Agglomeration and Productivity: New Estimates and Macroeconomic Implications*

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Abstract

We construct a dynamic general equilibrium model of cities and aggregate growth and use it to identify the effects of local agglomeration on aggregate per capita consumption. There is a fixed amount of land in each city; workers live and work in the same city and value consumption and land for housing; and identical firms in each city produce output using a Cobb-Douglas combination of land, labor and capital. The level of firm output in each city is also affected by Ciccone and Hall (1996)'s density externality. Our model predicts a relationship between wages, output prices, land prices, and labor input which we use to estimate the structural parameters of the model with panel data. We find a statistically significant and economically meaningful role for density in accounting for changes in output: Our estimates imply that along a balanced growth path, agglomeration accounts for 11 percent of growth in per-capita consumption.

Journal of Economic Literature Classification Numbers: E0, E1, E2, R1, R3
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1 Introduction

There is widespread agreement that cities emerge because of *agglomeration* effects: workers become more productive when they are near other workers and production is more efficient when transportation costs are reduced. Cities emerge because of agglomeration, and most aggregate growth actually occurs in cities. So, how important is local agglomeration for aggregate growth? To answer this question, we build and estimate a dynamic general equilibrium model of cities and aggregate growth in which city-based agglomeration affects per capita consumption growth. We estimate the structural parameters of our model using panel data and use these estimates to quantify the impact of local agglomeration on aggregate per capita consumption growth.

Our model embeds into the neoclassical growth model a version of Roback (1982)'s model of cities, augmented with agglomeration effects in the way proposed by Ciccone and Hall (1996). We study the model's stationary competitive equilibrium and show that along the balanced growth path per capita consumption growth depends on exogenous total factor productivity change and the average population or employment growth. The population growth rate effect is determined by the net impact of agglomeration on local productivity. We use our model and panel data on wages and prices for a sample of US cities to estimate the net impact on of agglomeration, thereby yielding the contribution to aggregate per capita consumption growth.

Our model predicts a specific relationship between wages, output prices, land prices, labor input, and exogenous total factor productivity. We exploit this relationship to estimate the key parameter underlying local agglomeration and its effect on aggregate growth. Our estimation uses three sets of data. Our first data set combines wage data from the CPS, output-price data from the Bureau of Economic Analysis (BEA), and land-price data from a study by Davis and Palumbo (2008). This annual panel data set covers 42 metropolitan statistical areas (MSAs) over the 1985-2004 period. The second annual data set uses the same annual wage and output-price data, but uses data on house prices instead of land prices for 149 MSAs over the 1985-2006 period. We create the house price data by merging available house price indexes with information in the 1990 Decennial Census. Our third panel data set merges the BEA data on output prices with data on wage and house prices exclusively from the

Decennial Census for the years 1970, 1980, 1990, and 2000.

The twenty year panel sample of the first two data sets is particularly amenable to applying recent advances in dynamic panel data analysis. We use the Arellano and Bover (1995) estimation strategy on the annual data. Our key finding from these data is that local agglomeration effects are statistically significant and economically important, regardless of the data source we use. However, the exact estimates are sensitive to our choice of data. When we use the land data, we estimate that a doubling of output per unit of productive land in a city increases output in the city by 1.2 percent. Our estimates from the house-price data are higher; they suggest that a doubling of the density of economic activity increases output by 7.5 percent. On the census data we explore several instrumental variables strategies and find [**TBD** xxx].

Depending on whether we use land or house prices we find between 1.6% and 9% of per capita consumption growth is due to local agglomeration. According to our model, Ciccone and Hall (1996)'s estimates of the agglomeration coefficient translate to a 6% contribution to per capita consumption growth. We prefer our focus on cities since they seem a more natural economic entity compared to the counties at the base of Ciccone and Hall (1996). There are two other key differences: we include an alternative use for land at a location and we allow for heterogeneity in output across locations.

Our work is related to [**TBD** .... old literature, ciccone-hall, ciccone-peri and related cites, island models of cities/other island models, production function, sources of growth - neutral, investment-specific, agglomeration...., Lucas - only externality can imagine is the one that creates cities].

The rest of the paper is organized as follows. The next section describes our model economy, including the equations underlying our estimation. After that we describe our econometric strategy and then the data. Section five discusses our empirical results and quantifies the impact of agglomeration on per capita consumption growth. Section six concludes.

2 Model Economy

Our model embeds a version of Roback (1982)'s model of cities, modified to include agglomeration effects in the way proposed by Ciccone and Hall (1996), into the neoclassical growth model.

2.1 Economic Environment

We consider a discrete time infinite horizon model with complete markets and no aggregate uncertainty. The economy consists of a unit measure of locations, called cities. Competitive firms in each city produce an intermediate good unique to the city. Each city is surrounded by a limitless supply of undeveloped land which can be developed into a form suitable for habitation or production at a cost. Competitive firms, which can be located anywhere, combine the intermediate goods into a final good. There is also a representative household composed of a unit measure of members. The large household structure allows for full risk sharing within each household, a standard device for studying complete markets allocations.

The representative intermediate goods producer in each city uses a Cobb-Douglas technology with inputs of land, l labor, n and capital, k. Total factor productivity (TFP) in each city, x is taken by households and firms to be given and is specified as

$$x = z^{(1-\alpha)\phi} \left[\frac{y}{l}\right]^{\frac{\lambda-1}{\lambda}}$$

where z is an exogenous city-specific stationary stochastic term and y is total city output.[1] The ratio of output to land is called the *density of economic activity.* If $\lambda = 1$ density has no impact on productivity and if $\lambda > 1$ firms' productivity is increasing in density. Ciccone and Hall (1996) show how this production technology can be derived as the reduced form of a micro founded model. Final goods are produced by combining the output of each city using a constant-elasticity-of-substitution production function in which, for simplicity, the goods produced by each city enter symmetrically. These

[1] We could incorporate non-stationary technology along the lines pursued by Alvarez and Shimer (2008) In their model idiosyncratic technology follows a random walk. They achieve a stationary aggregate distribution by assuming that locations are destroyed with constant probability replaced instantaneously by the same number of new locations drawn from the stationary distribution of technology.

goods are converted one-for-one into consumption and investment goods, and into newly developed land at the rate v, which is stochastic and idiosyncratic to each city.[2] The differences in land development costs across locations could emerge due to differences in the quality of land or legal restrictions on developing new land.

