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The attenuation of human capital spillovers

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Abstract

This paper uses 2000 Census data to estimate the relationship of agglomeration and proximity to human capital to wages. The paper takes a geographic approach, and focuses on the attenuation of agglomeration and human capital effects. Differencing and instrumental variable methods are employed to address endogeneity in the wage–agglomeration relationship and also to deal with measurement error in our agglomeration and human capital variables. Three key results are obtained. First, the spatial concentration of employment within five miles is positively related to wage. Second, the benefits of spatial concentration are driven by proximity to college educated workers, an instance of human capital spillovers. Third, these effects attenuate sharply with distance.

JEL classification: R0; J24

Keywords: Agglomeration; Human capital spillovers; Wages

1. Introduction

Understanding the economy is not possible without understanding cities. One fact that illustrates the importance of cities particularly clearly is the urban wage premium. Glaeser and Mare (2001) show that there is a wage premium of 33% between the largest metropolitan areas (with population 500,000 or more) and non-urban locations. Not all agglomerations are equal, however. Rauch (1993) and others have established the existence of human capital externalities, where the proximity to educated workers is associated with a higher wage. Both of these effects are instances of agglomeration economies. Other evidence of agglomeration economies has come from estimates of production functions (Ciccone and Hall, 1996; Henderson, 2003) and growth (Glaeser et al., 1992 and Henderson et al., 1995).[1]

The heart of the agglomeration literature is the idea that spatial concentration—either of population or human capital—enhances productivity. In all of the above papers and in most of the rest of the literature, workers are treated as being agglomerated if they share the same city or county. This approach leaves some fundamental questions unanswered. What is the spatial extent of externalities associated with the agglomeration of population or human capital? How quickly do these external economies attenuate with distance? These questions are important for both business location decisions and for local economic development policy. Businesses must choose locations, for instance in a downtown or an edge city, and this choice will depend on the how the benefits of agglomeration attenuate. Planners seek to create environments that are "competitive" in the sense that they can attract firms. They are also interested in the multiplier effects of local development policies such as building stadiums or attracting key firms. In both cases, the

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[1] See Rosenthal and Strange (2004) for a survey of the agglomeration literature.

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rate at which agglomeration economies attenuate impacts the cost-benefit calculus. Attenuation is also important for understanding urban sprawl, with its many social and environmental consequences.

This paper estimates a series of wage equations to assess the impact of agglomeration on wage rates. We devote special attention to human capital externalities and the rate at which the wage–agglomeration relationship attenuates with distance. Our approach makes use of geographic information software and 2000 Census data to characterize the spatial distribution of economic activity. Specifically, we create concentric ring variables that measure the employment of both educated and less educated workers at various distances from a given worker's place of employment (i.e., within 5 miles, between 5 and 25 miles, etc.). We then estimate the relationship between these concentric ring measures of agglomeration and local human capital and the log of individual worker wages.

In taking this geographic approach, we will focus on several key aspects of the agglomeration–wage relationship. The first is the urban wage premium, where workers are paid more in large cities, controlling for their characteristics.[2] The second is human capital externalities, where the proximity to more educated workers raises a worker's wage. Human capital externalities have been reported in wage studies by Rauch (1993) and, more recently, by Moretti (2004a), who instruments for the presence of college educated workers with the lagged presence of universities. Our third area of focus is whether agglomeration is of greater benefit to more educated workers. Considering a range of occupations, Wheeler (2001) finds that more educated workers enjoy a larger premium, while Adamson et al. (2004) find the opposite.[3]

None of these papers consider attenuation. The list of papers that do consider attenuation is short. Rosenthal and Strange (2003, 2005) consider births. The key result is that the effects of the local environment on births and on new firm employment both attenuate by roughly half after five miles. Anderson et al. (2004, 2005) consider the local impacts of a shift in the organization of higher education in Sweden. The policy change—a significant decentralization—is a kind of natural experiment. They find that the effects on productivity and patenting are highly localized. Arzaghi and Henderson (2006) show that external economies in advertising are also highly localized.

We face two econometric challenges when regressing wage on agglomeration, measurement error and endogenous regressors. The measurement error arises from the construction of our agglomeration variables. They are based on data at the level of the individual worker's Work Public Use Micro Area (PWPUMA). In characterizing the local economic environment of an individual worker, we treat the worker as being situated at the geographic centroid of the PWPUMA, with employment for each individual PWPUMA uniformly distributed throughout the given PWPUMA. We then draw concentric rings around the geographic centroid of each PWPUMA and measure the amount of employment within each distance band extending out from the PWPUMA centroid. While it is not obvious that a better procedure is feasible given our data, this nonetheless gives rise to an errors-in-variables problem: our agglomeration variables are measured with error, biasing our estimates of the influence of agglomeration towards zero. To deal with this, we restrict the estimating sample to individuals who live in MSAs and who work in PWPUMAs where the first concentric ring (five-mile) at least touches on two PWPUMAs. Restricting the sample to these small PWPUMAs reduces measurement error that would otherwise arise from larger PWPUMAs in sparsely populated areas.[4]

Our agglomeration measures may also be endogenous to an individual's wage. Concerns about endogenous measures of agglomeration dominate much of the empirical literature in this area (i.e., Combes et al., 2008). The issue of greatest concern has been that unusually skilled individuals are drawn to agglomerated areas. Selection of this sort would cause the error in a worker's wage equation to be correlated with the agglomeration variables, biasing the estimated effect of agglomeration on wage rates.[5] Balanced against the downward bias arising from measurement error, the net effect of the two biases is ambiguous.

To address endogeneity, we begin by including a rich set of observable worker-specific attributes in the regressions.[6] In addition, we difference our estimates in several ways. This has the effect of further stripping away the influence of unobserved worker-specific skill. As our first layer of differencing, all of our models include thousands of MSA/occupation fixed effects.[7] This ensures that the only endogenous sorting that might bias our estimates is within MSAs and occupations, a much narrower selection problem than is typical in agglomeration research. A second level of differencing occurs when we compare estimates of the effects of agglomeration in various concentric rings. Differencing in this fashion removes any unobserved effects that are common across rings. A third level of differencing is obtained when we estimate the influence of human capital spillovers: we difference the effect of proximity to college-educated workers relative to workers without college degrees. This removes unobserved effects associated with the total number of workers in a given ring. When estimating the attenuation of human capital externalities—by comparing human capital

[2] In addition to the previously mentioned paper by Glaeser and Mare (2001), several papers find evidence of an urban wage premium. See, for instance, Combes et al. (2003, 2008), Tabuchi and Yoshida (2000), Di Addario and Patacchini (in press), and Wheeler (2006). See also Diamond and Simon (1990) and Wheaton and Lewis (2002), who find that wages are higher in more specialized locations.

[3] Lee (2005), considering health care workers, also finds that workers with less skill benefit more from agglomeration.

[4] In earlier versions of the paper, we report results of models restricting the sample to just the New York MSA. The PWPUMAs in New York are smaller in geographic size relative to most parts of the US Results were similar.

[5] It is worth pointing out that Bacolod et al. (2007) document a pattern where skills increase only modestly with city size (as measured by Dictionary of Occupational Titles job characteristics).

[6] Our control variables include the worker's age, age squared, education, race, marital status, presence of children, and years in the United States.

[7] With 331 MSAs and many different occupations, over 24,000 fixed effects are included in some models.

effects across adjacent rings—all three levels of differencing are at work. In this last case, the only remaining unobserved skills of the worker that might influence our results are those that are uncorrelated with the worker's observable attributes, differ from MSA/occupation norms, and are unrelated to the overall level of agglomeration.

While the differencing strategy described above removes much of the bias associated with endogenous sorting based on unobserved worker skill, this approach nevertheless has two limitations. First, even for the triple-differenced results, we cannot rule out the possibility that some degree of endogeneity bias remains. Second, in some instances, it is desirable to focus on the coefficient levels rather than differences. For both reasons, our final procedure is to instrument for the agglomeration rings and estimate our wage equations by generalized method of moments (GMM). In principle, this can further alleviate biases arising both from endogenous regressors and measurement error. Our approach is motivated by the Manhattan Skyline. It is well known among architects that the observed pattern of big buildings downtown and midtown, with smaller buildings in between, reflects at least in part underlying geology. The tallest buildings are located where bedrock is relatively accessible. In this spirit, we employ as instruments several geological variables that vary at a micro level of geography.[8] This includes landslide hazard, seismic hazard, and the presence of sedimentary rock. Further details on these geological variables are provided in Section 3.

The paper's key results are as follows. First, the spatial concentration of employment is positively related to wage. Restricting our attention to activity within five miles of an individual's workplace, our GMM estimate of the elasticity of wage with respect to nearby employment is roughly 4.5%. Second, this urban density premium is driven by proximity to college educated workers, an instance of human capital externalities. These human capital effects are felt more strongly by college-educated workers than by those without college degrees. Third, and most importantly, these effects attenuate sharply with distance.

