The Spatial Variation of Wages in U.S. Cities and States

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Driving through American cities, I developed the informal impression that businesses are almost everywhere, and that every city has multiple high-density employment centers. Since most urban economics research is based on the monocentric city model, which assumes that jobs are concentrated in a single central business district (CBD), I sought a way to reconcile the conventional explanations with my experience. As an economist, I asked three questions:

1. Does econometric evidence support my impression that jobs are dispersed throughout cities? [1]
2. If cities are polycentric with distributed employment[2], what model should I use to analyze the effects of productivity shocks?
3. How do city structures affect urban wages?

This paper presents evidence that jobs are distributed throughout cities and that even after controlling for worker attributes, job attributes and firm attributes, job and residence locations are statistically significant in explaining the annual earnings of workers.

The model presented in this paper proposes a new way to think about optimization decisions by firms and households. In this model, wages are a continuous function of

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[1] Redfern (2007) demonstrated that Los Angeles is polycentric.

[2] White (1999) provides an overview of the literature that describes urban areas in which employment is decentralized and employment locations are exogenous.

geographic location. Wage surfaces evolve slowly, because they are caused by past investments in capital assets[3], or by unique attributes of a location[4]. Wage surfaces are continuous; because (with the exception of an international border) there is no barrier to a worker's commuting a little further to earn a higher wage. Both workers and firms assess whether they should relocate, so the possibility of moving assures utility equilization for workers and profit equilization for firms, at least in the long-run.

Firms need a mix of workers, some skilled and highly paid, others with fewer skills and paid much less. When many firms cluster together in a business center, households with diverse preferences and widely varying incomes compete for housing in the commuting region. The opportunity cost of time spent commuting is highest for the workers who earn the most per hour, but the situation is more complicated than saying that the most highly paid workers live closest to their jobs. Some of them may choose to commute further in order to live in a nicer neighborhood, have more land, or have a better quality house[5]. The housing market is incomplete, in that not all attributes of houses are available in all locations. All that is known is that workers with the most money get first choice of where to live.

As will be shown, wages vary greatly within cities. There are at least three reasons why one worker is paid more than another. The Neoclassical explanation is that the more

[3] Capital assets include buildings and equipment, workers' human capital, firms' organizational capital, public infrastructure and the societies' social capital.
[4] This explanation of wage rigidity is in addition to the explanations from the literature that discusses "sticky wages". Probably the most closely related explanation is Greenwald and Stiglitz's (2003) comment that inter-temporal worker retention considerations play an important role in wage-setting.
[5] Brueckner and Colwell (1983) is one of several articles that explore the relationship between geographic location and housing attributes.

highly paid worker is more productive. The Internal Labor Market (ILM) reason[6] is that a large firm has chosen to invest in selected workers' careers. The urban economics explanation[7] is that one worker commutes further, or pays a higher rent to live close to the job, and must be compensated for those costs. These effects are not mutually exclusive – any particular worker may receive wage premiums for unobserved productive attributes, for the match with the firm's expected future needs, compensation for commuting and compensation for the local cost of living[8]. Since wages for econometrically equivalent workers vary with micro-geographic location within a city, there are wage gradients, meaning that the derivative of wages with respect to location is non-zero.

Carlson (2009) presents a variant of the standard urban model that explains wage gradients[9] for homogeneous workers. To explain the wage premium paid by a highly productive firm, he uses the metaphor of a gold mine. The gold mine may be literally a mine, but it is more likely to be a large firm or cluster of firms that benefit from economies of scale[10].. What matters is that the marginal revenue product of a worker is disconnected from her next best employment opportunity. The existence of a

[6] Doeringer (1986) and Doeringer and Piore (1971) show that wage setting in large firms is very different from a market-based model. Instead, there is an ILM that is governed by administrative rules and customs

[7] See Eberts and McMillen(1999) for a review of this literature.

[8] Brueckner, Thisse and Zenou (2002) analyze job matching for local labor markets in relation to where workers live.

[9] Eberts (1981) and Madden (1985) are probably the first to demonstrate that jobs are distributed and that wage gradients exist. McMillen and Singell (1992) measured intraurban wage gradients. Timothy and Wheaton (2001) used micro-data from the 1990 Census to show that "observationally equivalent workers have wages that vary substantially across employment zones within a metro area."

[10] The study of economies of scale dates at least as far back as Adam Smith in *The Wealth of Nations* (1776), and has continued through Paul Krugman (2009). See Eberts and McMillen (1999) for a review of localization and urbanization economies of scale.

metaphorical gold mine is the result of good fortune, either natural resource endowments or market dynamics that give the employer pricing power.

Independent of why a metaphorical gold mine exists at a location, if it requires a large work force and capital to be productive, it will be willing and able to pay a premium wage to attract the workers it needs. Firms in a CBD (the gold mines) are often monopsonists[11] in their labor markets, so they pay the minimum wage that attracts the workers they need. The standard urban model explains the existence of rent gradients; Carlson's gold mine model explains why rent gradients create wage gradients.

The key innovation in the gold mine model is that not all jobs are located in the central business district[12]. Local labor services and capital construction require distributed employment. Each household demands local labor services[13] that must be consumed at or near where they live. Furthermore, capital investment is labor intensive[14], so both residential construction and business investment require labor at specific locations. Since (at least in theory) the workers have the option of commuting if any firm offers higher

[11] Manning (2003) emphasizes the importance of monopsony and monopsonistic competition in labor markets.
[12] Wheaton (2004) is an updating of the monocentric city model to take into account decentralized employment. He presents new empirical evidence to show that in U.S. cities, actual employment is almost as dispersed as residences.
[13] Kelley and Williamson (1987) claimed to have the first development model to stress the importance of non-tradable goods as an influence on spatial cost-of-living differentials.
[14] Phelps (1994) emphasizes that capital investment is labor intensive and plays a central role in structural slumps.

wages, the wage at any location is the maximum of the wage that can be earned by working locally or commuting, net of commuting costs[15].