Each household member supplies one unit of labor inelastically and enjoys utility from consumption, c and housing, h. For simplicity housing is just land; there are no structures in the model. The household derives income from labor and capital by allocating its members and its stock of capital, K across the cities, and by collecting rent on its land, d. Each period the household's members are randomly allocated across cities at zero cost, after observing the current level of TFP and land development costs in each city. Household members must consume and enjoy housing in the same city that they work. Capital is perfectly mobile and along with land is also allocated after the household observes TFP and land development costs.

Land and labor are traded in local markets while the intermediate goods, the final good, and capital services are traded in economy-wide markets. For simplicity, we initially assume the aggregate level of technology and the number of households are constant and focus on a stationary equilibrium.

2.2 Stationary Competitive Equilibrium

The stationary competitive equilibrium for the case without density effects, $\lambda = 1$, consists of the following. In each period, the household chooses how much to consume of the final good and housing, and how to allocate its members and stock of capital to each city, in order to maximize the equally weighted utility of all the household's members subject to the technological constraints on allocating members across cities, taking as given the stochastic processes for TFP and land development costs in each city and all prices. Each intermediate and final goods producer maximizes profits by choosing inputs taking their prices as given. The aggregate intermediate and final good and capital service markets and the local labor and land markets all clear.

In cases with a positive effect of density on productivity, $\lambda > 1$, an additional

[2] The underlying technology for land development is Leontief in undeveloped land and the final good.

productivity consistency condition must be satisfied. Recall that we assume that the distribution of TFP is taken as given by households and firms. When $\lambda > 1$ the decisions of households and firms affect the TFP distribution, through the resulting distribution of density. In a competitive equilibrium, the solutions of the household and firm problems must generate the underlying distribution of productivity that is taken as given when calculating those solutions.

2.3 Planning Problem

We initially focus on the case without any impact of density on productivity, $\lambda = 1$. The competitive equilibrium for this case solves a planning problem and the two welfare theorems apply. Without aggregate uncertainty decision rules are stationary and so we drop the time subscript where appropriate. Let s denote the vector of exogenous state variables for a city, $s = (x, v)$. Instead of indexing cities on the unit interval, it is convenient to index them according to their history of realizations of the state vector, s^t. Let $\pi(s^t)$ be the probability density of cities across histories.

Since the household perfectly insures itself against consumption risk, the planning problem can be written as

$$\max \sum_{t=0}^{\infty} \beta^t \int n(s^t) \left[\ln c_t + \psi \ln h(s^t)\right] \pi(s^t) ds^t$$

subject to

$$\begin{aligned}
c_t \int n(s^t)\pi(s^t)ds^t + K_{t+1} - (1-\kappa)K_t \quad &+ \quad \int v(s^t)\left[d_{t+1}(s^t) - d_t(s^{t-1})\right]\pi(s^t)ds^t \\
&\leq \quad \left[\int y(s^t)^{\eta}\pi(s^t)ds^t\right]^{\frac{1}{\eta}}; \qquad (1) \\
y(s^t) &\leq \quad x_t l(s^t)^{1-\phi} k(s^t)^{\alpha\phi} n(s^t)^{(1-\alpha)\phi}, \ \forall s^t; \\
\int k(s^t)\pi(s^t)ds^t &\leq \quad K_t; \\
n(s^t)h(s^t) + l(s^t) &\leq \quad d_t(s^{t-1}), \ \forall s^t; \qquad (2) \\
\int n(s^t)\pi(s^t)ds^t &\leq \quad 1; \\
& \quad K_0 \text{ and } d_0 \text{ for each city given.}
\end{aligned}$$

The first term on the right-hand side of (1) is the function mapping intermediate into final goods. In this mapping $\eta \leq 1$ and in addition we assume $\eta \neq 0$. Intermediate goods are perfect substitutes if $\eta = 1$ and as $\eta \to -\infty$ the final good is a Leontief function of intermediate goods. In writing the final good aggregator we have made use of the fact that intermediate good production is identical in cities with the same TFP history. This follows from the symmetric way in which intermediate goods enter into the final good aggregator. The variables c_t and $h(s^t)$ are in per capita terms. Finally $\psi > 0$ and $0 \leq \kappa \leq 1$ is capital's rate of depreciation.

Let the Lagrange multipliers for the above restrictions be $\beta^t \vartheta_t$, $\beta^t \vartheta_t \pi(s^t) q(s^t)$, $\beta^t \vartheta_t r_t$, $\beta^t \vartheta_t \pi(s^t) p(s^t)$ and $\beta^t \vartheta_t \theta_t$. Then the first order conditions for c_t, $y(s^t)$, K_{t+1}, $d_{t+1}(s^t)$, $k(s^t)$, $l(s^t)$, $h(s^t)$ and $n(s^t)$ are

$$\begin{aligned}
\frac{1}{c_t} &= \vartheta_t; && (3)\\
q(s^t) &= Y_t^{1-\eta} y(s^t)^{\eta-1}; && (4)\\
\vartheta_t &= \beta \vartheta_{t+1} \left[r_{t+1} + 1 - \kappa \right]; \\
v(s^t) &= \beta \frac{\vartheta_{t+1}}{\vartheta_t} \int \left[v(s^t, s_{t+1}) + p(s^t, s_{t+1}) \right] \frac{\pi(s^t, s_{t+1})}{\pi(s^t)} ds_{t+1}; && (5)\\
r_t &= \alpha \phi q(s^t) x_t l(s^t)^{1-\phi} k(s^t)^{\alpha\phi - 1} n(s^t)^{(1-\alpha)\phi}; && (6)\\
p(s^t) &= (1-\phi)\, q(s^t) x_t l(s^t)^{-\phi} k(s^t)^{\alpha\phi} n(s^t)^{(1-\alpha)\phi}; && (7)\\
\frac{\psi}{h(s^t)} &= \vartheta_t p(s^t); && (8)\\
\ln c_t + \psi \ln h(s^t) &= \vartheta_t \theta_t + \vartheta_t \left[c_t + p(s^t) h(s^t) - w(s^t) \right]; && (9)
\end{aligned}$$

where

$$w(s^t) = (1-\alpha)\phi q(s^t) x_t l(s^t)^{1-\phi} k(s^t)^{\alpha\phi} n(s^t)^{(1-\alpha)\phi - 1} \tag{10}$$

is the marginal product of labor in cities with history s^t, and

$$Y_t = \left[\int y(s^t)^{\eta} \pi(s^t) ds^t \right]^{\frac{1}{\eta}}$$

denotes aggregate final good production.

