \alpha_i$.

However, 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, those differences should not be compensated for by commute time differences, and the estimated relationship between the agglomeration variable and wages should remain after including a control for commute time. On the other hand, if the estimated value of γ based on equation (6) is near zero, the inclusion of residential location fixed effects must have eliminated any correlation between Z_j and the unobservable, and accordingly the estimates of agglomeration economies in equation (5) 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).[9] 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,[10] and metropolitan area fixed effects. Finally, the model includes controls for share of college-educated employee's in a worker's industry or occupation at the metropolitan level.[11] The mean and standard errors for these variables are shown in Table 1 separately for the college educated and non-college educated subsamples.

[9] 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 location 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.

[10] Workers are classified into 20 major occupation codes and 15 major industry codes.

[11] 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 are 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.

We consider two alternative specifications to capture employment concentration: the number of workers employed at the PUMA and the PUMA employment density.[12] The control for commute time is based on the average commute time for all full time workers employed at a workplace PUMA.[13] Additional specifications are estimated that control for the fraction of workers in the workplace PUMA who have a college degree, 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.

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. Adding 1000 workers to a one square mile area would raise wages by 0.62 percent while Rosenthal and Strange (2006) find that adding 1,000 college educated workers to within a 5 mile radius of a worker's location increases wages by 0.02 percent, which inflates to about 1.5 percent if the number of college educated workers increases by 1000 per square mile in a 5 mile radius.[14] The

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

[13] 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. However, the IV estimates on PUMA to PUMA commute time very similar in magnitude (slightly smaller) to the estimates presented and discussed in this paper, and obviously the estimated coefficients on the agglomeration variables are unaffected by such a specification change.

[14] Unlike our model, 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. Therefore, we include share of college educated workers in a later specification. When we estimate models that are directly comparable to Rosenthal and Strange (2006), the estimated effect sizes are similar in magnitude. Using the total employment model to illustrate the magnitude of the effect, the

model also identifies evidence of human capital externalities by industry and occupation at the metropolitan level, but these variables are included as controls and our analysis cannot shed any light on whether these estimated relationships are causal.

Table 3 contains the estimates for the models that include residential location fixed effects and 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 their residential locations are near these concentrations of employment. While workers may sort across employment location 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. Low skill workers are more likely to live in central cities, and therefore more likely to reside close to major employment concentrations.

Further, 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 coefficients 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

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replacement of 1,000 non-college educated workers with college educated workers increases wages by 0.14 percent. In comparison, Rosenthal and Strange (2006) find a 0.12 percent increase in wages if 1,000 non-college educated workers were replaced with college educated workers within a 5 mile radius of a worker's location. Simply adding 1,000 college educated workers, to a PUMA or 5 mile radius area respectively, increases wages by 0.05 percent in our paper and by 0.02 percent in Rosenthal and Strange (2006).

residential fixed effects reduces the estimates on greater than masters, masters degree, four year college degree, associates 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.[15]

Finally, the magnitude of these estimated within metropolitan agglomeration economies are comparable in magnitude to simple OLS estimates arising from comparisons across metropolitan areas. Specifically, 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 PUMA or metropolitan area fixed effects, and we find that a one standard deviation increase in either of these variables 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, respectively, which is somewhat smaller, but very comparable in magnitude to the across metropolitan area estimates.

The next column 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 productivity. Further, the inclusion of commute time model does not cause any attenuation in the estimated coefficients on the education variables. For the total employment specification with residential

[15] Estimates for the employment density model are virtually identical.

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. These findings support the notion that controlling for commutes captures the idea that agglomeration based wage premia are compensated away by longer commuters rather than the alternative explanation that high ability workers are systematically sorting into longer commutes after controlling for residential location.

As expected in a compensation model, the coefficient estimate on commute time is statistically significant and positive. 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 the magnitude of these estimates, we shift to an instrumental variables framework in which control for an individual's time spent commuting as a share of average daily work time including commuting time (commute time divided by the sum of commute time and one-tenth of average hours worked per week) and use the average commute time for the workplace PUMA as an instrument.[16] 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 are 2.0806 and 2.1824 suggesting that time spent commuting is compensated at

[16] 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.

approximately double the wage rate.[17] Automobile travel on a highway with no traffic congestion is likely to have minimal disamenities, and in that case with a 60 mile per hour travel speed and a $25 per hour wage rate compensation at double the wage rate comes to $0.41 per mile for monetary costs of commuting, which is comparable to standard mileage reimbursement rates. Therefore, these estimates appear reasonable in magnitude especially if households overvalue the monetary costs of commute relative to time costs.[18] 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 when the commute time share coefficient is restricted to 1.0. These findings 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.