To get a sense of magnitude, relocating an individual from a work site with 25,000 workers within five miles to one with 125,000 workers—an amount roughly equal to a move from the 25th to the 75th percentile—would increase a given individual's wage by 2 percent. If instead this change in local workforce took place 5 to 25 miles outside of the individual's place of work, the impact on the individual's wage would be roughly four times smaller. Transforming 100,000 less-than-college workers within 5 miles into college-educated—equivalent to the 25/90 difference in percentile—would increase the wage of a typical worker by 12 percent in the OLS model. That amount is roughly equal to one third of the incremental gain from acquiring a college degree beyond that of a high school degree. In the GMM models, the corresponding wage effects are even larger, equaling 15 and 30 percent depending on specification of the instruments. These effects have a still larger impact on individuals who themselves have a college degree. If the transformation of local low-skilled workers into college-educated took place 5 to 25 miles outside of the individual's workplace, the estimated effects would be half the size just noted. In some specifications, the effect would be insignificant. These findings indicate that human capital spillovers are economically important, especially for the college educated. These findings also confirm a continuing and vital role for traditional downtowns; proximity still matters.

The rest of the paper is organized as follows. Section 2 sets out the theory of the agglomeration–wage relationship and the econometric issues that bear on estimation. Section 3 reviews the data. Section 4 presents our results, highlighting the influence of urbanization and local human capital on wages. Section 5 concludes.

2. Agglomeration, productivity, and wages

The theoretical basis for a relationship between agglomeration and wages is well known (i.e., Roback, 1982). On the labor supply side, real wages must adjust so that mobile workers are indifferent between locations. On the labor demand side, nominal wages must equal the value of workers' marginal products. It is this equality that allows one to use nominal wages to look for evidence of agglomeration economies (see Moretti, 2004b). However, although competitive labor markets ensure that a worker will be paid the value of his or her marginal product, it is not necessarily the case that the influence of agglomeration on wages exactly reflects the benefits of agglomeration. Agglomeration may also impact rents.

To illustrate this, we adapt the open city model from Gyourko and Tracy (1991). Fig. 1 contains two curves. The first is combinations of rent and wage that give firms zero profit. It is labeled $\pi(A_a)=0$. If wage increases, land rents must fall if profits are to remain at zero, holding constant the attributes A_a of the local economic environment. The other curve ensures that workers enjoy equal utility in all locations. This locus, labeled $U(A_a)=U^*$, sets utility equal to a system-wide level, U^*. It is upward sloping. If wage increases, land rent must also be higher if individuals are to maintain equal utility, holding constant the set of local attributes. Of course, firms are concerned with land rents in the commercial sector, while workers are concerned with residential land rents. However, these will be positively related in a spatial equilibrium, so we will for simplicity consider only one land rent variable. Under these conditions, the equilibrium wage and land rent at location a are given by w_a^* and r_a^* where the zero-profit and equal-utility curves intersect.

Suppose that agglomeration enhances worker productivity, but does not have a direct effect on worker utility. In this case, an increase in agglomeration, denoted by $A_b > A_a$, will cause the firm's profit curve to shift out in order to maintain $\pi(A_b)=0$. If the iso-utility function were perfectly flat, then wages would rise by the full amount of the horizontal shift in the zero-profit locus, $w_b^{**}-w_a^*$ in the figure. However, with

[8] In the human capital and wage literatures, Hoxby (2000), Black et al. (2002), and Combes et al. (2008) are the only other papers of which we are aware that use geologic features as instruments to control for endogenous regressors.

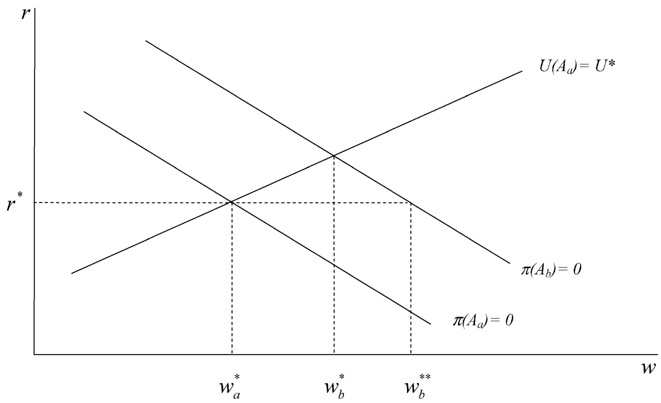


Fig. 1. Local attributes, wages, and land rents.

an upward sloping iso-utility function, some of the productivity gains from agglomeration will be capitalized into higher land rents, reducing the change in wage that would otherwise occur. In this case, the impact of agglomeration on wages is a lower bound on the productivity gains from agglomeration even though the impact of agglomeration on wages is an exact measure of the influence of agglomeration on the marginal productivity of labor.

Bearing these points in mind, an appealing estimating equation would be:

$$\ln w_{i,z} = S_i\theta + A_z\gamma + \varepsilon_i, \tag{1}$$

$w_{i,z}$ is the wage of worker i in location z. S_i is the worker's level of human capital. A_z is a vector of location-specific characteristics that affect productivity, including, for example, the total number of workers at the location or the number of workers with a college education. ε_i is a white noise error term that captures idiosyncratic differences in wage.

An immediate challenge, common to all wage studies, is that some elements of S_i are unobserved. Accordingly, we proxy for S using observable attributes of the individual worker. This leads to the following specification:

$$\ln w_{i,z} = H_i\delta_{\text{occ,msa}} + X_i\beta + A_z\gamma + \mu_{i,s} + \varepsilon_{i,z}, \tag{2}$$

where $\mu_{i,s} = S_i\theta - H_i\delta_{\text{occ,msa}} - X_i\beta$. In (2), $\delta_{\text{occ,msa}}$ is a vector of occupation/MSA fixed effects that capture the average level of productivity among workers belonging to a given occupation in a given metropolitan area and H_i is the associated vector of indicator variables.[9] X_i is a vector of worker i's observable characteristics, including age, age squared, education, marital status, presence of children, and years in the US. These variables control for deviations between the worker's level of human capital and the average skill level for his/her occupation group and MSA. The term $\mu_{i,s}$ represents that portion of the individual's skill that is not captured by the occupation/MSA fixed effects and X_i.

Two key assumptions are necessary if ordinary least squares (OLS) estimates of (2) are to yield unbiased and consistent estimates of γ. These are: (i) that A is measured without error and (ii) that sorting by worker skill does not cause A to be correlated with $\mu_{i,s}$.[10] Unfortunately, it is likely that neither of these assumptions holds exactly. Our response is described below.

2.1. Measurement error

As discussed in the Introduction, our agglomeration variables are likely measured with error. Thus, we observe $A_{z,m} = A_{z,\text{True}} + \mu_{z,m}$ where $A_{z,m}$ and $A_{z,\text{True}}$ are the measured and true levels of agglomeration, while $\mu_{z,m}$ is the measurement error which is assumed to be random with mean zero and finite variance. As is well established (see Greene, 1993, for example), even as sample size gets large, inserting $A_{z,m}$ for $A_{z,\text{True}}$ in the regression function causes estimates of the influence of A to be biased towards zero. Because the true agglomeration effect is expected to be positive, this implies a downward bias. Our first response to this problem, as noted in the Introduction, is to carry out our estimation for a sample with small PWPUMAs, specifically with five-mile rings that touch at least two PWPUMAs. This directly reduces measurement error. Our second response is to instrument for $A_{z,m}$ with variables that are correlated with $A_{z,\text{True}}$ but uncorrelated with both $\mu_{z,m}$ and the residual in Eq. (2). We therefore employ our geologic variables as instruments in a generalized methods of moments (GMM) model.

2.2. Endogenous agglomeration: Sorting by skill

Suppose now that agglomeration is measured without error. We are still concerned with the possibility that skilled workers within an occupation and MSA select into agglomerated areas (recall the occupation/MSA fixed effects). In this case, $\mu_{i,s}$ will be correlated with A_z and estimates of Eq. (2) will suffer from a standard omitted variable bias problem. This does not, however, necessarily affect our ability to identify the rate at which agglomeration economies attenuate.

To clarify, we rewrite (2) decomposing A_z into two rings

$$\ln w_{i,z} = H_i\delta_{\text{occ,msa}} + X_i\beta + A_{z,1}\gamma_1 + A_{z,2}\gamma_2 + \mu_{i,s} + \varepsilon_{i,z}, \tag{3}$$

where $A_{z,1}$ and $A_{z,2}$ are the inner and outer rings, respectively. Suppose further that $\mu_{i,s}$ is linearly related to $A_{z,1}$ and $A_{z,2}$ such that

$$\mu_{i,s} = a_1 A_{z,1} + a_2 A_{z,2} + s_i, \tag{4}$$

[9] In contrast, the subscript z on the agglomeration variables (A_z) denotes the individual's workplace which is measured at the Work PUMA level, a level below that of the MSA.