In the competitive equilibrium corresponding to the solution to this planning problem we use the final good as the numeraire. Then, $v(s^t), w(s^t)$, $p(s^t)$ and $q(s^t)$ are the price of new land, wages, rent on existing land and intermediate good prices at cities with history s^t, and r_t is the economy's rental rate on capital.

Most of the first order conditions are familiar and need no discussion. There are some differences with the traditional growth model and these are worth discussing briefly. First, as indicated by (5), (7) and (10), the price of new land, rent on existing land and wages are idiosyncratic to location. That wages depend on the local conditions follows directly from the inclusion of housing in preferences. Without a preference for housing, wages would be equalized across cities. This can be seen by inspecting (9). The only way for this condition to hold without housing is for wages to be equalized across cities.

Second, equation (5) describes optimal land development in each city. The price of new land depends on the realization of the cost in terms of final goods of land development, v in each city. The equation states that the price of new land in each city at any date equals the discounted expected value in the following period of rent on that land plus the price of new land. Equivalently, the price of new land equals the discounted expected value of future rents on that land.

Third, the *location indifference* condition (9) does not appear in the growth model. This condition contrasts with the static Roback (1982) model where utility is equated across cities. In our dynamic model with complete markets, utility net of the consumption price of the transfer is equated. Since transfers sum to zero, *ex ante expected* utility is equalized.

Without density effects the competitive equilibrium exists and is unique, by standard arguments. With density effects, the competitive equilibrium is found by finding the planning problem's solution that satisfies the productivity consistency condition. We have not found conditions under which a solution to this fixed point problem exists or is unique. However, using the argument in Kehoe, Levine and Romer (1992) we know that for λ sufficiently close to unity, there exists a unique competitive equilibrium, because the model without density effects has a unique equilibrium. Equilibrium existence and uniqueness under the size of density effects we estimate remain open questions since we do not need to find a solution of the model to identify the impact of density on local productivity or quantify the density effect on aggregate growth, and so do not do so in this paper.

2.4 Balanced Growth

Our choices of preferences and technology guarantee that the model has a balanced growth path. We now derive the balanced growth path and show how to use this to quantify the impact of local agglomeration effects on aggregate consumption growth. For this we assume the neutral technology and development costs in each city evolve as

$$z_t = \gamma^t \tilde{z}_t \text{ and } v_t = \tau^t \tilde{v}_t \tag{11}$$

where $\tilde{z}_t$ and $\tilde{v}_t$ are stationary random variables, $\gamma \geq 1$, and $\tau \geq 1$. The number of households grows at the rate $\mu \geq 1$. While we continue to assume that workers are homogeneous, the derivation here also holds under the model of worker heterogeneity considererd below.

The aggregate resource constraint (1) implies per capita consumption, capital and land, all in units of the final good, each grow at the same rate, denoted γ_c. The land constraints (2) imply that in each city per capita land used for production grows at the same rate as per capita developed land, which grows as the rate γ_c/τ. Output in a city is

$$y = z^{(1-\alpha)\phi} \left[\frac{y}{l}\right]^{\frac{\lambda-1}{\lambda}} l^{1-\phi} k^{\alpha\phi} n^{(1-\alpha)\phi.} \tag{12}$$

Let $\delta = \lambda\phi$. This parameter measures the net effect on productivity of diminishing returns to land, otherwise known as congestion, and density. Dividing equation (12) through by n yields an expression involving per capita variables:

$$y/n = z^{(1-\alpha)\phi} \left[\frac{y/n}{l/n}\right]^{\frac{\lambda-1}{\lambda}} [l/n]^{1-\phi} [k/n]^{\alpha\phi}.$$

Dividing this equation by the equivalent one for the previous period and making appropriate substitutions for the growth rates of the variables in the resulting expression, yields

$$\gamma_c = \gamma \tau^{\frac{\delta-1}{(1-\alpha)\delta}}. \tag{13}$$

Below we use this equation, in combination with estimates of δ, to quantify the contribution of agglomeration to aggregate consumption growth.

Equation (13) shows that per capita consumption growth depends on the rate of neutral technology growth and, if $\delta \neq 1$, the rate of growth in development costs

as well. If the relative price of new land is growing, $\tau > 1$, then land growth will not keep up with output growth so that the density of economic activity must grow. If agglomeration effects outweigh congestion effects, $\delta > 1$, then this provides an endogenous source of consumption growth in addition to exogenous neutral technical change. Without any productivity effect of density, $\lambda = 1$ and $\delta = \phi$, and (13) implies

$$\gamma_c = \gamma \tau^{\frac{\phi-1}{(1-\alpha)\phi}}.$$

Since $0 < \phi < 1$, in this case per capita consumption growth is lower than the rate of growth of the neutral technology because of decreasing returns to land. Finally, if agglomeration and congestion effects cancel out, that is $\delta = 1$, then consumption growth equals the rate of neutral technology growth, as in the standard neoclassical growth model.

3 Implications of the Model

In this section we examine some implications of our model. To begin, we derive the key equation underlying our estimates of agglomeration's effect on local productivity. We then characterize the model's implications for the cross-sectional pattern of output, employment and prices. After this we consider two extensions to the model involving city-specific amenities and worker heterogeneity.