Finally, we consider an alternative instrument for commute time based upon average commute between place of residence PUMA to place of work PUMA. In a monocentric urban model including the models by Fujita and Ogawa (1982) and Ogawa and Fujita (1980), commute costs arising from residential location are entirely compensated by differences in housing prices, and only firm location is relevant to equilibrium wages. However, in complex multi-centric city, a worker's residential location may influence their wage. The replacement of workplace average commutes with residence to workplace average commutes dramatically reduces the estimated

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[17] These estimates are consistent with a back of the envelop calculation using the estimates from 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.

[18] The literature on commute times (Small, 1992) typically finds that time costs of commutes are valued at approximately half the wage rate, but those studies estimate this valuation based on comparing time costs to monetary costs of commute. An equally reasonable, alternative explanation for these results is that individuals over value the monetary costs of commuting relative to time costs, rather than undervaluing their time spent commuting relative to the value of their time at work. This phenomenon would increase compensation for commutes relative to the market wage. Also see Brownstone and Small (2005) for more recent evidence that finds commuting time cost values of up to 90% of the wage rate.

compensation of commute time to a value that is much closer to one or to compensation at the wage rate. Unlike workplace average commutes, this alternative instrument does not completely eliminate the estimates of agglomeration economies, but does reduce the estimated magnitude by about half as compared to the residential fixed effect estimates in Table 3. Again, suggesting that at least half of our agglomeration effect is compensated away and cannot be associated with individual unobservable productivity differences.

The final column presents a model using both commute time variables as instruments. The residential to workplace PUMA average commute time variable dominates the first stage, and these estimates are nearly identical to the model that only uses residential to workplace PUMA average commute as an instrument. Not surprisingly, however, the overidentification restriction is rejected for this model leaving open the question of which model is most appropriate. A reduced form model of log wages that includes both commute time variables as controls yields estimates on the agglomeration variables that are very similar to the near zero estimates obtained from a model that only controls for workplace PUMA average commute; specifically, 0.0006 (1.20) and 0.0005 (1.09) for total employment and employment density.

In summary, the estimated agglomeration effects are robust to controlling for unobserved heterogeneity and are also completely compensated for by longer commutes into a workplace PUMA, as we would expect if the observed wage differences that drive the agglomeration effects represent place based productivity differences arising in a comparison of intrinsically similar workers in terms of overall ability. Further, even when controlling for average place of residence to place of work commute time, approximately half of the estimated effect of agglomeration economies appears to be associated with place based productivity differences.

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, more dense metropolitan statistical areas, however, these areas will be divided into more residential PUMA's, which presumably allows for more across residential PUMA sorting.[19] Specifically, we examine three subsamples where 1999 metropolitan population must exceed two, three, and five million, respectively. The results are shown in Table 5, 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 samples from the inclusion 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 neighborhood, 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 price and amenity levels. Alternatively, physical residential locations might be divided into different submarkets based on the type of housing 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.

[19] 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.

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 6, 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 unobservable productivity variables that exist and generate 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 wages and employment concentration. If commute time acts as a proxy for these 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 the urban environment and 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 samples.

Table 7 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 commuted 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 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.[20]

Table 8 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 commuter, mass transit commuter, 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 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 have 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

[20] 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.

productivity differences across locations. Further investigation of these issues will be the subject of future research.

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.[21]

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

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[21] 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.

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 creating distinct housing submarkets. Specifically, in table 9, we present the same models presenting in table 6 except that those models also include the control for commute time. In all models, the estimated effect of agglomeration is near zero when commute time is included in the model, and the results are robust.

Extended Model Specifications

Table 10 estimates models that also include controls for the workplace PUMA share of workers with a college education, share of workers in the worker's own occupation, and share of workers in the worker's own industry. 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). 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).

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 and share in own occupation decline. These findings are consistent with the notion that high skill individuals sort into places with concentrations of highly educated workers, as well as places with concentrations of workers in similar occupations. Occupation provides a very good indication of the skills possessed by a worker (Bacolod and Blum, 2005; Bacolod, Blum, and Strange, 2007), and the occupation result may arise from sorting based on skills where more highly skilled individuals sort into locations with workers of similar skills.[22]

The inclusion of commute time as a regressor again leads to very large reductions in the magnitude of and statistical insignificance of the overall agglomeration effect and the agglomeration effect associated college educated workers. These results provide strong evidence in favor of the existence of agglomeration economies associated with both the overall concentration of employment and human capital externalities. The inclusion of commute time, however, does not erode the magnitude of the estimates on the localization economy variables over industry and occupation. While the commute time results do not further strengthen our confidence in the results for the localization economy variables, these findings should not be viewed as a rejection of the findings concerning localization economies. Unlike the employment concentration and education variables, the localization economy variables represent factors that vary 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 also compensate a worker in industry B because of low wages associated with little employment in that worker’s industry.