[10] The challenge of controlling for unobserved individual worker human capital is present in virtually all wage studies and is certainly not unique to our work. In the agglomeration literature, Glaeser and Mare (2001) address the issue in several ways, including using as instruments the characteristics of a worker's parents' place of residence. They conclude that roughly half of the raw urban wage premium can be attributed to selection of skilled workers into large cities and that the rest is associated with agglomeration.

where s_i is that portion of the worker's unobserved skill that is uncorrelated with $A_{z,1}$ and $A_{z,2}$. Substituting (4) into (3) gives

$$\ln w_{i,z} = H_i\delta_{\text{occ,msa}} + X_i\beta + A_{z,1}(\gamma_1 + a_1) + A_{z,2}(\gamma_2 + a_2) + s_{is} + \varepsilon_{i,z}. \tag{5}$$

Consider now our estimate of the rate at which agglomeration economies attenuate. This is given by the difference in the estimated coefficients on $A_{z,1}$ and $A_{z,2}$,

$$d_{1,2} = (\gamma_1 - \gamma_2) + (a_1 - a_2). \tag{6}$$

From (6) it is clear that if $a_1 = a_2$ then the bias associated with wage level effects differences away, and OLS estimates of (6) yield unbiased measures of $\gamma_1 - \gamma_2$, the rate of attenuation. This suggests that our estimate of $\gamma_1 - \gamma_2$ is less sensitive to unobserved worker skill than are our estimates of the levels of γ_1 and γ_2. The argument is even stronger when we further difference estimates of $\gamma_1 - \gamma_2$ based on differences in proximity to college-educated versus less-than-college educated workers (human capital spillovers).

Suppose, however, that $a_1 > a_2$; this would mean that adding one more worker to the nearby ring presents more of an attraction to an individual with unobserved talent than adding one more worker to the environment further away. Under these conditions, OLS estimates of $\gamma_1 - \gamma_2$ would still suffer from some degree of upward bias. To mitigate this concern, in the Introduction we outlined our plan to use within-MSA variation in geologic features as instruments to further control for measurement error and endogeneity. If the geologic measures are exogenous and sufficiently correlated with agglomeration, then GMM yields consistent estimates. In that regard, the GMM estimates based on the geologic instruments almost certainly work to reduce any bias associated with both measurement error and endogeneity.

3. Data and variables

The primary data for the paper are drawn from the year 2000, 5% Integrated Public Use Microdata Series (IPUMS).[11] Hourly wage rates are calculated by dividing annual wage earnings by the usual number of hours worked per week and the number of weeks worked in the last year. In our wage regressions, we control for a standard set of demographic attributes. These include the worker's level of education, the presence of children, marital status, age, race, and years of residency in the United States. Each of the models further controls for MSA/occupation fixed effects in order to capture unobserved MSA-wide effects that are specific to individual occupations and might affect a worker's wage rate. With occupations measured at the 3-digit level, this yields up to 24,000 fixed effects in some models.[12]

A primary focus of the paper is the spatial reach of agglomeration economies. In order to achieve this focus, we need to characterize the spatial distribution of employment as viewed from each individual worker's place of work. To do this, we created a set of concentric ring employment variables, each of which measures the number of workers present at a given distance from the workplace: 0 to 5 miles, 5 to 25 miles, 25 to 50 miles, and 50 to 100 miles. In forming these variables, person weights from the IPUMS were used to ensure that our employment counts correct for the non-random nature of the year 2000 Census. In addition, each of the employment rings reports the number of full-time male and female workers aged 30 to 65. For these purposes and elsewhere in the paper, full time workers are defined as individuals who report that their usual number of hours worked per week in the last year was 35 hours or more.

In selecting this structure of employment rings, our intention is to be flexible with regard to the geographic range of agglomeration effects. Most of the prior work on agglomeration effects has assumed the effects to operate MSA level, sometimes aggregated to the Consolidated Metropolitan Statistical Area (CMSA). These specifications roughly correspond to agglomeration effects that extend out to the 5 to 25-mile ring. By including also a 5-mile ring, we will be able to test whether agglomeration effects operate differently at a level of geography below that of large MSAs. By including 25 to 50-mile and 50 to 100-mile rings in some of the specifications to follow, we will be able to test whether effects operate at even larger levels of geography, as in, for instance, the state level work on agglomeration by Ciccone and Hall (1996).

Several steps were necessary to form the employment rings. First, we identified the individual's place of work using the place-of-work PUMA (PWPUMA), the most detailed indicator available in the data. In total, there are 1239 PWPUMAs in the United States. Second, we created an electronic map of the PWPUMA boundaries. To do this, geographic information software (MapInfo and MapBasic) was used to aggregate up from residential PUMA boundary files available at the census website.[13]

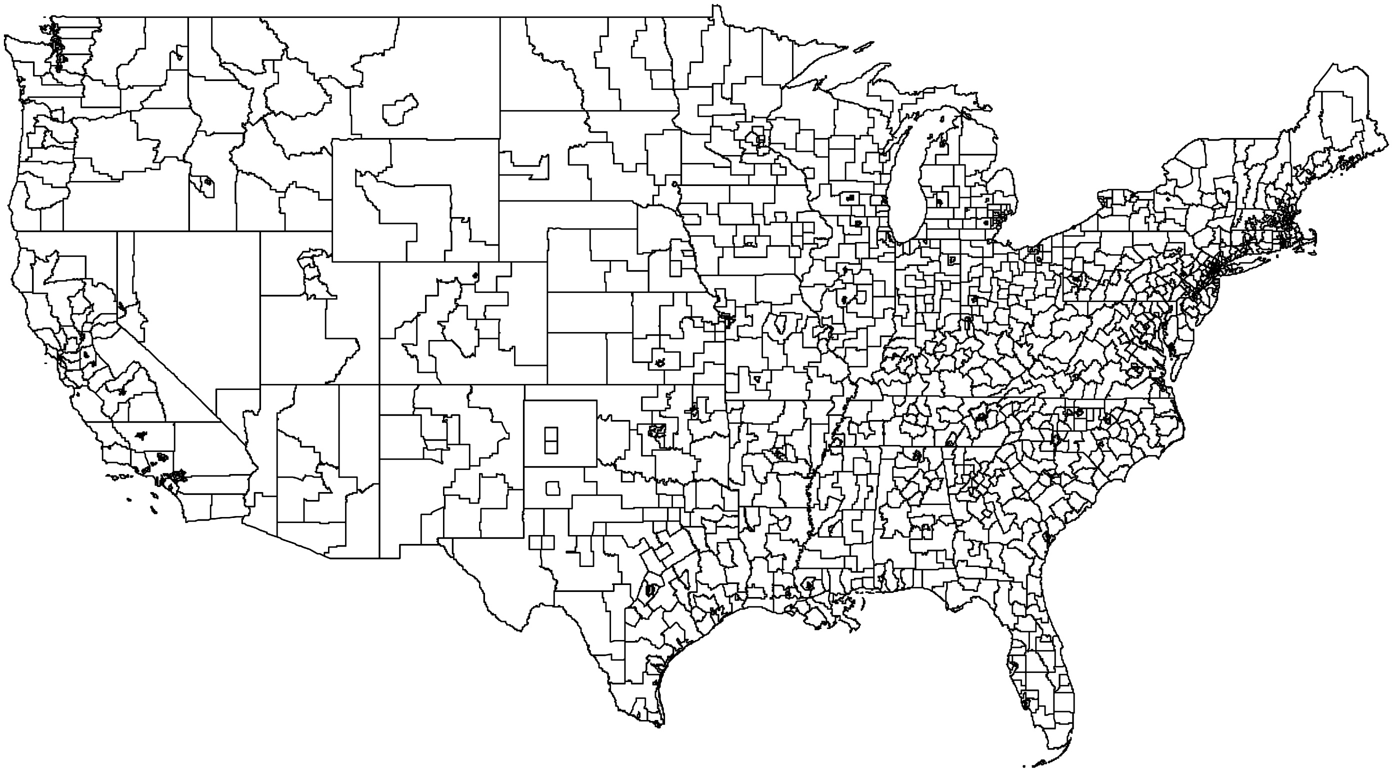
Our next step was to measure the level of employment present in each PWPUMA, using the person sampling weights in the IPUMs to ensure representative counts. Mapping software was then used to draw circles of radius 5, 25, 50, and 100 miles around the geographic centroid of each PWPUMA. Treating all employment within a given PWPUMA as uniformly distributed throughout the area, the level of employment contained in a given circle was calculated by constructing a proportional (weighted) sum of employment for those portions of the PWPUMAs intersected by a given circle.[14] We then differenced the employment levels for adjacent circles to obtain the level of employment within a given concentric ring. For exam-

[11] See http://www.ipums.org.

[12] When specifying the fixed effects, we treat self-employment as a separate occupation.

[13] PUMAs are smaller than PWPUMAs, and are used by census to identify residential locations. A correspondence file that matches PUMAs to PWPUMAs is available at the IPUMs website. In most cases, PWPUMAs correspond to regions identified by the first three digits of the 5-digit residential PUMA code. However, in some instances, PWPUMAs correspond to a more idiosyncratic group of residential PUMAs.