3.1 Equation Underlying Our Estimation

Consider any two cities with different histories, indexed i and j, in some arbitrary period. Solving for output in (12) and dividing output in city i by that in city j yields

$$\frac{y_i}{y_j} = \left[\frac{z_i}{z_j}\right]^{\delta(1-\alpha)} \left[\frac{l_i}{l_j}\right]^{1-\delta} \left[\frac{k_i}{k_j}\right]^{\delta\alpha} \left[\frac{n_i}{n_j}\right]^{\delta(1-\alpha)}.$$

Using (6) to eliminate the capital terms in this last equation we have

$$\frac{y_i/l_i}{y_j/l_j} = \left[\frac{z_i}{z_j}\right]^{\frac{\delta(1-\alpha)}{1-\delta\alpha}} \left[\frac{n_i/l_i}{n_j/l_j}\right]^{\frac{\delta(1-\alpha)}{1-\delta\alpha}} \left[\frac{q_i}{q_j}\right]^{\frac{\delta\alpha}{1-\delta\alpha}} \tag{14}$$

Equation (14) is closely related to equation 19 in Ciccone and Hall (1996), which is the basis for their estimation equation. It differs in two key respects. First, because

Ciccone and Hall (1996) assume intermediate goods are perfect substitutes in producing final goods, $\eta = 1$, their equation does not contain any output prices. In this case their equation is subject to an omitted variable bias. Second, they assume all land in a given location is used in production while we have competing uses for land. Since the allocation of land between residential and non-residential uses in U.S. cities is unavailable to us, we cannot use (14) as a basis for estimation. Further complicating our analysis, annual data on real city output that is produced by the BEA is available for too short a time period (2001-2006) to be useful.

We eliminate land and output from (14) using (7) and (10) to arrive at the key equation underlying our estimation:

$$\frac{w_i}{w_j} = \frac{z_i}{z_j} \left[\frac{p_i}{p_j}\right]^{\frac{\delta-1}{\delta(1-\alpha)}} \left[\frac{q_i}{q_j}\right]^{\frac{1}{\delta(1-\alpha)}}. \tag{15}$$

It is important to note that (15) follows directly from profit maximization by firms and the functional form of the production function. In particular, it does not depend on the assumption of perfect risk sharing or any assumptions about preferences. If we were to add other local factor inputs to the model with competing uses, such as energy, their prices would also appear in (15) in the same way that land prices do.

3.2 Characterization of the Cross-Section of Cities

It is useful to characterize the cross-sectional relationships among the model's endogenous variables. The implications of idiosyncratic development costs for the cross-section are ambiguous. Consequently, we proceed under the assumption that idiosyncratic variation in development costs is sufficiently small such that it does not impact the qualitative pattern of variation among the model's endogenous variables determined by idiosyncratic productivity alone. Our characterization strategy considers small perturbations to the exogenous component of technology of a given city, holding fixed all aggregate variables and local variables in other cities.

Combining (3), (8) and (9) and differentiating it is straightforward to show that

$$\frac{d\ln p}{d\ln z} = \frac{w\,n}{p\,nh}\frac{d\ln w}{d\ln z}. \tag{16}$$

It follows immediately that the model predicts land prices and wages are positively correlated in a cross-section of cities.

The cross-sectional relationship between employment and wages is derived as follows. From (2), (3) and (8)

$$\frac{d\ln l}{d\ln z} = \frac{p\,nh}{p\,l}\left[\frac{d\ln p}{d\ln z} - \frac{d\ln n}{d\ln z}\right]. \tag{17}$$

This derivation uses the fact that developed land in a city is fixed in a given period. Taking logs of (7) and (10) and subtracting one resulting expression from the other leaves an equation in employment, wages, land and its price. Substituting for land in this last equation using (17) and the price of land using (16) and solving for the employment elasticity yields

$$\frac{d\ln n}{d\ln z} = \frac{\frac{p\,l}{p\,nh}wn + wn - p\,l}{p\,nh + p\,l}\frac{d\ln w}{d\ln z} \tag{18}$$

Any empirically plausible calibration of the model will have labor's share exceeding land's share in production, *i.e.* $wn > p\,l$. From now on we assume that this condition is satisfied. It follows that employment is positively correlated with wages.

The relationships of output and its price with wages depend on the degree of substitutability of intermediate goods in the production of final goods. To see this, eliminate the local output price from (10) using (4),

$$\frac{d\ln y}{d\ln z} = \frac{1}{\eta}\left[\frac{d\ln n}{d\ln z} + \frac{d\ln w}{d\ln z}\right].$$

Use this last expression to substitute for output in (4),

$$\frac{d\ln q}{d\ln z} = \frac{\eta - 1}{\eta}\left[\frac{d\ln n}{d\ln z} + \frac{d\ln w}{d\ln z}\right]$$

Given our previous result for the employment elasticity, it is clear that if $\eta > 0$, that is if intermediate goods are substitutes, then output is positively correlated with wages and the local output price is negatively correlated with wages. The opposite relationships hold if $\eta < 0$, that is if intermediate goods are compliments.

Land use in production is positively related to wages. This follows from substituting for prices and employment in (17) using (16) and (18):

$$\frac{d\ln l}{d\ln z} = \frac{nh}{nh + l}\frac{d\ln w}{d\ln z}.$$

This last equation is interesting in light of our result for output. The two results imply that the density of employment activity can be positively or negatively related to wages in the cross section, depending on the degree of substitutability of intermediate goods in the production of final goods, η. In particular, even without any effects of density on total factor productivity, we could observe a positive relationship between wages, or labor productivity since this is proportional to wages in our model, and density in a cross-section of cities.

3.3 Amenities

Cities clearly vary by amenities in addition to productivity and the ease with which land can be developed. Therefore it is natural to ask whether our results in the previous two subsections are affected by including amenities in the model. The short answer to this question is that if amenities appear in individuals' preferences in a logarithmically separable way, then none of our results thus far are affected. We now elaborate on this answer briefly.

Suppose the new planning objective is given by

$$\sum_{t=0}^{\infty} \beta^t \int n(s^t) \left[\ln c_t + \psi \ln h(s^t) + \varsigma \ln a(s^t)\right] \pi(s^t) ds^t$$

where we redefine $\pi(s^t)$ to be the distribution of cities across productivity, land development cost *and* amenity histories, $a(s^t)$ denotes the quantity of amenities at a city with history s^t, and $\varsigma > 0$. The only first order condition affected from the problem without amenities is the location indifference condition. This becomes

$$\ln c_t + \psi \ln h(s^t) + \varsigma \ln a(s^t) = \pi_t \theta_t + \pi_t \left[(1+\psi)c - w(s^t)\right].$$

Amenities matter because they effect the allocation of labor, which then effects relative prices across cities. We pointed out earlier that introducing housing was important for generating a non-trivial wage distribution in the model. This is only true if we exclude amenities. Inspection of the new indifference condition shows that wages can differ by city if amenities do, even without housing.