Table 11 repeats the extended analysis for subsamples based on whether the worker obtained a four-year college degree. The qualitative results are quite similar for both samples. The estimated effects of the agglomeration variable are somewhat larger for the college educated

[22] It is worth noting that Bacolod, Blum, and Strange (2007) find evidence of agglomeration economies based on the concentration of skilled workers using occupation to characterize the skill levels of workers.

sample, while the effect for share educated appears to be somewhat smaller for the college educated sample. Accordingly, this paper contributes to, but does not explicitly resolve, the question of whether agglomeration economies are larger for educated workers (Wheeler, 2001) or for workers with less education (Adamson, Clark, and Partridge, 2004). The results in Table 7 suggest that economies might be somewhat larger for college educated workers, but the results in Table 11 unpack this overall result suggesting that while the agglomeration effects of employment concentration might be larger for college educated workers human capital externalities appear to be smaller for those workers.

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 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 location. Estimates for the individual education variables attentuate 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 estimates are sizable with standardized effects of about two thirds of the estimated across metropolitan wage premium for the same sample

The inclusion of commute time dramatically reduces the overall agglomeration effect. This finding suggests that these wage differences cannot represent differences in ability across workers because the wage differences are explained by commuting costs 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 finding that the inclusion of commute time does not cause any attenuation in the estimated coefficients on the education variables. Still, in light of this concern, we consider models that yield smaller, more conservative estimates on the impact of commutes on wages and the results are consistent with at most only half of the estimated agglomeration effect being driven by unobservable individual differences in productivity. Further, 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.

Finally, an extended specification is estimated that includes additional variables capturing human capital externalities and localization economies based on industry and occupation. As in the previous literature, we find that wages increase with the concentration of college-educated workers, as well as with the concentration of workers in a worker’s own industry and occupation. 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 and localization economies by occupation fall with the inclusion of fixed effects, possibly because high productivity individuals are sorting across work locations based on skill 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 estimated effects of share of workers in a workers own industry or occupation do not disappear once commute time has been included, but this result is not entirely surprising since commutes are unlikely to be able to compensate for workplace attributes that vary across individuals.

The results in this paper also have more general implications concerning the nature of urban economies. No previous evidence has been found to support that idea that urban labor markets are in a locational equilibrium, where differences in wages across locations are completely compensated for by differences in commute times. 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 low levels of traffic congestion, 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 mile	0.984 (3.506)	1.568 (4.673)
Share of college educated workers in PUMA	0.353 (0.082)	0.387 (0.087)
Share in own occupation in PUMA	0.094 (0.054)	0.110 (0.074)
Share in own industry in PUMA	0.109 (0.080)	0.128 (0.080)
Average commute time in PUMA in minutes	27.326(6.136)	28.877(6.854)
Metropolitan Area Controls		
Percent college educated in MSA and occuption	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 mile		0.0062 (11.28)
Percent college educated in MSA and occuption	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		
	Baseline	Fixed Effects	Commute Time	Baseline	Fixed Effects	Commute Time
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)
MSA-Occ. College	0.9186 (3.37)	0.8983 (3.26)	0.8342 (2.91)	0.9173 (3.32)	0.8866 (3.19)	0.8315 (2.90)
MSA-Ind. College	1.7158 (6.38)	1.4861 (5.94)	1.3678 (5.56)	1.6726 (6.47)	1.4446 (6.00)	1.3677 (5.56)
R-Square	0.2883	0.3029	0.3045	0.2885	0.3031	0.3045

Note: The baseline columns contain the results from table 2, the fixed effect columns contain the results from a 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. Fixed effect and commute time 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 4: Agglomeration Wage Models Instrumenting for Commute Time as Share of Work Day					
Instrumental Variables Model	Workplace PUMA Average Commute	Workplace PUMA Average with Coefficient at 1.5	Workplace PUMA Average with Coefficient at 1.0	Residence to Workplace PUMA Average Commute	Both Average Commute Instruments
Total Employment					
Employment	0.0007 (0.92)	0.0028 (4.02)	0.0045 (4.13)	0.0038 (3.53)	0.0038 (3.47)
Share Commute	2.0806 (18.41)	1.5000	1.0000	1.1764 (26.77)	1.1661 (26.29)
R-Square	0.3045	0.2993	0.3001	0.3051	0.3051
Employment Density					
Density	-0.0002 (0.41)	0.0027 (11.50)	0.0048 (17.47)	0.0045 (10.52)	0.0046 (10.70)
Share Commute	2.1824 (22.24)	1.5000	1.0000	1.1443 (42.69)	1.1337 (42.39)
R-Square	0.3045	0.2992	0.3001	0.3052	0.3052