According to the basic gold mine model, wages in a monocentric city are determined outside-in, based on the commuting cost from the urban fringe to the city center. The gold mine does not pay its workers their marginal revenue products. It decides how many workers it wants, and pays the wage necessary to convince the infra-marginal worker on the urban fringe to make the commute. The premium wages paid by the firms in the CBD create a housing rent gradient, as is formalized in standard urban models. As shown in the gold mine model, there is a corresponding exponential variation in wages, with wages peaking at the center and declining smoothly to the fringe. Importantly, the distributed demand for local labor services increases the size of the urban region and increases the wages in the CBD.

The situation is only slightly more complicated if a city is polycentric. In that case, each productive firm or cluster of productive firms creates a wage peak. Imagine a tent supported by multiple poles. The surface of the tent is analogous to the wage level at each micro location. Wages fall between the peaks, but still remain well above the level in the surrounding countryside.

The next section of this paper formalizes the model of wages that vary continuously with micro-geographic location. The gold mine model is not described, since it is so much

[15] Lee (1987) shows the extent of employment decentralization in Bogota and Cali, Columbia, for four major industry groups. Finance is heavily concentrated in the CBD; manufacturing, commerce and services are fairly evenly distributed, with slightly more jobs in the outer rings.

like other urban models. The remainder of the paper demonstrates that the expected wage gradients are found in 2005 American Community Survey Public Use Micro-sample (ACS-PUMS) data, and makes suggestions for future research. The fact that wages vary with micro-location implies that a new approach to economic modeling is needed that has large firms and spatial persistence in its microfoundations.

I. Model Set-Up

A finding that location dummies are statistically significant in wage regressions can be viewed as rejection of the assumption that it is easy to move production to minimize costs. If large firms are no more than collections of workers who relate to each other through market transactions, then it would be easy to move elements of the production process to lower cost areas with no loss in productivity. On the other hand, if it is costly to break the connections among firms, workers and geographical locations, then in equilibrium wages and prices will vary substantially among locations, both between cities and among micro-locations within a city.

By paying premium wages, firms can increase the sizes of their labor pools. The wage premium attracts workers who must commute from further away. Willingness to commute as a function of the wage offered defines the labor supply curve. Hence, in the inverse labor supply function, the proxy for labor quantity is commuting time[16].

[16] The real situation is more complicated, because as Manning (2003) points out, modern labor markets are "thin".

The inverse labor demand curve also relates wages to commuting distance. The firm determines how many workers it wants for each type of job[17], as a function of the wage it must offer. The desired number of workers can be mapped onto a commuting region. In the short run, the labor pool consists of the qualified workers who already live in the commuting region. Most of these potential workers are currently employed; but they can be enticed to change jobs, by a sufficiently attractive combination of wages, benefits and working conditions. In the longer-run, a firm can draw workers from the national and international labor markets, if it is willing (and able) to pay relocation costs, either through direct reimbursement or indirectly through higher wages.

As discussed in Carlson (2009), each cluster of highly profitable firms also creates a derived demand for the local labor services its employees need and for housing. Examples of local labor services are home maintenance, restaurant meals, and medical services. Often tradable goods are bundled with local labor services, such as the advice and customer support that employees of a department store provide to complement the tradable products sold by the store. The cost of these services, which is proportional to the local wage rate, varies with spatial location. Thus, the premium wages attributable to the possibility of commuting to a large profitable firm also raise the wages of all workers in the commuting region, even those who provide competitive local services.

If the most highly paid executives and engineers live in a community thirty minutes from a CBD, their demand for local services creates another high wage attractor for labor,

[17] By job type, I mean similar workers are needed to perform each job of the type. Similarity of workers is based on experience, education and interest. In the tables, I refer to job type as "occupation".

centered on their expensive residential community. This phenomena is one of the reasons why cities tend to be polycentric. Another reason is that firms in the CBD tend to create satellite operations on the urban periphery, to benefit from lower labor costs while keeping the operations close enough for convenient oversight[18].

Equilibrium is achieved through the adjustment of asset prices. When houses are expensive, rents are high. When it costs a premium rent to live within commuting distance of a good job, the income net of housing cost is equalized with the income in other urban and rural settings. Thus, as is standard in urban models, a spatial equilibrium is characterized by utility equalization at all residential locations where similar workers choose to live. My models assume that utility maximization is conditional on the distribution of housing prices, jobs and wages, and expectations about how those levels will change in the future.

There will be spatial sorting of the labor pool, because the more productive (better paid) workers get first choice of where they want to live. While wages are partially explained by observable worker attributes, actual wages reflect worker attributes that are omitted from standard wage regressions, perhaps because they can't be measured. These omitted attributes have a significant effect on the value of the worker to the employer. When a firm decides how much of its economic profits to share with the employees, it must consider the cost of losing unique skills, and must realize that any employee in that job

[18] Renkow and Hoover (2000) is a recent study of commuting, migration, and the dynamics of population shifts between urban and rural settings.

will have to live in the commuting region and pay rent[19] for a place to live. Thus, the owners of local residential real estate benefit from economic profits earned by local firms, as long as those firms cannot easily move their operations to a less expensive site.

Labor Supply

Because transaction costs to change residence are high, workers search first for a new job that is within commuting distance of their current residence. Therefore, we expect the error terms in standard wage regressions to be correlated with residence location. The spatial sorting is on many dimensions. As discussed above, there is income sorting, based on the matches between workers and firms. This income sorting causes housing price gradients and wage gradients. Surrounding each high productivity firm will be workers who, through selection, training and experience, are a good fit for the firm's needs[20]. This spatial sorting is persistent, because of relocation costs, because even firms in the same industry will tend to use slightly different processes, and because over time houses are remodeled or replaced to fit the income levels of their occupants.