Since the other first order conditions are unaffected by introducing amenities, the equation underlying our estimation, (15), is also unchanged. It also follows that

the relationship between the endogenous variables due to idiosyncratic variation in technology is qualitatively unchanged. Moreover, idiosyncratic variation in amenities induces the same qualitative pattern of variability as with idiosyncratic variation in technology. This latter result can be verified by following the same proof strategy as before. Assuming that amenities are orthogonal to productivity, it follows that the general model including both sources of cross-sectional variability will share the same relationship between endogenous variables as with cross-sectional variation in technology only.

3.4 Heterogeneous Workers

So far we have assumed that workers are homogeneous. This is a questionable assumption from an empirical perspective. Locations with a high density of economic activity may have high wages because of a concentration of high human capital workers, not because of a density effect on productivity. Without accounting for cross-sectional variation in the distribution of human capital we could overstate density effects. Ciccone and Hall (1996) address this concern by accounting for the average level of educational attainment in a location. [**TBD** xxx rewrite this next sentence]. Ciccone and Peri (2006) have raised doubts about this approach. Their argument is focused on the issue of identifying human capital externalities, but is relevant in our context as well. They argue that the kind of approach adopted by Ciccone and Hall (1996) confounds positive externalities with wage changes due to a downward sloping demand curve for human capital. Consistent with Ciccone and Peri (2006), we address the issue by allowing high skill and low skill workers to be imperfect substitutes in producing labor services. We now derive a version of the equation underlying our estimation which incorporates heterogeneous workers.

Suppose that effective labor input in (12) is a constant elasticity of substitution aggregate of unskilled and skilled labor:

$$n = \left[\sigma u^{\xi} + (1-\sigma)e^{\xi}\right]^{1/\xi}.$$

We can exploit previous derivations from above by using the notion of the demand for composite labor n. Composite labor satisfies (10) as before. Efficient use of unskilled

and skilled labor implies

$$\begin{aligned} w_{ui} &= \sigma w_i {n_i}^{1-\xi} {u_i}^{\xi-1} \\ w_{ei} &= (1-\sigma) w_i {n_i}^{1-\xi} {e_i}^{\xi-1} \end{aligned}$$

where w_{ei} and w_{ui} are wages paid to skilled and unskilled workers respectively in city i. Notice that

$$\frac{w_{ui}u_i + w_{ei}e_i}{w_{ui}u_i} = 1 + \frac{1-\sigma}{\sigma} m_i^{\xi} \equiv \chi_i,$$

so that

$$w_{ei} = (1-\sigma)\sigma^{1/\xi-1}(1-\alpha)\phi w_i \chi_i^{1/\xi-1} m_i^{\xi-1}$$

where w_i is interpreted as the implicit wage for the composite labor input, n_i, and $m_i = e_i/u_i$. Substituting for composite wages using (15), we have the version of our key estimation equation incorporating skilled and unskilled labor:

$$\frac{w_{ei}}{w_{ej}} = \frac{z_i}{z_j} \left[\frac{p_i}{p_j}\right]^{\frac{\delta-1}{\delta(1-\alpha)}} \left[\frac{q_i}{q_j}\right]^{\frac{1}{\delta(1-\alpha)}} \left[\frac{\chi_i}{\chi_j}\right]^{1/\xi-1} \left[\frac{m_i}{m_j}\right]^{\xi-1}. \tag{19}$$

Equation (19) reduces to equation (15) if $\xi = 1$, that is if unskilled and skilled labor are perfect substitutes.

4 Econometric Strategy

This section describes how we estimate the parameters of our model, in particular the net agglomeration effect coefficient, δ. To begin, take logs of equation (19) and rearrange terms:

$$\begin{aligned} \ln(w_{ei}) - \ln(w_{ej}) &= \frac{\delta-1}{\delta(1-\alpha)}\left[\ln(p_i) - \ln(p_j)\right] + \frac{1}{\delta(1-\alpha)}\left[\ln(q_i) - \ln(q_j)\right] \\ &\quad + \frac{1-\xi}{\xi}\left[\ln(\chi_i) - \ln(\chi_j)\right] + (\xi-1)\left[\ln(m_i) - \ln(m_j)\right] \\ &\quad + \ln(z_i) - \ln(z_j) \end{aligned}$$

At all points in time, this equation holds for any two cities i and j. Therefore, it must also hold for city i and the average of the $j = 1, \ldots, N$ cities. Define a "hat" over a

variable for city i to mean the difference of the log of that variable and the average of the same logged variable for all j cities in a sample, for example

$$\hat{w}_{ei} \equiv \ln(w_{ei}) - \frac{1}{N}\sum_{j=1}^{N} \ln(w_{ej}).$$

It follows that

$$\hat{w}_{ei,t} = \frac{\delta - 1}{\delta(1-\alpha)}\hat{p}_{i,t} + \frac{1}{\delta(1-\alpha)}\hat{q}_{i,t} + \frac{1-\xi}{\xi}\hat{\chi}_{i,t} + (\xi - 1)\,\hat{m_{i,t-1}} + \hat{z}_{i,t}. \tag{20}$$

Equation (20) holds at all dates.

We have direct observations on all variables in this equation except for $\hat{z}_{i,t}$. The model tells us that $\hat{z}_{i,t}$ and the other right hand side variables are correlated. So, to estimate the structural parameters δ, α, and ξ we must use an instrumental variables approach. If we had one wave of data, we would need to argue for an instrument that is correlated with the observable variables and uncorrelated with the $\ln(\hat{z}_{i,t})$ term. This is the econometric approach adopted by Ciccone and Hall (1996). Since we have access to a long panel, we use a different estimation strategy.