Note: The first column presents two stage least squares estimates for the residential PUMA fixed effects agglomerations models controlling for an individual's commute time as a share of their entire work day (average hours worked per week divided by 10 plus 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 using the same predicted commute time share, but restricts the coefficient on commute time share to 1.5 and 1.0, respectively. The last two columns present estimates instrumenting with the average place of residence PUMA to place of work PUMA commute time and with both the average workplace commute time and average residence to workplace commute time, respectively. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 5: 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 table 2. 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 6: 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 results presented in 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 is 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 7: Agglomeration Wage Models by Region for Total Employment					
Region	Full Sample	Northeast	Midwest	South	West
Baseline Model					
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)	0.00242 (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 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 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 8: Agglomeration Wage Models by Subsample for Total Employment						
Subsample	No Four Year Degree	Four Year Degree	Automobile	Mass Transit	Non-Hispanic White	Minority
			Baseline Model			
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: 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. 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 9: 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 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 is 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 10: Extended Agglomeration Wage Models without and with Location Controls						
Variables	Total Employment			Density		
	Baseline	Fixed Effects	Commute Time	Baseline	Fixed Effects	Commute Time
Employment	0.0019 (2.31)	0.0061 (4.17)	0.0012 (1.59)			
Density				0.0024 (7.47)	0.0063 (13.77)	-0.0004 (0.99)
Share College	0.4953 (14.69)	0.3349 (9.70)	0.0479 (1.46)	0.4881 (14.90)	0.3099 (8.69)	0.0457 (1.41)
Share in Occ.	0.5959 (9.42)	0.5203 (8.46)	0.5036 (7.80)	0.5820 (9.16)	0.4991 (7.87)	0.5009 (7.76)
Share in Ind.	0.2741 (3.61)	0.2778 (3.97)	0.2569 (3.82)	0.2635 (3.54)	0.2511 (3.76)	0.2540 (3.78)
Commute Time			0.0082 (15.50)			0.0091 (17.29)
R-Square	0.2909	0.3042	0.3051	0.2910	0.3042	0.3051

Note: The table presents results for the specifications in table 3 after including variables for the share of workers in the workplace PUMA who have a four year college degree, who work in the same one digit Occupation as the worker, and who work in the same one digit industry as the worker. The extended model uses the same sample of 831,046 observations. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.

Table 11: Extended Agglomeration Wage Models without and with Location Controls by Education Level						
Variables	Total Employment			Density		
	Baseline	Fixed Effects	Commute Time	Baseline	Fixed Effects	Commute Time
No Four Year College Degree						
Employment	0.0001 (0.20)	0.0047 (4.19)	0.0005 (0.50)			
Density				0.0012 (3.68)	0.0050 (10.01)	-0.0017 (3.31)
Share College	0.4754 (15.38)	0.4076 (11.08)	0.1047 (3.17)	0.4568 (15.73)	0.4000 (11.92)	0.1046 (3.33)
Share in Occ.	0.4554 (6.72)	0.4399 (6.84)	0.4087 (6.29)	0.4504 (6.61)	0.4374 (6.71)	0.4070 (6.28)
Share in Ind.	0.2854 (5.27)	0.2667 (5.28)	0.2551 (5.30)	0.2842 (5.33)	0.2451 (5.07)	0.2572 (5.27)
Commute Time			0.0086 (15.36)			0.0097 (16.53)
R-Square	0.2137	0.2273	0.2285	0.2137	0.2273	0.2286
Four Year College Degree or More						
Employment	0.0048 (4.54)	0.0074 (4.16)	0.0019 (2.90)			
Density				0.0037 (8.31)	0.0076 (18.54)	0.0015 (2.74)
Share College	0.5617 (10.83)	0.2642 (6.72)	0.0006 (0.01)	0.5776 (10.60)	0.2109 (4.88)	-0.0021 (0.05)
Share in Occ.	0.5580 (5.33)	0.4033 (4.20)	0.4259 (4.46)	0.5083 (4.98)	0.3626 (3.79)	0.4147 (4.34)
Share in Ind.	0.2824 (2.69)	0.3350 (3.46)	0.3051 (3.25)	0.2590 (2.48)	0.3060 (3.25)	0.2982 (3.18)
Commute Time			0.0075 (12.57)			
R-Square	0.1759	0.1965	0.1973	0.1757	0.1967	0.1973

Note: The top panel presents the results for the same specifications that were presented in table 7 for the non-college educated sample of 519,530 observations, and the bottom panel presents the results for the four year college degree sample of 311,516 observations. T-Statistics based on standard errors clustered at the workplace PUMA are shown in parentheses.