The short-run inverse labor supply equation defines the minimum wage a worker will accept, given her current residence and human capital. The minimum annual earnings a worker will accept is a function of hours worked, compensation for commuting, individual worker attributes, including especially education and experience, attributes of

[19] In the U.S., about two-thirds of households live in dwellings they own. National income statistics and the consumer price index are based on the equivalent rent for owner-occupied dwellings; see Poole, Ptacek and Verbrugge (2005).

[20] Glaesser and Mare (2003) argue that wage premiums emerge over time, because cities are engines for growing human capital.

the job, and a shift factor for the cost of living at the residence location. The shift factor not only models the local cost of living, but it also absorbs the effects of historical sorting on unobserved worker attributes. This shift factor is the concrete representation of the wage surface for this econometric study. In the short-run, it is reasonable to assume that residence locations are fixed. When firms are hit by market shocks, the first response is for workers to change jobs and commuting patterns. Over time, people relocate, and the housing stock adjusts to improve efficiency.

I use the natural log of annual earnings as the dependent variable. As explanatory variables, I use functions of hours worked per week and the one way commuting time in minutes, because those are the variables that are available in the dataset, along with an extensive set of the usual variables used in wage regressions. Note that wage regressions often use the natural log of the hourly wage as the left hand (dependent) variable. If that is a correct model, then it should be deducible from the coefficients in the model I estimated. I chose not to derive a proxy[21] for the hourly wage, and instead I use hours worked per week as one of the many determinants of annual earnings.

The labor supply equation defines the minimum annual earnings that a worker with particular attributes will accept. In this system, it has the following form:

$$Lnearn = f\left[C(Hrs, Commute), Person, HH, Job, Residence, J*Commute\right] ...(1)$$

[21] For example, a typical approach is to estimate hours per year as 50 weeks per year times usual hours worked per week. Then a wage per hour can be estimated as annual earnings divided by estimated hours per year.

Lnearn is the natural log of total labor income during the previous twelve months, whether derived from wages or from self-employment. The data on self-employment income has been transformed, by setting negative values equal to zero[22]. The function *C(•)* relates hours worked and commuting time to earnings. *Hrs* is the "usual" hours that the survey respondents reported that they worked per week during the past twelve months. *Commute* is the one-way travel time to work, in minutes. The vector *Person* characterizes the individual, the vector *HH* describes the household, and *Job* describes the job, including *J*, which is a vector of dummy variables identifying the standard occupation code *("soc")*. *Residence* is a vector of dummies that identify the "PUMA" of residence[23]. The intersection of the job category and commuting time *("J*Commute")* incorporates the fact that people who work in well paying jobs are probably less willing to commute.

The most complicated model considered used a third order Taylor series expansion of the two dimensional function *C(Hours, Commute)*. Hence, the linear regression equation included *hours, hours squared, hours cubed, commute, commute squared, commute cubed, hours*commute, hours* commute squared, and commute * hours squared.* In the end, I decided to represent *C(Hours, Commute)* as *[a*ln(hours)+b*ln(commute)]*. The Taylor series representation does not gain enough explanatory power to justify its complexity. I also dropped the interaction term, *J*commute* , because when the model was applied to

[22] The goal is to eliminate the effects of capital income and investment, to the extent that doing so is possible. Negative self-employment income in a particular year is usually an indication of investment in the business.

[23] PUMAs are the small geographic areas for which the 5% and 1% samples of all U.S. households are collected in the American Community Survey. The minimum population of a PUMA is 100,000.

Massachusetts data in the 2005 ACS-PUMS dataset, the coefficients were not statistically different from zero.

Labor Demand

The inverse labor demand equation is the following:

$$Lnearn = g\left[T(Hrs, Commute), Person, Job, POW, Localserv * POW, Industry * Commute\right] ...(2)$$

As in the labor supply equation, the function *T(•)* represents the combined effect of hours worked and commuting time on earnings. *Person* describes the individual, and *Job* describes the job. *POW* (an abbreviation for "place of work") is a vector of dummies that indicate the PUMA where the job is located. The coefficients on *POW* estimate the differences in relative wage levels at job locations. The *Job* dummies are included, because firms can consider individual (unobservable) attributes when selecting for promotion. The *Industry* dummies reflect the fact that firms both select the workers who are the best match to the industry, and they train them. Industries that pay the highest wages get first choice of workers.

Localserv is a dummy that selects a set of relatively low paying local services jobs. Finally, the labor demand equation must take account of the fact that efficient firm sizes vary by industry. After exploring a variety of specifications, I decided to approximate the commuting function, *T(Hrs, Commute)* with *ln(Hrs)* in the labor demand equation, ignoring commuting time. I also dropped the interaction terms *industry*commute* and *localserv*POW* . With this dataset, I could not reject the hypothesis that the coefficients on these variables equal zero. I still believe that with a different dataset, I will be able to prove that these interactions matter[24].

II. Regression Results

This paper presents an empirical study of seven states that contain the largest U.S. Metropolitan Statistical Areas (MSAs), plus the farm state of Iowa. The data comes from the American Community Survey Public Use 1% Micro-Sample ("ACS-PUMS"), which is collected every five years by the U.S. Census Bureau. The most recent data available is for 2005. This sample is organized geographically into Public Use Micro Areas ("PUMAs"). Each PUMA is a section of a city, a town, or two or more adjacent towns[25]. Due to privacy concerns, the Census Bureau has transformed some records in a way that maintains the validity of aggregate statistics, but that may invalidate statistical results for small geographical areas. For this study, I viewed this uncertainty as an additional source of measurement error, and hence as one of the many factors that contribute to the random error term in regressions. Because the ACS-PUMS dataset provides information about personal characteristics, household characteristics, job characteristics and wages for individuals, the "ecological fallacy" is not a concern[26].