[14] For example, if a circle includes all of PWPUMA 1 and 10 percent of the area of PWPUMA 2, then employment in the circle is set equal to the employment in PWPUMA 1 plus 10 percent of the employment in PWPUMA 2.



(a)

Fig. 2. PWPUMA boundaries for the Continental United States.

ple, the 25-mile ring reflects employment between the 5 and 25-mile circles.

Fig. 2(a) displays the PWPUMA map for the entire United States, while Fig. 2(b) displays the PWPUMA boundaries for six large cities. The PWPUMAs partition the entire country. In some situations, they are quite irregular in shape. As is apparent, large metropolitan areas have numerous PWPUMAs, but in rural areas a single PWPUMA can cover a large geographic area. This raises concerns both about measurement error and our ability to identify the independent influence of the individual rings in regressions on workers in large PWPUMAs. For that reason, we restrict our sample to workers whose place of residence is within a metropolitan statistical area (MSA) and whose place of work (PWPUMA) is sufficiently small that a five mile ring drawn around its geographic centroid extends beyond the border of the own-PWPUMA (or equivalently, touches at least two PWPUMAs).[15]

As discussed earlier, we also estimate all of our models both by OLS and GMM. As instruments, we draw on geologic data from the United States Geological Survey (USGS). Specifically, for those portions of each concentric ring that lie within some defined PWPUMA (e.g., not over the ocean or the Great Lakes), we use data from the US Geological Survey to compute three measures: the fraction of the ring underlain by sedimentary rock, the fraction of the ring designated as seismic hazard, and the fraction designated as landslide hazard. These data were obtained over the web as boundary files for the entire United States (including Alaska and Hawaii). Portions of these maps are shown in Fig. 3.

The top picture in Fig. 3 displays the bedrock that underlies New York. As is clear, many different types of bedrock are identified in the USGS boundary file. We coded all regions in the bedrock map to equal one if they were associated with sedimentary rock, and zero otherwise. We did this because construction can be more costly on sedimentary rock. Overlaying the bedrock map on top of the PWPUMA map from Fig. 2, we then calculated the proportional average area of each PWPUMA underlain by sedimentary rock. Similarly, seismic hazard varies on a scale from zero to 100 in the USGS file, as shown for San Francisco in the middle picture of Fig. 3. We calculated the average seismic hazard for each PWPUMA by also overlaying the seismic map on top of the PWPUMA map, allowing for the relative contribution from each seismic region to a given PWPUMA. Landslide hazard is coded into several different categories by the USGS, low, medium, and high, as shown for Los Angeles in bottom picture of Fig. 3. We attached numerical values to each of these categories, 1, 2, and 3, respectively, and then calculated the proportional average landslide hazard for each PWPUMA following the same procedure as for the other geological variables. Summary measures of the geologic variables are provided in Appendix A.

15 Restricting the sample as above also ensures that information used to measure any given concentric ring is drawn from at least two different PWPUMAs. This reduces collinearity in the regressors and helps to identify the underlying effects.

(b)

Fig. 2. PWPUMA boundaries for selected metropolitan areas.

4. Results

This section presents estimates of the influence of agglomeration on wage. For all models, coefficients on the demographic attributes (e.g. age, education, etc.) were consistent with estimates in the labor literature and are not reported except (see Table A2 in the Appendix for an example).[16] The samples used

16 These variables include dummy variables for the worker's education, less than a High School degree, High School degree, College degree, Masters de-

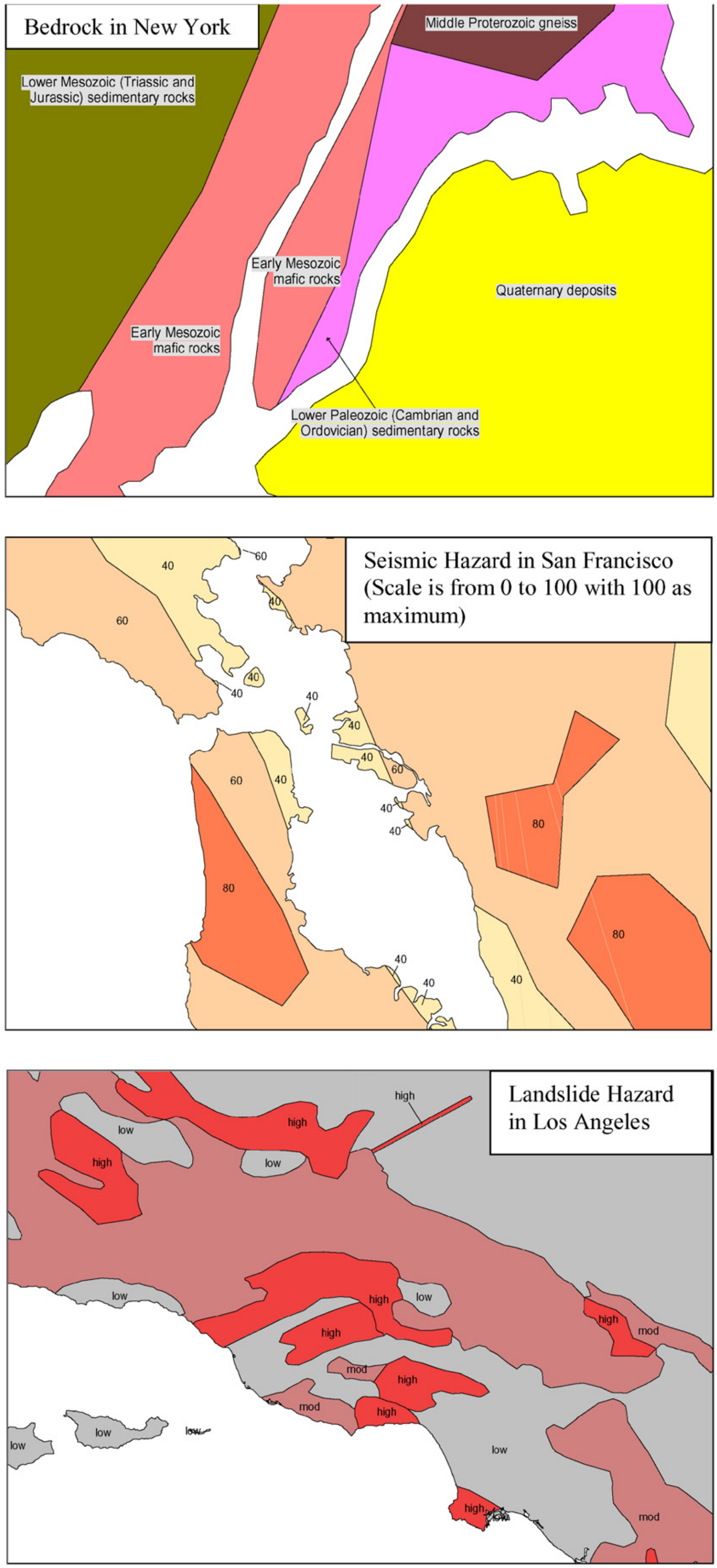


Fig. 3. Geologic features in select cities.

Table 1
Sample percentiles for concentric ring employment variables

Number of workers	Sample percentile				
	10th	25th	50th	75th	90th
Within 0–5 miles	5798	23,775	57,665	115,296	323,247
Within 5–25 miles	87,306	196,790	481,330	998,782	2,314,140
Within 25–50 miles	109,766	244,331	630,561	1,208,729	1,514,734
Within 50–100 miles	333,768	658,219	1,137,258	2,289,170	2,726,202
Less-than-college, 0–5 miles	3982	15,272	36,722	71,464	162,717
Less-than-college, 5–25 miles	64,840	137,374	316,513	600,081	1,463,621
Less-than-college, 25–50 miles	79,417	178,695	419,542	728,686	912,667
Less-than-college, 50–100 miles	245,844	507,280	818,407	1,541,408	1,813,270
College-or-more, 0–5 miles	1815	7483	19,545	42,203	138,823
College-or-more, 5–25 miles	23,795	60,277	159,468	387,907	850,519
College-or-more, 25–50 miles	26,288	60,830	210,632	464,792	576,886
College-or-more, 50–100 miles	86,340	173,675	335,174	840,719	941,523

The sample is restricted to individuals who reside in MSAs and who work in "small" PWPUMAs. "Small" in this context means that a 5-mile ring drawn around the geographic centroid of the PWPUMA extends beyond the boundary of the own-PWPUMA.

to estimate the models were restricted to male workers between the ages of 30 and 65 who report usual hours worked per week in the previous year as equal to or greater than 35 hours. This reduces concerns about the possible endogenous decision to work full time. It is worth re-iterating that all of the agglomeration variables are based on counts of workers that include both males and females.