We exploit the panel nature of our data by making an explicit assumption about the stochastic process driving exogenous neutral technology in the model. In particular, we assume the stationary component in (11) is the sum of two random variables, one which is a city-specific first-order auto-regressive process, and one which is common to all cities, but we do not specify explicitly. This second term is included to make it clear that our analysis is consistent with there being aggregate uncertainty in the model. For every city i, $\ln(z_{i,t})$ evolves according to:

$$\begin{aligned} \ln(z_{i,t}) &= \ln(z_{i,0}) + \gamma t + \ln(\tilde{z}_{i,t}) + u_t; \\ \ln(\tilde{z}_{i,t}) &= \rho \ln(\tilde{z}_{i,t-1}) + e_{i,t}, \end{aligned}$$

where γ is the deterministic rate of growth from (11), $-1 < \rho < 1$, u_t is the economy-wide stationary part of technology, and $e_{i,t}$ is a city-specific i.i.d. shock that is orthogonal to all variables dated $t-1$ and earlier. Both γ and ρ are assumed to be common to all cities. The variable $z_{i,0}$ is the initial level of neutral technology specific to city i.

We now use our assumption on the evolution of $\ln(\tilde{z}_{i,t})$ to manipulate (20) into an equation with an unobserved variable that is uncorrelated with all variables from

previous years. This forms the basis of our instrumental variables estimation. Let $\hat{z}_{i,t}$ denote the deviation of $ln\hat{z}_{i,t}$ from its cross-section average. Notice that $\hat{z}_{i,t}$ eliminates both the growth term and the economy-wide stochastic term. It follows that

$$\hat{z}_{i,t} - \rho\hat{z}_{i,t-1} \quad = \quad (1-\rho)\,\hat{z}_{i,0} + \epsilon_{i,t}, \tag{21}$$

where $\epsilon_{i,t} = [e_{i,t} - \bar{e}_t]$ with $\bar{e}_t$ equal to the average value of $e_{j,t}$ for all j cities in the sample in period t. Now, from each variable in equation (20) subtract ρ times its once-lagged value. This is a valid operation since equation (20) holds at all dates. Then, using equation (21) we have

$$\begin{aligned} \hat{w}_{ei,t} \quad = \quad & \hat{z}_{i,0} + \rho\hat{w}_{ei,t-1} + \frac{\delta-1}{\delta(1-\alpha)}\left[\hat{p}_{i,t} - \rho\hat{p}_{i,t-1}\right] + \frac{1}{\delta(1-\alpha)}\left[\hat{q}_{i,t} - \rho\hat{q}_{i,t-1}\right] \\ & + \frac{1-\xi}{\xi}\left[\hat{\chi}_{i,t} - \rho\hat{\chi}_{i,t-1}\right] + (\xi-1)\left[\hat{m}_{i,t} - \rho\hat{m}_{i,t-1}\right] + \epsilon_{i,t}. \end{aligned} \tag{22}$$

To make further progress on estimating ρ, δ, α, and ξ, we need to find a set of instruments that are correlated with the wage, price, and skill variables and are uncorrelated with $\epsilon_{i,t}$. Finding valid instruments for equation (22) is straightforward because $\epsilon_{i,t}$ is an i.i.d. shock; any variable dated $t-1$ or earlier is potentially a valid instrument. In addition, we need to eliminate the unobserved variable $\hat{z}_{i,0}$. This variable is a "fixed effect" in the sense that it varies across cities, but is fixed over time in each city.

Several strategies have been proposed to handle the city-level fixed effect. The most common one involves eliminating the fixed effect by taking first differences. A second strategy that has been proposed is to assume that the level of the fixed effect, $\hat{z}_{i,0}$, is uncorrelated with the first-differences of all model variables. The application of this method to our case would involve using equation (22) with lagged growth rates of model variables as instruments. A third strategy, which is more powerful and consequently has been widely used, combines the first two strategies. This approach was originally proposed by Blundell and Bond (2000). We are uncomfortable assuming that the fixed effect is uncorrelated with lagged changes of model variables, since we have no theory suggesting this to be the case. Therefore we not use the Blundell and Bond (2000) estimation procedure.

Instead we use a procedure, which, like the first strategy, directly removes the city-level fixed effects. When more waves of data are available than are the minimum

necessary to implement the first strategy, taking first-differences does not use all the available information on the fixed effect and so is inefficient. Consequently we use the estimation procedure proposed by Arellano and Bover (1995) which takes advantage of the additional information on the fixed effects which comes with long panel data.

In this approach, each time-t variable in equation (22) is expressed as a deviation from the average of all future observations for city i in the sample. For any variable x_t with observations $t = 1, \ldots, T$, define the Arellano-Bover difference operator as of date t, Δ_t, as follows:

$$\Delta_t x_t = \omega_t \left[x_t - \frac{1}{T-t} \sum_{s>t} x_s \right].$$

where

$$\omega_t = \left(\frac{T-t}{T-t+1} \right)^{1/2}.$$

Applying the Arellano-Bover difference operator to (22) yields

$$\begin{aligned} \Delta_t \hat{w}_{ei,t} &= \rho \Delta_t \hat{w}_{ei,t-1} + \frac{\delta - 1}{\delta(1-\alpha)} \left[\Delta_t \hat{p}_{i,t} - \rho \Delta_t \hat{p}_{i,t-1} \right] + \frac{1}{\delta(1-\alpha)} \left[\Delta_t \hat{q}_{i,t} - \rho \Delta_t \hat{q}_{i,t-1} \right] \\ &\quad + \frac{1-\xi}{\xi} \left[\Delta_t \hat{\chi}_{i,t} - \rho \Delta_t \hat{\chi}_{i,t-1} \right] + (\xi - 1) \left[\Delta_t m_{i,t} - \rho \Delta_t \hat{m}_{i,t-1} \right] + \Delta_t \epsilon_{i,t}. \quad (23) \end{aligned}$$

Including the weight term ω_t in Δ_t guarantees that the error term $\Delta_t \epsilon_{i,t}$ in (23) has a constant variance. We use equation (23) to estimate the key structural parameters of our model using the levels of $\hat{w}_{ei,t-s}$, $\hat{p}_{i,t-s}$, $\hat{q}_{i,t-s}$, $\hat{\chi}_{i,t-s}$, and $\hat{m}_{i,t-s}$ for $s = \{3, 4\}$ as instruments. We do not use $s \geq 5$ as instruments because typically they do not add much information. We do not use earlier lags to accommodate classical measurement error in all the variables.