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[24] The data experimentation summarized in this section was performed using Massachusetts data. As discussed next, results for the other seven states have not been compromised by such data mining.

[25] The Census data uses a set of PUMA identification numbers and state identification numbers. For example, Massachusetts is state "025". I constructed a global PUMA_ID by concatenating the state ID onto the within state PUMA number. For Massachusetts, I then determined the names of the cities and towns within each PUMA, by using the Census provided equivalence table that relates PUMA boundaries with a map of the political boundaries.

[26] The ecological fallacy can occur when inferences about individual behavior are made based on data about aggregates. As discussed by Freedman (1999), this fallacy occurs if the statistical

To define the model, I experimented with data for Massachusetts. The 1% ACS-PUMS dataset for Massachusetts contains 28,864 workers. Each ACS-PUMS record contains a primary weight, and a set of eighty (80) alternate weights[27]. Using the primary weights, the estimated Massachusetts population in 2005 was 6,200,944, of whom 3,032,075 (48.9%) were employed[28]. 4% of the employed workers report an employment location in another state or in a foreign country.

As discussed in Carlson (2009), a variety of different models have been estimated for Massachusetts. I chose Massachusetts to explore the data, because I have knowledge of the local geography and economy. This process can, of course, be criticized as data mining. That is why I used the Massachusetts data to choose a preferred model, and then I evaluated that model in terms of its ability to explain data on the other states.

The two-equation model discussed in the previous section was estimated using Stata's 2SLS command. Two vectors of independent variables shift the labor supply equation and therefore identify the labor demand: attributes of the household and residence location. Similarly, the following vectors of independent variables shift the labor demand equation and identify labor supply: job location and industry dummies. The rationale is that residences that provide access to better paying jobs command higher rents. How

behavior of a demographic group depends on the area of residence. Thanks to Steve Ross for bringing this issue to my attention.

[27] According to the Census Bureau, parameter estimates using the standard weights are unbiased. The recommended way to estimate error bounds is to use the alternate weights.

[28] According to the Census Bureau's "Quick Facts", the Massachusetts population in 2006 was 6,437,193, which is 3.8% higher than the estimate I got by taking the weighted sum of the records in the 1% ACS-PUMS sample for the previous year.

valuable that access is depends on characteristics of the household, and the kinds of jobs to which each person aspires. Rents strongly affect the local cost of living, and hence the reservation wages demanded by the residents. Rents also reflect geographic sorting of workers, based in part on unobservable attributes. People choose where to live, taking into account how much they expect to be able to earn and the kinds of jobs that will be accessible to them.

Similarly, more productive firms are located in particular places. Whether their location is a historical accident, the result of natural resource endowments, caused by transportation efficiencies, or the result of agglomeration economies, the fact is that firms in some locations pay more than similar firms located elsewhere. Hence the maximum wage a firm will pay is shifted by the coefficient on the relevant place of work dummy.

Each worker offers (supplies) labor to the circular commuting region surrounding her house, which includes the firm with which she is currently matched. Each firm attracts (demands) labor from the circular commuting region surrounding its facility location. Included in that region are the residences of its current employees.

A final issue that must be discussed is estimation of standard errors, and the determination of the statistical significance of coefficients. Sample design for the ACS-PUMS is sophisticated and complex. Each record contains a sampling weight that must be applied in estimations. The sample design also reflects stratification and clustering. ACS-PUMS data includes a set of alternate weights that the Census Bureau recommends be used in a particular way to estimate standard errors. I used unweighted data for Massachusetts to choose the preferred model. I then applied the preferred model using weighted data for all eight states. To estimate standard errors, I used the procedure recommended by the Census Bureau. Results of these weighted regressions are reported in the remainder of this paper.

Table 1 summarizes the results from estimating the inverse labor supply and demand equations. An expanded version of table 1 is presented in Carlson (2009). The four page summary table consists of two pages for each of two groups of states. In all cases, the dependent variable is *lnEarn*, and the two additional endogenous variables are *lnHours* and *lnCommute*. All other variables are treated as exogenous. The labor supply equation models a worker's employment decision looking outwards from her residence. The labor demand function predicts the maximum wage a firm will pay.

The R^2 for the labor supply and demand equations[29] are reported at the top of Table 1. For most states, this model explains a substantial portion of the variation in earnings. The greatest explanatory power is for Michigan, where the labor supply equation explains 44.8% of the variation in earnings, and the labor demand equation explains 58.6% of the variation. The labor supply equation for Texas has the least explanatory power, among these sixteen equations, at 29.8%. The labor demand equation with the least explanatory power is for Georgia, at 38.0%, followed closely by Texas at 42.0% and California at 42.7%.

[29] Stata does not report an adjusted R^2 for the 2SLS command.

Estimated Wage and Price Surfaces

One of my key claims is that workers sort into residences based on the spatial distribution of firms. The validity of this claim is supported by the results using unweighted data in table 2 and weighted data in table 3. Table 2 reports the results of F-tests that reject the hypothesis that the coefficients on all location dummies equal zero. Table 3 reports the actual magnitudes of the effects of location on annual earnings.

As reported in Table 1, the regression equations control for a conventional set of worker attributes, including education, age and household characteristics. Furthermore, a job type dummy has been included to absorb variation that is signaled by the fact that the worker has been selected to perform a particular kind of job. For example, selection as an executive is worth about a 52.3% increase in annual earnings offered by Massachusetts firms[30], all else equal. In addition, the model has controlled for working hours, and for job attributes such as being self-employed, having to report to work between 7:00am and 9:30am, and jobs providing a local service. Finally, the model has controlled for commuting time.