4.1. Summary statistics

It is useful to begin with a brief review of how much employment is typically found within different distances, as this will help to put the magnitude of the estimated effects in perspective. Accordingly, Table 1 presents sample percentiles (the 10th, 25th, 50th, 75th, and 90th) of the concentric ring employment variables used in the regressions.[17] A 100,000 person increase in the total number of workers within 5 miles is roughly equivalent to the 25/75 spread. For college-or-more workers, increases of 50,000 and 100,000 are roughly equivalent to the 25/75 and 25/90 spreads, respectively.

4.2. Instrumental variable diagnostics

Our primary results are presented in Tables 2 through 4. Before discussing the tables in detail, we digress briefly here to clarify the nature of the instrument diagnostic tests reported at the bottom of each table, and their sensitivity to model specification. This is important because assessment of instrument validity has gained increasing attention, but at the same time is still an evolving science.

It has been shown that weak instruments bias estimates from instrumental variable models (e.g. Murray, 2006 and Stock and Yogo, 2005). Correlation between the instruments and the model error terms, of course, also biases the estimates. The tests reported at the bottom of Tables 2 through 4 are designed to help identify the presence of these conditions. In checking the robustness of our results, it is important to note that we found these test statistics to be sensitive to the manner in which the model standard errors are clustered.

Clustering the standard errors at the MSA level greatly lowers the Kleibergen–Paap and first-stage F statistics, increasing the tendency to view the instruments as weak. At the same time, clustering at the MSA level greatly lowers the Hansen-J test statistic, increasing the tendency to view the model as correctly specified (including that the instruments are exogenous).[18] Clustering at the MSA level also greatly increases the coefficient standard errors and reduces their associated t-ratios (the coefficients, of course, are not affected). Unfortunately, theory offers little guidance as to the "correct" level and type of clustering. We have experimented with clustering at the individual's PWPUMA, clustering by the individual's occupation, and not clustering at all. In Tables 2 through 4 we report only the MSA-clustered results, both for the coefficient t-ratios and also for the instrument diagnostic tests. Clustering at the MSA level is a conservative approach in the sense that it has the greatest downward impact on the model test statistics (e.g. Hansen-J, Kleibergen–Paap, t-ratios) of the different clustering strategies we explored. In this sense, the test statistics and coefficient t-ratios reported in Tables 2 through 4 may well be smaller than is warranted, but we cannot offer concrete evidence on this point.

Additional robustness checks also revealed that the instrument diagnostic tests are sensitive to differences in the number and type of geologic concentric rings included in the first stage regressions. For that reason, in models where the geography of

gree, and more than a Masters. Also included are controls for whether a child is present in the household, whether the worker is married, age and age squared of the worker, race of the worker (white, African American, Hispanic, Asian, and other), and the number of years the worker has been in the United States (less than 6 years, 6 to 10 years, 11 to 15 years, 16 to 20 years, 20 years or native citizen).

17 As might be expected, there is more variation in the inter-quartile range in the more distant rings. The inter-quartile range (the difference between the 75th and 25th percentiles) for the total number of workers in the local economy is 91,521 for the 0 to 5-mile ring, but rises to 1,630,951 for the 50 to 100-mile ring.

18 In part, this reflects that the Hansen-J statistic has weak power.

Table 2
Urbanization elasticity (dependent variable: log of individual wage; t-ratios based on standard errors clustered by MSA)

	Full sample			Less than college degree			College degree or more		
	OLS	GMM[a]	GMM[b]	OLS	GMM[a]	GMM[b]	OLS	GMM[a]	GMM[b]
Log number of full-time workers	0.0305	0.0463	0.0469	0.0255	0.0323	0.0473	0.0364	0.0580	0.0516
Age 30–65 within 5 miles	(9.38)	(1.68)	(6.27)	(8.89)	(1.33)	(7.15)	(8.93)	(1.66)	(6.23)
Hansen-J over ID test statistic[c]	–	1.740	11.22	–	2.126	10.56	–	0.603	12.18
	–	(0.4189)	(0.4249)	–	(0.3454)	(0.4811)	–	(0.7396)	(0.3504)
Kleibergen–Paap rk weak inst. F-stat.[c]	–	1.907	18.380	–	1.94	12.770	–	1.895	21.789
	–	–	–	–	–	–	–	–	–
Kleibergen–Paap rk underl. F-stat.[c]	–	6.522	32.679	–	5.496	30.715	–	8.281	33.424
	–	(0.0888)	(0.0011)	–	(0.1389)	(0.0022)	–	(0.406)	(0.0008)
1st stage F-stat. on inst. for # of workers[c]	–	1.91	18.38	–	1.94	12.77	–	1.890	21.79
	–	(0.1285)	(0.0000)	–	(0.1228)	(0.0000)	–	(0.1310)	(0.0000)
Observations	730,281	724,509	724,509	461,264	455,708	269,017	455,708	264,091	264,091
MSA/occupation FE	24,453	18,681	18,681	20,764	15,208	14,995	15,208	10,069	10,069
MSA clusters	297	290	290	296	286	295	286	254	254
R-square within	0.0974	0.0968	0.0968	0.0782	0.0780	0.0600	0.0769	0.0591	0.0595
R-square between	0.3051	–	–	0.1834	–	0.12103	–	–	–
R-square overall	0.2209	–	–	0.1390	–	0.0830	–	–	–

Each model includes additional controls for the worker's education (less than a High School degree, High School degree, College degree, Masters degree, and more than a Masters); whether a child is present in the household; whether the worker is married, age and age squared of the worker, race of the worker (white, African American, Hispanic, Asian, and other), and the number of years the worker has been in the United States (less than 6 years, 6 to 10 years, 11 to 15 years, 16 to 20 years, 20 years or native citizen).

[a] GMM instruments include circle measures 0 to 5 miles of seismic hazard, landslide hazard, and percent of area underlain by sedimentary rock.

[b] GMM instruments include concentric ring measures (0 to 5 miles, 5 to 25 miles, 25 to 50 miles, and 50 to 100 miles) of seismic hazard, landslide hazard, and percent of area underlain by sedimentary rock.

[c] Test statistic is cluster-robust.

the agglomeration variables is restricted to the first two innermost rings (0 to 5 miles and 5 to 25 miles) as in Tables 2 and 4, two sets of GMM estimates are presented. The first set is based on first-stage concentric rings for the geologic instruments that match exactly the geography of the agglomeration variables used in the wage regression. The second set is based on a more expansive set of first-stage geologic measures that include rings for 0 to 5 miles, 5 to 25, 25 to 50, and 50 to 100 miles. In models in which all four agglomeration rings are included in the wage regression as in Table 3, only the GMM estimates based on the expanded set of geologic rings are reported. As will become apparent, the qualitative and often quantitative patterns of our model coefficient estimates are largely robust to the alternative instrument lists used in the first stage.

4.3. Urbanization

We begin by presenting estimates of the impact of agglomeration on wage. Instead of considering the effect of an increase in total employment in an MSA or the MSA's level of human capital, our approach is geographic. We focus initially on the effect of employment within 5 miles. Instead of estimating the log-linear models described above, we will first estimate log-log models, with coefficients interpreted as elasticities. We carry out this estimation because we consider the elasticity estimates to be of inherent interest and because they help to relate our estimates to prior work. This specification also allows us to highlight the econometric issues in a simpler setting before moving on to a set of models that demand more from the data.

Consider now the first three columns of Table 2. In the OLS model (the first column) doubling total employment within 5 miles is associated with an increase in wage of 3.1 percent. This estimate is highly significant. In the two GMM models (columns two and three) the corresponding estimates are 4.6 and 4.7 percent based on the restricted and expanded instrument lists, respectively. The first of these GMM estimates is only marginally significant (the t-ratio is 1.68), while the latter is precisely estimated (the t-ratio is 6.27). These estimates are broadly in line with prior work. Combes et al. (2008) report urbanization elasticities in France that range from 2.5 to 4.7 percent depending on the number of controls included in the model. Ciccone (2002) estimates an elasticity of 4.5 percent drawing on data from several countries in Europe (specifically, Germany, Italy, France, Spain, and the UK). Ciccone and Hall (1996) estimate an elasticity of 5 percent based on state-level data in the United States.

Also reported in Table 2 are the instrument diagnostic tests noted earlier. In each of the six GMM models, the Hansen-J statistics are low and we fail to reject the overidentifying restrictions. This is consistent with the idea that the geologic instruments are exogenous. Observe also that the Kleibergen–Paap test statistics are considerably higher when the expanded instrument list is used in the second of the GMM models, as is the first-stage F-statistic. Stock and Yogo (2005) developed critical values for weak instrument tests when the model errors are i.i.d. No such critical values are available in the literature for the case when the model error structure allows for robust forms of heteroskedasticity and clustering. Nevertheless, relative to the Stock–Yogo benchmarks, the GMM models based on the restricted instrument set fail the weak instrument test while the reverse is true for the GMM models based on the expanded instrument list.[19] We also should emphasize that when we employ robust standard errors without clustering, all of the GMM models resoundingly pass the weak instrument tests. Given these different results and the caveats about instrument diagnostic tests noted earlier, we cannot say with certainty that the geologic instruments are both exogenous and sufficiently strong. On the other hand, it is encouraging that the GMM full-sample estimates reported in Table 2 are nearly identical for the two different sets of instruments as this should be the case if the instruments are valid.