5 Data

We estimate the parameters of the model using three data sources. The exact procedures we use to construct and merge the data are detailed in the data appendix. A brief summary follows here.

Our first data set is a balanced annual panel covering 42 MSAs over the 1985-2004 period. We construct our wage and employment variables – $\hat{w}_{ei,t}$, $\hat{\chi}_{i,t}$, and $\frac{\hat{e_{i,t}}}{u_{i,t}}$ – from the March Current Population Survey (CPS). All workers with at least four years of college are considered as high-skill workers and all other workers are labeled as low skill. We use data from the Bureau of Economic Analysis (BEA) to construct output prices $\hat{q}_{i,t}$ by MSA. Specifically, we create a price index for output that varies by MSA by merging annual data on income earned by industry by MSA from the Regional Economic Accounts with price indexes for industry output from the Annual Industry Accounts. Because the mix and intensity of industries varies by MSA, and price indexes vary by industry, the price index for output produced in an MSA will vary across MSAs. Finally, we use data on the price of land in residential use as estimated by Davis and Palumbo (2008) to construct $\hat{p}_{i,t}$. Davis and Palumbo (2008) construct time-series estimates of the price of land for 46 MSAs. Four of the MSAs in their study had to be discarded because of lack of corresponding CPS and BEA data, explaining the dimensions of the panel data in this first data set.

The data on output prices is available from 1969-2006. We normalize the price index for MSA-level output to equal 1.0 in every MSA in 1969. This arbitrary normalization introduces another MSA-level fixed effect that is differenced-out by the Arellano and Bover (1995) procedure. The first year of data for both the CPS and the Davis and Palumbo (2008) data is 1985.[3] The CPS data are available through 2006, but the last year of Davis and Palumbo (2008) data is 2004, explaining the range of the sample. The CPS and BEA data are annual. The Davis and Palumbo (2008) data are quarterly; we set the annual estimate equal to the average of the reported quarterly values.

Our second data set is a balanced annual panel covering 149 MSAs over the 1985-2006 period. As with the first data set, we use annual CPS data to construct $\hat{w}_{ei,t}$, $\hat{\chi}_{i,t}$, and $\frac{\hat{e_{i,t}}}{u_{i,t}}$ variables and data from the BEA to construct output prices $\hat{q}_{i,t}$. We combine micro-level data from the 1990 Decennial Census of Housing (DCH) with price indexes for existing homes from the Office of Federal Housing Enterprise Oversight (OFHEO) to compute estimates of the price of housing, by MSA, over the 1985-2006 period. We use the data from the 1990 DCH to estimate the level of house prices by MSA in 1990,

[3] The CPS identifies only 15 metropolitan areas in prior years.

and then use the OFHEO price indexes to extrapolate the price level backwards to 1985 and forwards to 2006. After dropping MSAs with incomplete or missing wage, employment, output price or house price data, we are left with 149 MSAs, including all of the 42 MSAs covered in the first data set.

Our third and final data set is balanced annual panel covering 83 MSAs over 4 years. As before, the data on output prices is from the BEA. All other variables on wages, employment, and house prices are taken from the 1970, 1980, 1990, and 2000 DCH.

Why three data sets? The first data set is exactly consistent with the model. We use the second data set (house prices rather than land prices) for two reasons: By using house-price data, we extend the sample by two years and more than triple the sample of MSAs from 42 to 149. Related, because we have many more MSAs in the sample, this data set includes the experiences of MSAs with relatively small populations that are largely excluded from the Davis and Palumbo (2008) data. We use the third data set (the DCH data) because it includes the experiences of MSAs prior to 1985. Also, since the DCH data are used to construct the wage and employment variables, sample sizes are much larger than in the first two data sets that use the CPS data to construct these data.

Table 1 summarizes the key variables in each of our three data sets. Given the definition of the hatted variables as deviations from the average, the sample average of all variables is zero in every year. Therefore, in table 1 we report standard deviations. Since the variables are in logs, the standard deviations we report have the interpretation of cross-sectional percent standard deviations of the levels. In every data set, output prices are least dispersed, land/house prices are most dispersed, and high-skill wage rates are less dispersed than the inverse of the share of labor income accruing to unskilled workers which are less dispersed then high-low skill ratios. Table 2 shows more details, specifically the standard deviations of all variables by year. This table enables a full comparison of the data over time (within data sets) and across data sets at a point in time. In every data set, wages paid to high-skill workers have become more dispersed over time and the price of land/housing has also become more dispersed over time.[4] Wages are more dispersed and house prices are less dispersed

[4]Output prices have become more dispersed over time, but this may be due to our normalization

in our second data set than in our first data set.

6 Results and Analysis

Table 3 reports our parameter estimates and standard errors for equation (**??**) from our first two data sets. Standard errors are computed using the "delta" method. Column (1) reports the estimates for the first data set – the data set with land prices – when all parameters are unrestricted in the estimation procedure. When our estimation algorithm runs unrestricted, we estimate that capital's share of output is negative, which is infeasible. In column (2), we report estimates for the parameters of the model after forcing α to exactly equal 0.30. Columns (3) and (4) are identical to columns (1) and (2), except that in these columns we report the estimates for the second data set (house prices). Columns (5) and (6) report estimates for the second data set, and for α set to 0.30, but with the sample restricted: In column (5), we only consider the 42 MSAs used in the first data set, but over the entire 1985-2006 sample period. We use the same sample in column (6) as column (5), but with the time period restricted to be 1985-2004, the identical time period as the first data set.

7 Conclusions

TBD

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A Data Appendix

In this appendix, we document how we construct key variables from our various data sources (section A.1) and then document how we merge our different data sources together to create our three data sets for estimation (section A.2).

A.1 Data Sources

A.1.1 CPS Data (Wages and Hours Worked by Skill)

The March CPS data are available for download at *http://cps.ipums.org/cps/* as part of the Integrated Public Use Microdata Series (IPUMS-CPS) project at the University of Minnesota Population Center: See King et al. (2004).

We download the March CPS data from 1986 through 2007. We chose 1986 as our starting year because the CPS identifies only 15 metropolitan areas in prior years. The CPS wage and employment questions refer to the "previous calendar year." Therefore, data for any given year's CPS is treated as data appropriate for the previous calendar year. For example, variables generated from the March 2005 CPS would be treated as data for the year 2004.