Table 2 reports the results of F-tests that all coefficients on residence location dummies equal zero in the labor supply equation, and that all coefficients on job location dummies equal zero in the labor demand equation. To the extent that the occupation and industry dummies have absorbed unobserved productive attributes of the worker, the coefficients on residence dummies should reflect local cost of living differences, and coefficients on

[30] Results for the additional explanatory variables are reported in Carlson (2009). The actual increase for being in a job with the title of executive is exp(0.5229) = 1.69, or a 69% increase.

job location dummies should reflect productivity premiums of firms that are at the location. For all eight states, the hypothesis that the coefficients on residence location and job location equal zero (tested independently) can be rejected at a 99.9% confidence level.

Wages at an urban center create a wage gradient in relation to wages at the edge of the commuting region. The wage surface is relatively smooth, not a step function, because workers require both local services and construction labor where they live[31]. Workers who provide local services achieve the same utility as workers who commute, so the cost of commuting creates a smooth wage surface that matches the rent surface. The extent to which the large observed differences are due to unobserved productive attributes[32] of the worker versus differences in local wage gradients and local cost of living is left as a topic for future research.

Correlation of Residence and POW Coefficients

The coefficients on the location of residence dummies should be positively correlated with the coefficients on the job location dummies. The reason is that people who live near a high paying job will be forced to pay a high rent for their house, so they will demand a high wage. I tested this expectation by using a regression to explain the coefficients on place of residence by the coefficients on place of work plus a constant.

[31] In the real world, the distinction is between services "near" to home versus services "near" the place of work. The model has been simplified, by assuming wages are earned at two points: the place of work and the place of residence, and further that all locations in a PUMA are the same.
[32] For example, is a waiter working in a restaurant in the urban center delivering higher quality service than a waiter working in the suburbs, or is he paid more simply because of the local cost of housing and commuting?

For all states, the coefficient on the POW coefficients is positive and significantly different from zero. The values, reported in the right two columns of Table 2, range from 0.508 in Massachusetts to 0.843 in New York.

Magnitudes of Earnings Differences

The coefficients on the location variables are statistically significant, but are they important in practice? Table 3 addresses this question. The left three columns show the range between the minimum and maximum wage levels. The smallest range for employers' willingness to pay based on the *PUMA* containing the job site, is the 28% premium in Iowa. The largest ranges are factors of 2.0 in New York and 3.58 in Texas.

Another measure of the spread is to identify the *PUMA*s such that 25% of *PUMA*s have a larger wage premium (coefficient) and the *PUMA*s such that 75% of the *PUMA*s offer a larger premium. Wage spreads between the 75% *PUMA*s and the 25% *PUMA*s are in the 10% to 20% range.

Thus, people who live in some *PUMA*s can expect to earn substantially higher nominal wages than people who live elsewhere in the same state. Similarly, people who work in some *PUMA*s earn substantially more than people who work in other *PUMA*s in the same state. These nominal wage premiums are absorbed by higher prices for housing and local services. The locations of jobs that pay more are highly correlated with the locations of houses whose owner-occupants expect to earn a premium wage. These relationships are consistent with expectations, as discussed in the next section.

III. High Productivity Firms and Wage Peaks

To better understand my results, I did further analysis on the situation for Massachusetts. According to the 2005 County Business Patterns data, firms with 10,000 or more employees employed 27% of U.S. workers, and firms with at least 500 employees employed 50% of U.S. workers. The average establishment size in 2005 was 51.8 employees for firms having more than 10,000 employees, and 54.2 for firms having 500-999 employees[33]. Thus, the average establishment was not very large in comparison to the size of urban labor markets, but even relatively small firms concentrate groups of fifty or more workers into individual facilities. The largest firms operate many facilities (establishments) in geographically dispersed locations.

I checked the regression results for Massachusetts to confirm that large firms have significant facilities in the PUMAs with the largest wage premia. Boston includes the CBD used in conventional monocentric city models. Industries with large facilities in Boston include finance, healthcare and education. All else equal, a job in Boston pays 7.9% more than an equivalent job in Worcester. Jobs in Cambridge, across the river from the Boston CBD, pay the similar wage premium of 9.0%. Cambridge is the center of the biotechnology industry in Massachusetts, with Biogen Idec, Novartis, Genzyme, Millennium Pharmaceuticals, Vertex Pharmaceuticals, Wyeth, and Shire Pharmaceuticals included in a list of the top 25 Cambridge employers in 2007.

[33] 2005 County Business Patterns data.

As shown in Table 4, the highest wage peak in Massachusetts is not in the Boston-Cambridge CBD; it is in Metrowest. Employers in Framingham-Natick pay 13.8% more than employers in Worcester, and employers in the PUMA that includes Wellesley pay 12.5% more. Framingham-Natick is home to the headquarters of three large companies: Bose Corporation, Staples and TJX. Other major employers include Lifeline, Natural Microsystems, Perini, Genzyme, ADEESA and MetroWest Medical Center.

Wellesley is an example of a town that provides a very high quality but expensive lifestyle. People who live in Wellesley expect a 14.8% higher wage, even higher than the 12.5% premium paid by firms located in Wellesley. Within Boston, residents of Beacon Hill and Back Bay demand a 10.7% premium, relative to equivalent workers who live in Worcester. People who live in other Boston neighborhoods (Brighton-Allston, Dorchester-South End, and Roxbury-Mattapan) are willing to accept lower wages than econometrically equivalent workers in Worcester.

The theory presented in this paper is about matching unique workers with unique places to live and with jobs in unique firms, conditional on spatially dependent wage levels and living costs. Individual examples are not sufficient to prove a theory, and much work remains to be done. Nonetheless, it is reassuring that every time I have investigated the details lying behind a peak in the wage distribution, I have found a cluster of famous firms that are leaders in their respective industries. The internal operations of these firms seem to fit Adelstein’s (2005) description of firms as evolving multilateral contracts.

Modern economies are hybrid combinations of large firms and smaller producers. The County Business Patterns data suggests that large firms that benefit from significant economies of scale, and that impose a hierarchical decision process on their employees employ about half of all U.S. workers. Wages in these large firms are determined in internal labor markets that manage worker careers over one to four decades.