The results in the first three columns of Table 2 restrict the wage effect associated with agglomeration to be the same for both educated and less-educated workers. There is reason to believe that this might not the case. Workers with limited education might have greater potential to benefit from the knowledge spillovers associated with agglomeration. On the other hand, highly educated workers might have more ability to communicate and, as a result, a greater ability to learn from nearby human capital.[20] Of course, learning is only one of the mechanisms by which agglomeration can impact productivity and wages.[21] As far back as Marshall (1890), it was recognized that agglomeration also encourages labor market pooling and input sharing. In both cases a better match between complementary labor and capital adds to worker productivity, and so increases wage. But as with knowledge spillovers, whether these economies have a greater effect on the productivity and wages of skilled versus low-skilled workers is ambiguous. *A priori*, therefore, it is not clear whether highly educated workers would benefit more or less from agglomeration.

Because of this ambiguity, the last six columns of Table 2 present the results of separate estimation for workers without college degrees (columns 4–6) and with college degrees (columns 7–9). Regardless of estimation method, estimates of the effect of agglomeration are larger for workers who themselves have a college degree than for those who do not. Based on the GMM models that draw upon the expanded instrument list, the urbanization elasticity is 5.16 percent for the college-educated and 4.73 percent for individuals with less than a college degree. Diagnostic tests for the instruments used in these regressions are similar qualitatively to those from the full-sample regressions.

[19] Stock and Yogo (2005) report that when the first-stage F-statistic is above 10, weak instrument bias is small.

[20] This echoes the idea of *absorptive capacity* introduced by Cohen and Levinthal (1990), who found that firms that conducted research and development enjoyed greater spillovers from other firms' research.

[21] Marshall (1890) wrote of the "secrets of the trade" being passed from worker to worker in an industry cluster. Jacobs (1969) wrote of "new work" being created in diverse cities. In both cases, cities foster knowledge spillovers. But as emphasized below, knowledge spillovers is just one of the channels by which agglomeration likely affects productivity.

4.4. Attenuation: urbanization economies

We now turn to the issue of attenuation, beginning with the relationship between urbanization and log wages. Our goal is to answer the following sort of question: by how much would an individual's wage be affected if a given number of local workers were relocated to a site closer to the individual's work place? Answers to this question will help us to better understand the rate at which spillovers associated with proximity to nearby employment attenuate with distance. Estimating the rate at which agglomeration economies attenuate requires that we consider a linear shift in the spatial distribution of existing employment, as with the relocation of 1000 workers from the 25 to 50-mile ring to the 0 to 5 mile ring, for example. For that reason, in all of the remaining estimation we focus on log-linear models.

Table 3 presents estimates of the attenuation models for the full sample as well as for the less-than-college and college samples. Each of these models includes all four concentric rings for the agglomeration variables, from 0 to 5 miles, 5 to 25, 25 to 50, and 50 to 100 miles. In each case, we report OLS and GMM estimates, with the latter based on the expanded set of instruments.

Two patterns stand out. First, the agglomeration of employment within 5 miles continues to be positively related to wages. Focusing initially on the 0 to 5-mile distance band, the OLS and GMM full sample estimates are quite close. Both estimates imply that a 100,000 increase in full-time workers within 5 miles (equivalent to roughly the 25/75 spread) is associated with a wage increase of roughly 2 percent. Thus, the estimates in Table 4 continue to be consistent with prior evidence of an urban wage premium associated with the greater productivity of urban labor. Analogous results are evident for both the less-than-college and college samples as well.

The second pattern in Table 3, which we believe to be more important, is that the effect of employment agglomeration attenuates sharply with distance. For the full sample models, both for the OLS and GMM estimates, the coefficient on the 0 to 5-mile agglomeration variable is four to five times larger than on the corresponding coefficient on the 5 to 25-mile agglomeration variable. Once again, these patterns are echoed in the less-than-college and college samples. In addition, in all cases the 0 to 5-mile and 5 to 25-mile coefficients are significant.

Turning to the outer rings (25 to 50 miles and 50 to 100 miles), it is evident that the impact of agglomeration continues to attenuate, though less so than in the closer-in environment. All of the outer ring coefficients are small, and in most cases, several times smaller than the 5 to 25-mile coefficients. In addition, many of the 25 to 50-mile coefficients and all of the 50 to 100-mile coefficients are not significantly different from zero. Our reading of these patterns is that most of the spillover effects of agglomeration occur within five miles although some spillovers extend out even as far as 50 miles. This finding—while consistent with classical urban land use theory—is new to the wage literature.[22]

[22] The closest relevant work is the estimation of wage gradients. This involves specifying an exogenous city center and estimating the rate of decline in wage

Table 3
Urbanization attenuation (dependent variable: log of individual wage; t-ratios based on standard errors clustered by MSA)

		Full sample		Less than college degree		College degree or more	
		OLS	GMM	OLS	GMM	OLS	GMM
Number of full-time workers age 30 to 65	0 to 5 miles	2.01e–07	2.14e–07	1.62e–07	3.47e–07	2.30e–07	2.29e–07
		(7.96)	(3.87)	(5.21)	(3.79)	(14.42)	(3.87)
	5 to 25 miles	3.88e–08	5.20e–08	4.43e–08	5.43e–08	2.96e–08	3.92e–08
		(4.07)	(2.84)	(5.21)	(2.41)	(2.38)	(1.92)
	25 to 50 miles	3.01e–08	8.39e–08	2.45e–08	−1.79e–08	3.60e–08	1.32e–07
		(4.47)	(1.52)	(3.33)	(−0.44)	(4.43)	(2.15)
	50 to 100 miles	−9.01e–09	2.02e–08	−8.78e–09	1.91e–08	−8.69e–09	1.43e–08
		(−1.68)	(1.42)	(−1.78)	(1.30)	(−1.13)	(0.71)
Hansen-J over ID test statistic[a]		–	16.041	–	12.634	–	14.031
		–	(0.0418)	–	(0.1251)	–	(0.0810)
Kleibergen–Paap rk weak inst. F-stat.[a]		–	1.142	–	1.078	–	1.945
		–	–	–	–	–	–
Kleibergen–Paap rk underl. F-stat.[a]		–	11.886	–	9.345	–	17.787
		–	(0.2198)	–	(0.4060)	–	(0.0377)
1st stage F-stat. 0–5 mile workers[a]		–	2.12	–	2.19	–	2.27
		–	(0.0158)	–	(0.0122)	–	(0.0096)
1st stage F-stat. 5–25 mile workers[a]		–	4.13	–	3.64	–	4.50
		–	(0.0000)	–	(0.0000)	–	(0.0000)
1st stage F-stat. 25–50 mile workers[a]		–	2.79	–	2.41	–	5.44
		–	(0.0013)	–	(0.0055)	–	(0.0000)
1st stage F-stat. 50–100 mile workers[a]		–	9.02	–	9.76	–	7.56
		–	(0.0000)	–	(0.0000)	–	(0.0000)
Observations		730,281	724,509	461,264	455,708	269,017	264,091
MSA/occupation FE		24,453	18,681	20,764	15,208	14,995	10,069
MSA clusters		297	290	296	286	295	254
R-square within		0.0983	0.0975	0.0786	0.0738	0.0613	0.0587
R-square between		0.3131	–	0.1993	–	0.1259	–
R-square overall		0.2260	–	0.1446	–	0.0897	–

Each model includes additional controls for the worker's education (less than a High School degree, High School degree, College degree, Masters degree, and more than a Masters); whether a child is present in the household; whether the worker is married, age and age squared of the worker, race of the worker (white, African American, Hispanic, Asian, and other), and the number of years the worker has been in the United States (less than 6 years, 6 to 10 years, 11 to 15 years, 16 to 20 years, 20 years or native citizen). GMM instruments include concentric ring measures (0 to 5 miles, 5 to 25 miles, 25 to 50 miles, and 50 to 100 miles) of seismic hazard, landslide hazard, and percent of area underlain by sedimentary rock).

[a] Test statistic is cluster-robust.

Turning to the instrument diagnostics in Table 3, it is evident that the tendency to reject the model specification and especially the overidentifying restrictions is greater than in Table 2 (based on the Hansen-J test). Similarly, the test statistics for instrument strength are smaller than before. Our earlier comments about the effect of clustering notwithstanding, these diagnostic tests suggest that the GMM point estimates in Table 3 are less reliable than those reported in Table 2. On the other hand, the differencing used to assess attenuation patterns helps to strip away unobserved heterogeneity as discussed earlier.

4.5. *Attenuation: human capital externalities*

The models in Tables 2 and 3 restrict the spillover effects generated by different types of workers to be alike. While this could be correct, the literature on human capital spillovers suggests otherwise. As noted in Moretti (2004b), there are at least three potential sources of a social return to education: (i) educated people commit fewer crimes, (ii) educated people make more informed decisions when voting, and (iii) proximity to educated workers may enhance productivity. It is the latter effect that we focus on here. Accordingly, we turn now to the question of how workers with different levels of education contribute to agglomeration economies.