Firms are often built around fixed facilities that are difficult or impossible to relocate. The average facility employees about fifty workers; many facilities are much larger. If a firm wants to relocate a team of fifty people, the move will be expensive, and critical members of the team may be lost. Wage inertia and geographic fixity are inherent attributes of modern economies. The empirical section of this paper has demonstrated that job location and residence location are significant determinants of annual income. The empirical results are consistent with the view that the U.S. economy is a hybrid combination of large firms producing tradable products and small firms providing local services.

IV. Conclusion

In all states studied, which include the largest U.S. MSAs plus the rural state of Iowa, there is less than a 0.1% probability that annual earnings of a worker are independent of where she works and where she lives, even after controlling for attributes of the worker, the job, and the industry. This econometric result cannot be reconciled with the assumptions of “perfect” competition, since the labor cost differentials are so large that firms would rapidly move and decentralize if they could. On the other hand, the result is consistent with the alternate hypothesis that a large fraction of U.S. jobs (roughly half) are in large firms that benefit from significant economies of scale and that are price setters in their product and labor markets.

This research has demonstrated that urban wage gradients exist and are significant. The fact that wages vary with micro-location implies that a new approach to economic modeling is needed that has large firms and spatial persistence in its microfoundations.

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Table 1 page 1 of 4 Weighted Estimates of Labor Supply and Demand Equations

Dependent Variable: ln(annual earnings from labor)

	MA labor		CA labor		GA labor		IA labor	
	supply	demand	supply	demand	supply	demand	supply	demand
Observations[1]	28,864		138,098		37,868		13,658	
R-squared	0.397	0.584	0.301	0.427	0.371	0.380	0.459	0.580
(Standard errors in parentheses)								
Time Budget								
lnHours	2.6611	1.5044	2.7199	2.3007	2.4971	2.5756	2.1849	1.5037
	(0.2650)	(0.1085)	(0.1606)	(0.1904)	(0.2715)	(0.1961)	(0.0259)	(0.2339)
lnCommute	0.1456		0.2597		0.2596		0.1688	
	(0.0298)		(0.0210)		(0.0330)		(0.0400)	
Residence PUMA[2,3]	x		x		x		x	
Job PUMA[2,3]		x		x		x		x
Worker Attributes[6,7]								
Age	0.0084	0.0717	0.0236	0.0470	0.0340	0.0362	0.0277	0.0679
	(0.0143)	(0.0063)	(0.0073)	(0.0082)	(0.0118)	(0.0091)	(0.0175)	(0.0150)
Age_squared	0.0000	-0.0007	-0.0002	-0.0005	-0.0003	-0.0003	-0.0001	-0.0006
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Female	0.0126	-0.1302	-0.0192	-0.0869	-0.0522	-0.0769	-0.1131	-0.1879
	(0.0370)	(0.0212)	(0.0174)	(0.0219)	(0.0303)	(0.0255)	(0.0408)	(0.0343)
Moved[4]	-0.1174	-0.0833	-0.1022	-0.0823	-0.1169	-0.1184	-0.1962	-0.1502
	(0.0319)	(0.0189)	(0.0139)	(0.0137)	(0.0227)	(0.0172)	(0.0419)	(0.0349)
Ethnicity - Black	-0.0752	-0.0490	-0.0717	-0.0742	-0.0697	-0.0580	-0.2072	-0.1793
	(0.0436)	(0.0361)	(0.0184)	(0.0174)	(0.0366)	(0.0364)	(0.1315)	(0.1279)
Ethnicity - Hispanic	-0.0860	-0.0747	-0.0748	-0.0698	-0.0290	-0.0271	-0.1777	-0.1382
	(0.0362)	(0.0341)	(0.0111)	(0.0106)	(0.0324)	(0.0346)	(0.0993)	(0.0897)
Ethnicity - White	0.0500	0.0766	0.0337	0.0458	0.0936	0.1042	0.0284	0.0484
	(0.0351)	(0.0303)	(0.0094)	(0.0092)	(0.0309)	(0.0317)	(0.0834)	(0.0743)

Table 1 page 2 of 4 Weighted Estimates of Labor Supply and Demand Equations

Dependent Variable: ln(annual earnings from labor)

	MA labor		CA labor		GA labor		IA labor	
	supply	demand	supply	demand	supply	demand	supply	demand
Education								
HS[5]	-0.1080	0.0822	0.0469	0.0719	-0.0441	-0.0560	-0.1437	-0.0302
	(0.0639)	(0.0448)	(0.0226)	(0.0210)	(0.0352)	(0.0338)	(0.0736)	(0.7371)
Bach[5]	0.1276	0.1242	0.0671	0.0948	0.0950	0.0923	0.0989	0.0981
	(0.0250)	(0.0218)	(0.0144)	(0.0148)	(0.0225)	(0.0220)	(0.0327)	(0.0286)
AdvDeg[5]	0.0886	0.0991	0.0090	0.0332	-0.0376	-0.0290	0.0156	0.0309
	(0.0308)	(0.0255)	(0.0158)	(0.0134)	(0.0330)	(0.0340)	(0.0509)	(0.4654)
EducYrs	0.0198	-0.0397	-0.0237	-0.0370	-0.0193	-0.0137	0.0851	0.0431
	(0.0334)	(0.0288)	(0.0109)	(0.0096)	(0.0211)	(0.0206)	(0.0612)	(0.0545)
EducYrs * Age	0.0006	0.0002	0.0002	0.0003	0.0000	0.0000	-0.0003	-0.0005
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
EducYrs_squared	-0.0007	0.0024	0.0020	0.0024	0.0029	0.0028	-0.0005	0.0015
	(0.0012)	(0.0009)	(0.0004)	(0.0004)	(0.0008)	(0.0008)	(0.0023)	(0.0021)
Household[2,7]	x		x		x		x	
Job[2,7]	x	x	x	x	x	x	x	x
Occupation[2,3,7]	x	x	x	x	x	x	x	x
Industry[2,3,7]		x		x		x		x

Note 1: Number of workers in the 2005 ACS-PUMS 1% sample for the state, unweighted.

Note 2: X's indicate which groups of variables are included in each regression.

Note 3: Sets of dummy variables are used for Residence and Job PUMA, and for industry and occupation.

Note 4: Moved means did not live in the same house a year ago.

Note 5: HS means diploma and/or any post-high school education. Bach means B.A., B.S., and/or any advanced degree. AdvDeg means Master's, Professional degree, and/or PhD.

Note 6: All regressions also include additional worker attributes such as disabled, decade of immigration, and citizenship.

Note 7: Results for the full set of variables are presented in Carlson(2009) Table A-3.

Table 1 page 3 of 4 Weighted Estimates of Labor Supply and Demand Equations

Dependent Variable: ln(annual earnings from labor)

	IL labor		MI labor		NY labor		TX labor	
	supply	demand	supply	demand	supply	demand	supply	demand
Observations[1]	54,157		41,728		76,892		90,980	
R-squared	0.322	0.492	0.448	0.586	0.386	0.458	0.298	0.420
(Standard errors in parentheses)								
Time Budget								
lnHours	2.8773	2.2514	2.4544	1.7041	2.4361	2.1493	2.7713	2.3874
	(0.2318)	(0.1661)	(0.0224)	(0.1291)	(0.2350)	(0.1475)	(0.2864)	(0.2009)
lnCommute	0.1892		0.2433		0.2106		0.2766	
	(0.0283)		(0.0380)		(0.0225)		(0.0312)	
Residence PUMA[2,3]	x		x		x		x	
Job PUMA[2,3]		x		x		x		x
Worker Attributes[6,7]								
Age	0.0056	0.0434	0.0296	0.0727	0.0328	0.0488	0.0242	0.0456
	(0.0123)	(0.0094)	(0.0121)	(0.0076)	(0.0113)	(0.0069)	(0.0115)	(0.0087)
Age_squared	0.0000	-0.0004	-0.0002	-0.0006	-0.0003	-0.0004	-0.0001	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female	0.0031	-0.0948	-0.0627	-0.1489	-0.0335	-0.0783	-0.0183	-0.0809
	(0.0282)	(0.0246)	(0.0282)	(0.0208)	(0.0244)	(0.0209)	(0.0319)	(0.0250)
Moved[4]	-0.1209	-0.0924	-0.1418	-0.1032	-0.1121	-0.0877	-0.1370	-0.1207
	(0.0222)	(0.0172)	(0.0292)	(0.0185)	(0.0220)	(0.0165)	(0.0175)	(0.0144)
Ethnicity - Black	-0.1567	-0.1353	-0.0731	-0.1203	0.0144	0.0070	-0.1545	-0.1350
	(0.0333)	(0.0252)	(0.0445)	(0.0370)	(0.0183)	(0.0173)	(0.0226)	(0.0187)
Ethnicity - Hispanic	-0.0702	-0.0704	-0.0855	-0.0683	-0.0177	-0.0295	-0.0815	-0.0768
	(0.0294)	(0.0201)	(0.0351)	(0.0277)	(0.0175)	(0.0163)	(0.0133)	(0.0117)
Ethnicity - White	0.0694	0.0956	0.0470	0.0540	0.1488	0.1738	0.0220	0.0323
	(0.0247)	(0.0225)	(0.0302)	(0.0278)	(0.0176)	(0.0164)	(0.0130)	(0.0126)

Table 1 page 4 of 4 Weighted Estimates of Labor Supply and Demand Equations

Dependent Variable: ln(annual earnings from labor)

	IL labor		MI labor		NY labor		TX labor	
	supply	demand	supply	demand	supply	demand	supply	demand
Education								
HS[5]	-0.0406	0.0241	-0.0374	0.0576	0.0187	0.0578	0.0108	0.0414
	(0.0412)	(0.0322)	(0.0389)	(0.0377)	(0.0344)	(0.0311)	(0.0305)	(0.0257)
Bach[5]	0.1170	0.1310	0.0777	0.0854	0.0846	0.0991	0.1000	0.1123
	(0.0215)	(0.0190)	(0.0207)	(0.0175)	(0.0158)	(0.0155)	(0.0176)	(0.0161)
AdvDeg[5]	0.0342	0.0634	0.0279	0.0487	0.0840	0.0916	-0.0669	-0.0630
	(0.0265)	(0.0236)	(0.0302)	(0.0286)	(0.0163)	(0.0172)	(0.0191)	(0.0163)
EducYrs	-0.0073	-0.0159	0.0333	0.0050	-0.0183	-0.0386	-0.0408	-0.0515
	(0.0233)	(0.0204)	(0.0295)	(0.0295)	(0.0183)	(0.0180)	(0.0131)	(0.0125)
EducYrs * Age	0.0004	0.0001	-0.0001	-0.0005	0.0003	0.0003	-0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
EducYrs_squared	0.0011	0.0019	0.0010	0.0027	0.0017	0.0026	0.0040	0.0046
	(0.0009)	(0.0008)	(0.0011)	(0.0011)	(0.0007)	(0.0007)	(0.0005)	(0.0005)
Household[2,7]	x		x		x		x	
Job[2,7]	x	x	x	x	x	x	x	x
Occupation[2,3,7]	x	x	x	x	x	x	x	x
Industry[2,3,7]		x		x		x		x

Note 1: Number of workers in the 2005 ACS-PUMS 1% sample for the state, unweighted.

Note 2: X's indicate which groups of variables are included in each regression.