Before presenting our results, some background is useful. Rauch (1993) estimated the impact of the average level of education at the MSA level on both wages and house rents. He found that a one year increase in the average level of schooling was associated with an increase of 3% in wages and 13% in rents. Acemoglu and Angrist (2000) report that education at the state level has a positive effect on wages, but one that is small and insignificantly different from zero.[23] Moretti (2004a) finds that the presence of college graduates has a positive effect on

associated with moving away from it. See Ihlanfeldt (1992) and McMillen and Singell (1992) for particularly careful examples of this sort of analysis. In these models, firms pay higher wages to downtown labor because it is productive, while workers are willing to accept lower wages for employment outside the downtown because commuting costs are lower.

[23] To allow for the possibility that education levels may be endogenous, Acemoglu and Angrist (2000) instrument for the state level of education using compulsory schooling laws.

wages at the MSA level. Together, these and other studies of human capital spillovers suggest that the presence of educated workers generates positive productivity spillovers that exceed those associated with the presence of low-skilled workers. Simon and Nardinelli (2002) document a positive relationship between a city's human capital level and its growth. da Mata et al. (2007) and Liu (2007) reach parallel conclusions for Brazil and China.[24]

Table 4 reports results for a human capital specification. In these models, we separately estimate the effects of the numbers of workers with- and without-college degrees within various distances. In estimating these models we restrict the concentric rings to just the 0 to 5 and 5 to 25-mile segments. We do this primarily because of evidence from Table 3 that most effects occur within 25 miles and also to avoid further increase in the number of endogenous agglomeration variables. As before, estimates are presented for the full sample, the less-than-college sample, and the college sample. In addition, as in Table 2, two sets of GMM estimates are reported for each model, the first based on the geographically matched instrument list and the second based on the expanded instrument list.

Two important patterns emerge from this table. First, regardless of the sample composition (e.g. full sample, less-than-college, or college-or-more), proximity to college educated workers increases an individual's wage. This is evident from the uniformly positive and largely significant coefficients in the top two rows in each column. Conversely, proximity to less-than-college workers decreases an individual's wage, especially for individuals with a college degree. This is evidenced by the largely negative coefficients in the bottom two rows in each column. This pattern is consistent with the spatial concentration of employment generating two types of spillover effects, one positive and one negative. On the positive side, agglomeration of employment enhances productivity for reasons we have already discussed. On the negative side, the spatial concentration of employment can increase congestion, lengthen commutes, and in so doing reduce labor productivity and wages, *ceteris paribus*. In principle, both low- and high-skilled workers can contribute to both types of spillovers. The estimates in Table 3 suggest that for educated workers, the positive productivity effect outweighs the negative congestion effect, but the reverse is true for workers with less than a college degree.[25]

The second important pattern in Table 4 is that spillover effects again attenuate with distance. The attenuation associated with nearby high-skilled workers is sharp. In the full sample OLS model, the 0 to 5-mile coefficient for proximity to college educated workers is 3.5 times larger than the corresponding 5 to 25-mile effect. The degree of attenuation is smaller in the GMM models but still clearly present. In many of Table 4 models, there is also attenuation of the negative effect associated with the proximity to less-than-college educated workers.

The human capital effects documented in Table 4 are economically important. For the college-educated sample, if 100,000 college-educated workers are added to the 0 to 5-mile ring (approximately equivalent to the 25/90 spread in Table 1), the OLS estimate implies that wages of a college-educated worker would increase by 12 percent. For the GMM models with the restricted and expanded instrument lists, the corresponding estimates are 24.5 percent and 16 percent, respectively. The corresponding impacts on workers with less than a college degree are roughly half these amounts, but they are clearly still important.

Alternatively, we can also consider the impact of transforming a given number of less-than-college workers into college educated workers, holding constant the total number of workers in a concentric ring. Mechanically, this equals the wage effect of proximity to college-or-more workers minus the effect from proximity to less-than-college workers. As an example, in the full sample OLS regressions, transforming 100,000 less-than-college workers within 5 miles into college-educated would increase the wage of a typical worker by 11.8 percent. The corresponding estimates in the restricted and expanded instrument GMM models are 30.4 and 16.7 percent, respectively. In the college-educated sample, these effects are roughly 50 percent larger in magnitude. This is somewhat stronger than the result for urbanization economies. For human capital effects, the college-educated are more sensitive to proximity to human capital than are the less-than-college educated.

Summarizing, our estimates in Table 4 reveal that proximity to highly educated workers increases a given worker's wage, while proximity to low-skilled workers does the opposite. This holds regardless of whether the individual in question has a college degree although the magnitude of the effect is larger for college educated workers. These effects also generally attenuate sharply with distance, especially for individuals with a college degree, and especially with respect to proximity to highly educated workers. These attenuation patterns have important implications for economic development. Much has been made in recent years of the importance of human capital for urban growth (see, for instance Glaeser and Saiz, 2004). Our results are consistent with this work, but with a twist. We find a relationship that is geographically localized. Put concretely, the high human capital in Wall Street contributes much more to the general prosperity of Manhattan than it does to the Bronx.

4.6. Social versus private returns to education

We have thus far presented estimates only of the social returns to education. In this section, we compare these estimates to the private returns from education. The latter are presented in Table 5, which reports estimates of our education coefficients based on an OLS model that omits the agglomeration variables but retains all other controls. Consistent with the huge literature on the private returns to education, on average, each additional year of schooling adds roughly 10 percent to an individual's

[24] In a paper written simultaneously to ours, Fu (2007) finds attenuation of human capital externalities (percent educated) in Boston. See Moretti (2004b) for a more complete survey of this literature.

[25] It is worth observing that we find an effect of college educated workers on other college educated workers. This is different than some wage models that consider the effect on all workers of the percent college educated. As shown by Ciccone and Peri (2006), the latter sort of model may confound human capital spillovers with complementarities in production between more- and less-educated workers.

Table 4
Human capital attenuation (dependent variable: log of individual wage; t-ratios based on standard errors clustered by MSA)

		Full sample			Less than college degree			College degree or more		
		OLS	GMM[a]	GMM[b]	OLS	GMM[a]	GMM[b]	OLS	GMM[a]	GMM[b]
Number of full-time	0 to 5 miles	7.80e–07	1.99e–06	1.10e–06	4.79e–07	1.36e–06	7.10e–07	1.19e–06	2.45e–06	1.61e–06
college-or-more		(2.73)	(3.46)	(2.60)	(1.75)	(2.61)	(1.79)	(3.49)	(3.02)	(2.77)
workers age 30–65	5 to 25 miles	2.20e–07	1.16e–06	1.04e–07	2.57e–07	1.20e–06	5.68e–07	1.59e–07	1.01e–06	−2.19e–07
		(2.52)	(2.56)	(0.37)	(3.27)	(2.33)	(1.71)	(1.49)	(1.56)	(−0.79)
Number of full-time	0 to 5 miles	−3.97e–07	−1.05e–06	−5.74e–07	−1.34e–07	−3.60e–07	2.90e–07	−8.00e–07	−1.58e–06	−1.43e–06
less-than-college		(−1.12)	(−1.92)	(−1.07)	(−0.38)	(−0.48)	(0.54)	(−2.01)	(−2.05)	(−2.07)
workers age 30–65	5 to 25 miles	−1.04e–07	−7.73e–07	1.85e–08	−1.26e–07	−7.81e–07	−3.36e–07	−6.71e–08	−7.33e–07	2.53e–07
		(−1.54)	(−2.40)	(0.09)	(−2.23)	(−2.06)	(−1.40)	(−0.79)	(−1.55)	(1.28)
Hansen-J over ID test statistic[c]		–	1.844	24.761	–	1.206	13.83	–	2.905	14.46
		–	(0.3978)	(0.0017)	–	(0.5471)	(0.0863)	–	(0.2340)	(0.0706)
Kleibergen–Paap rk weak inst. F-stat.[c]		–	0.441	0.860	–	0.340	1.077	–	0.579	0.924
		–	–	–	–	–	–	–	–	–
Kleibergen–Paap rk underl. F-stat.[c]		–	2.439	6.807	–	1.962	9.627	–	2.975	11.257
		–	(0.4865)	(0.6573)	–	(0.5803)	(0.3815)	–	(0.3955)	(0.2585)
1st stage F-stat. coll. + 0–5 mile workers[c]		–	1.64	1.86	–	1.52	2.06	–	1.77	2.10
		–	(0.1346)	(0.0386)	–	(0.1706)	(0.0206)	–	(0.1058)	(0.175)
1st stage F-stat. coll. + 5–25 mile workers[c]		–	3.52	4.07	–	3.84	3.71	–	3.53	3.90
		–	(0.0023)	(0.0000)	–	(0.0011)	(0.0000)	–	(0.0022)	(0.0000)
1st stage F-stat. LT-Coll. 0–5 mile workers[c]		–	1.76	2.42	–	1.52	2.37	–	1.90	2.55
		–	(0.1061)	(0.0053)	–	(0.1703)	(0.0064)	–	(0.0806)	(0.0034)
1st stage F-stat. LT-Coll. 5–25 mile workers[c]		–	3.81	4.17	–	4.06	3.62	–	3.49	4.67
		–	(0.0011)	(0.0000)	–	(0.0006)	(0.0000)	–	(0.0025)	(0.0000)
Observations		730,281	724,509	724,509	461,264	455,708	455,708	269,017	264,091	264,091
MSA/occupation FE		24,453	18,681	18,681	20,764	15,208	15,208	14,995	10,069	10,069
MSA clusters		297	290	290	296	286	286	295	254	254
R-square within		0.0983	0.0948	0.0972	0.0786	0.0742	0.0730	0.0615	0.0611	0.0611
R-square between		0.3059	–	–	0.1888	–	–	0.1219	–	–
R-square overall		0.2228	–	–	0.1408	–	–	0.0862	–	–