Note 3: Sets of dummy variables are used for Residence and Job PUMA, and for industry and occupation.

Note 4: Moved means did not live in the same house a year ago.

Note 5: HS means diploma and/or any post-high school education. Bach means B.A., B.S., and/or any advanced degree. AdvDeg means Master's, Professional degree, and/or PhD.

Note 6: All regressions also include additional worker attributes such as disabled, decade of immigration, and citizenship.

Note 7: Results for the full set of variables are presented in Carlson(2009) Table A-3.

Table 2 F-Tests of Unweighted Significance of Geographic Locations

		Residence Loc # PUMAs	Job Loc #PUMAs	Sample Size	Residence Location dummies equal zero F-Stat	Residence Location dummies equal zero (p-value)	Job Location dummies equal zero F-Stat	Job Location dummies equal zero (p-value)	Residence/Job Location Regression $ß^1$	Residence/Job Location Regression (p-value)
MA	supply	52		28,864	3.84	(0.00)			0.508	0.000
	demand		67				5.34	(0.00)		
CA	supply	233		138,098	6.49	(0.00)			0.696	0.000
	demand		126				12.15	(0.00)		
GA	supply	63		37,868	3.70	(0.00)			0.726	0.000
	demand		89				6.87	(0.00)		
IA	supply	19		13,658	5.69	(0.00)			0.725	0.000
	demand		50				5.14	(0.00)		
IL	supply	87		54,157	7.21	(0.00)			0.729	0.000
	demand		88				15.43	(0.00)		
MI	supply	68		41,728	7.51	(0.00)			0.659	0.000
	demand		101				9.18	(0.00)		
NY	supply	143		76,892	15.00	(0.00)			0.843	0.000
	demand		113				21.99	(0.00)		
TX	supply	153		90,980	4.87	(0.00)			0.748	0.000
	demand		128				11.23	(0.00)		

Note 1: To test whether job location and residence location wage premia are additive for a person who lives and works in the same PUMA, the following regression was run: Residence_Location_Coef = $\alpha + ß*$Job_Loc_Coef.

Table 3 page 1 of 2 Extreme Values of Location Effects in Weighted Regressions

		Maximum PUMA Coef	Minimum PUMA Coef	Earnings difference (%) low to high	25% Level PUMA Coef	75% Level PUMA Coef	Earnings difference (%) 25% to 75%
(Standard errors in parentheses)							
MA	Residence Pumas	0.148	-0.166	36.78%	0.033	-0.081	12.09%
		(0.076)	(0.067)		(0.070)	(0.070)	
	Job Pumas[1]	0.138	-0.204	40.74%	0.029	-0.068	10.18%
		(0.052)	(0.056)		(0.043)	(0.043)	
CA	Residence Pumas	0.441	-0.330	116.22%	0.147	-0.023	18.58%
		(0.061)	(0.078)		(0.061)	(0.061)	
	Job Pumas[1]	0.228	-0.285	67.01%	0.042	-0.081	13.04%
		(1.341)	(1.341)		(1.341)	(1.340)	
GA	Residence Pumas	0.173	-0.215	47.44%	0.055	-0.036	9.54%
		(0.048)	(0.053)		(0.054)	(0.055)	
	Job Pumas[1]	0.280	-0.124	49.79%	0.147	0.020	13.54%
		(2.798)	(2.800)		(2.797)	(2.804)	
IA	Residence Pumas	0.184	-0.041	25.20%	0.086	0.032	5.51%
		(0.040)	(0.053)		(0.060)	(0.044)	
	Job Pumas[1]	1.188	0.940	28.14%	1.097	0.997	10.47%
		(2.709)	(2.712)		(2.720)	(2.707)	
IL	Residence Pumas	0.381	-0.152	70.47%	0.238	0.100	14.79%
		(0.067)	(0.053)		(0.084)	(0.064)	
	Job Pumas[1]	-0.367	-0.864	64.47%	-0.494	-0.689	21.51%
		(1.940)	(1.938)		(1.934)	(1.939)	

Table 3 page 2 of 2 Extreme Values of Location Effects in Weighted Regressions

		Maximum PUMA Coef	Minimum PUMA Coef	Earnings difference (%) low to high	25% Level PUMA Coef	75% Level PUMA Coef	Earnings difference (%) 25% to 75%
MI	Residence Pumas	0.324	-0.138	58.81%	0.155	0.013	15.36%
		(0.072)	(0.105)		(0.048)	(0.047)	
	Job Pumas[1]	0.743	0.293	56.89%	0.638	0.462	19.22%
		(2.675)	(2.676)		(2.669)	(2.667)	
NY	Residence Pumas	0.350	-0.343	99.86%	0.096	-0.102	21.92%
		(0.068)	(0.152)		(0.062)	(0.053)	
	Job Pumas[1]	0.237	-0.306	72.00%	0.107	-0.142	28.26%
		(0.042)	(0.064)		(0.039)	(0.041)	
TX	Residence Pumas	0.123	-0.479	82.62%	-0.029	-0.162	14.19%
		(0.049)	(0.100)		(0.058)	(0.074)	
	Job Pumas[1]	0.225	-1.049	257.53%	-0.691	-0.847	16.85%
		(3.114)	(3.134)		(3.135)	(3.129)	

Note 1: Job locations outside the state are ignored.

Table 4 page 1 of 1 Wage Peaks in Massachusetts

	Maximum Job PUMA[1] Coef[2]	Residence PUMA Coef[2]
Framingham-Natick	13.8%	6.8%
Wellesley-Weston	12.5%	14.8%
Cambridge	9.0%	2.4%
Boston	7.9%	
Beacon Hill-Back Bay		10.7%
Brighton-Allston		-9.0%
Dorcester-South End		-5.6%
Roxbury-Mattapan		-8.7%

Note 1: Job locations outside the state are ignored.

Note 2: Coefficients are relative to wage levels in Worcester