Each model includes additional controls for the worker's education (less than a High School degree, High School degree, College degree, Masters degree, and more than a Masters); whether a child is present in the household; whether the worker is married, age and age squared of the worker, race of the worker (white, African American, Hispanic, Asian, and other), and the number of years the worker has been in the United States (less than 6 years, 6 to 10 years, 11 to 15 years, 16 to 20 years, 20 years or native citizen).

[a] GMM instruments include concentric ring measures 0 to 5 miles and 5 to 25 miles of seismic hazard, landslide hazard, and percent of area underlain by sedimentary rock.

[b] GMM instruments include concentric ring measures (0 to 5 miles, 5 to 25 miles, 25 to 50 miles, and 50 to 100 miles) of seismic hazard, landslide hazard, and percent of area underlain by sedimentary rock.

[c] Test statistic is cluster-robust.

Table 5
Private returns to education (dependent variable: log of individual wage; t-ratios based on robust standard errors)

	Coefficient
High school degree	0.1141
	(44.20)
Some college	0.1902
	(70.98)
College degree	0.3964
	(125.40)
Masters degree	0.5111
	(130.16)
Professional or PhD degree	0.5636
	(94.84)
Observations	750,759
MSA/occupation FE	26,018
R-square within	0.0946
R-square between	0.2826
R-square overall	0.2079
Root MSE	0.5910

The model excludes the agglomeration variables but includes additional controls for whether a child is present in the household; whether the worker is married, age and age squared of the worker, race of the worker (white, African American, Hispanic, Asian, and other), and the number of years the worker has been in the United States (less than 6 years, 6 to 10 years, 11 to 15 years, 16 to 20 years, 20 years or native citizen).

wage; the incremental contribution of a college degree beyond that of a high school degree is roughly 30 percent.

Compared to these benchmarks, our estimates suggest that the social returns to education are large. Based on the estimates in Table 4, adding 50,000 college-educated workers within 5 miles would increase a college-educated individual's wage by roughly 6 to 12 percent depending on whether one focuses on the OLS or GMM estimates. Transforming 50,000 less-than-college workers within 5 miles into college-educated would increase the wage of a typical worker by roughly 6 to 15 percent depending on the model specification. These effects are comparable to 20 to 50 percent of the incremental private returns associated with obtaining a college degree following high school. Thus, while the private returns to education predominate as might be expected, the social returns to education are also important.[26]

5. Conclusions

This paper has considered the attenuation of agglomeration economies and human capital spillovers. The paper obtains strong evidence of an urban wage premium: the elasticity of wage with respect to the number of workers within five miles is roughly 4.5 percent, close to estimated elasticities of wage with respect to city population found in prior work. Completely new to this paper, further analysis reveals that the positive effect of agglomeration is really due to the presence of human capital. Proximity to college educated workers is shown to enhance wages, while proximity to less-than-college workers has the opposite effect. These effects impact the wages of both college-educated workers and those without college. These effects also attenuate sharply with distance.

The magnitude of these effects is economically important. Endowing 50,000 less-than-college workers within five miles with college-or-more degrees is associated with an increase a given college-educated individual's wage of 6 to 15 percent depending on the model specification. By comparison, the private return from one additional year of schooling is roughly 10 percent, while the private return from obtaining a college degree after high school is roughly 30 percent. Endowing the workforce 5 to 25 miles away with additional education also would increase a given individual's wage, but by an amount several times smaller than if the shift in workforce composition took place within five miles.

The paper's attenuation results are important for several reasons. The evidence that productivity spillovers attenuate sharply with distance suggests that the concentration of economic activity continues to be valuable. This concentration could take the form of traditional downtowns or newer "edge cities" (Garreau, 1991). The results are thus at least somewhat favorable to traditional downtowns and also to more concentrated forms of development outside of downtowns. Regarding sprawl, the result that spatial concentration matters is consistent with the result in Burchfield et al. (2006) that relatively little growth in urban footprints takes place far from existing development.

A few final comments on robustness are also in order. Our estimates of the elasticity of wage with respect to agglomeration within five miles are particularly robust. In this case, diagnostic tests tend to support the validity of our geologic instruments, even with a very aggressive form of clustering imposed on the model errors (at the MSA level). When focusing on the impact of human capital spillovers and attenuation, we implicitly difference estimates, in some cases by up three different dimensions (by MSA/occupation, by proximity to highly educated versus low-skilled labor, and by adjacent distance bands or rings). This differencing helps to sweep out unobserved effects and increases the credibility of the OLS estimates. These models also demand more of the data. Possibly for that reason, the instrument diagnostic tests largely do not support our geologic instruments in the more demanding models. On the other hand, the qualitative and often quantitative nature of the coefficient estimates is largely robust to estimation method (e.g. OLS versus GMM, and also the set of instruments used), as are the coefficient t-ratios. On balance, therefore, we believe that the key findings in this paper are robust.

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[26] It should be emphasized that our estimates understate the social returns to human capital by focusing only on productivity spillovers. As noted earlier, previous studies have argued that educated people also commit fewer crimes and are more informed voters.

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Appendix A. Summary statistics for geologic variables

Table A1
Sample percentiles for concentric ring geologic variables

Of census tracts	Sample percentile				
	10th	25th	50th	75th	90th
Seismic hazard: ave. ind. within 0–5 mi.	0.99	2.00	3.97	5.67	28.51
Seismic hazard: ave. ind. within 5–25 mi.	0.99	1.99	3.86	5.42	23.84
Seismic hazard: ave. ind. within 25–50 mi.	1.06	1.99	3.72	4.67	25.64
Seismic hazard: ave. ind. within 50–100 mi.	1.21	2.00	3.57	4.31	28.09
Landslide hazard: ave. ind. within 0–5 mi.	0.97	0.99	1.04	1.49	1.91
Landslide hazard: ave. ind. within 5–25 mi.	0.99	1.00	1.18	1.29	1.68
Landslide hazard: ave. ind. within 25–50 mi.	0.99	1.01	1.14	1.27	1.57
Landslide hazard: ave. ind. within 50–100 mi.	1.00	1.06	1.22	1.34	1.53
% underl. by sed. rock within 0–5 mi.	0.01	0.27	0.85	0.99	1.00
% underl. by sed. rock within 5–25 mi.	0.13	0.40	0.72	0.99	1.00
% underl. by sed. rock within 25–50 mi.	0.20	0.54	0.67	0.98	1.00
% underl. by sed. rock within 50–100 mi.	0.25	0.55	0.82	0.95	1.00

The sample is restricted to individuals who reside in MSAs and who work in "small" PWPUMAs. "Small" in this context means that a 5-mile ring drawn around the geographic centroid of the PWPUMA extends beyond the boundary of the own-PWPUMA.

Table A2
Complete results for Table 2 full sample OLS elasticity regression (dependent variable: log of individual wage; t-ratios based on cluster-robust standard errors)

	Coefficient	t-ratio
Log No. full-time workers 30–65 within 5 miles	0.03048	9.38
High school degree	0.11434	20.27
Some college	0.18919	24.31
College degree	0.39247	45.91
Masters degree	0.50589	40.34
Professional or PhD degree	0.55881	46.55
Child under 18 present	0.00771	1.97
Married	0.17266	43.54
Age of household head	0.04636	28.82
Age squared	−0.00043	−26.78
African American	−0.13302	−26.84
Asian	−0.14596	−7.29
Hispanic	−0.12238	−16.48
Other	−0.15747	−12.60
No. of years in US 6 to 10	0.01513	1.44
No. of years in US 11 to 15	0.07830	8.39
No. of years in US 16 to 20	0.10723	15.39
No. of years in US 20 or more or native citizen	0.20190	17.51
Observations	730,281	
MSA/occupation FE	24,453	
MSA clusters	297	
R-square within	0.0974	
R-square between	0.3051	
R-square overall	0.2209	

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