In each year of our data, we use the following criteria to restrict the sample (with IPUMS-CPS variables in italics)

- Respondent lives in a household, not in group quarters or vacant units ($gq = 1$)
- Is aged 20 to 65 ($age \geq 20$ and $age \leq 65$)
- Wage and salary income in the previous calendar year is identified and is nonzero ($incwage > 0$ and $incwage < 999998$)
- Educational attainment is recorded ($educrec \geq 1$ and $educrec \leq 9$)
- Has an identified metro area of residence ($metarea$ non missing)[5]

For each MSA, we create the following three variables:

1. Ratio of labor input of high skill to labor input of low skill, e_i/u_i
2. Ratio of total wages paid to total wages paid to low skill workers, χ_i
3. Average weekly wage of high skill workers, $w_{e,i}$.

We use the *educrec* categorical variable to label respondents as either "low" or "high" skill workers. High skill workers are assumed to have completed 1+ years of college. Everyone else in the sample is assumed to be a low skill worker.

e_i is created as the total of weeks worked the previous calendar year ($wkswork1$) multiplied by the number of hours per week the respondent usually worked ($uhrswork$) for high skill workers. u_i is created as the same product, but for low skill workers.

[5]According to notes from the IPUMS-CPS, the metro area of residence was not collected from respondents, but added by the Census Bureau. The metro areas of residence is based on FIPS codes used in the 1990 census.

For each respondent, we weigh the product of $wkswork1$ and $uhrswork$ using the IPUMS-CPS sampling person weights, $perwt$.

χ_i is computed as

$$\frac{w_{e,i}e_i + w_{u,i}u_i}{w_{u,i}u_i} = \frac{\sum_{j\epsilon MSA_i} perwt_j \cdot wages_j}{\sum_{j\epsilon MSA_i} perwt_j \cdot wages_j \cdot 1\{unskilled_j\}}$$

for respondent j in MSA i, i.e. as the sum of all workers' pre-tax wage and salary income for the previous calendar year ($incwage$) divided by the sum of all low skill workers' pre-tax wage and salary income for the previous calendar year. We weigh pre-tax wage and salary income for all persons using the IPUMS-CPS sampling person weights.

$w_{e,i}$ is created as the sum of all high skill workers' pre-tax wage and salary income for the previous calendar year (created as an input into χ_i) divided e_i.

A.1.2 BEA Data (Output Prices)

We use two data sources from within the BEA web site: The Annual Industry Accounts, *http://www.bea.gov/industry/index.htm#annual*, and the Regional Economic Accounts data on Local Area Personal Income, *http://www.bea.gov/regional/reis/*.

Chain-type price indexes for industry output are available over the 1947-2007 period in the Annual Industry Accounts. Many industry price indexes are missing in 2007, so we do not use data from that year. To construct a price index for output produced by MSA, we merge this information with MSA-level data on earnings by industry that is available in Tables CA05 and CA05N of the Regional Economic Accounts. Earnings is inclusive of wage and salary disbursements, supplements to wages and salaries, and proprietors' income.

Thus, we assume that the price of output varies across MSAs because that industry composition varies across MSAs, and the price index for industry output varies across industries.

Denote $g_{t,j}$ as the growth rate of the price of industry output j from periods t to $t+1$ and g_t^i as the growth rate of the price of all output produced in MSA i between years t and $t+1$. Assuming output from $j = 1, \ldots, N$ industries is produced in MSA

i in year t, we set the growth rate of the price of output produced in MSA i between years t and $t+1$ as

$$g_t^i = \sum_{j=1}^{N} \omega_{t,j}^i g_{t,j}. \tag{24}$$

The weight on each industry, $\omega_{t,j}^i$, is the share of total MSA earnings attributable to earnings of industry j in MSA i in year t:

$$\omega_{t,j}^i = \frac{\epsilon_{t,j}^i}{\sum_{k=1}^{N} \epsilon_{t,k}^i}, \tag{25}$$

where $\epsilon_{t,j}^i$ stands for total earnings of employees in industry j in MSA i during year t. In these computations, we only consider earnings from non-farm private industries. For each MSA, we construct a price index for output, normalized to 1.0 in the year 1969, that is consistent with the sequence of time-series estimates of g_t^i.

Ideally, we would compute the growth rate of the price of output produced in city i between years t and $t+1$ as

$$\sum_{j=1}^{N} \phi_{t,j}^i g_{t,j}, \tag{26}$$

with $\phi_{t,j}^i$ equal to the fraction of the nominal value of output in year t in MSA i that is accounted for by industry j. In an environment in which (a) output in each industry is produced by a set of identical firms all using a Cobb-Douglas combination of capital, labor, and land and (b) the labor-share of output is identical in each industry, assumptions that hold in our model, then industry j's share of nominal GDP in MSA i in year t, $\phi_{t,j}^i$, is equal to its earnings share $\omega_{t,j}^i$, and equations (24) and (26) are equivalent. In these calculations, we assume that proprietors' income are payments to labor.[6]

A few details complicate these calculations.

First, on a somewhat infrequent basis, Tables CA05 and CA05N do not report estimates of earnings for a given industry in an MSA in a given year. In these cases,

[6] In the event that proprietors' income includes some payments to capital, equations (24) and (26) are equivalent as long as capital's share of proprietors' income and the fraction of earnings attributable to proprietors' income are both constant across industries.

we set earnings for this industry-MSA-year cell to zero.[7] Also, some of the industry-MSA-year employment estimates are marked with code E. According to the BEA web site, these estimates "constitute the major portion of the true estimate." In these cases, we assume that the reported estimate is equal to the actual estimate.

Second, the definition of industries in the Regional Accounts is not consistent across years. Table CA05 reports employment based on SIC-industry classifications over the 1969-2000 period and CA05N reports employment based on NAICS industry classifications spanning the years 2001-2006.

We map SIC and NAICS industry employment from Tables CA05 and CA05N to prices from the Annual Industry Accounts according to the tables below. The tables below list all the categories of nonfarm private employment. The sum of the earnings estimates in each of these categories is considered as total nonfarm private earnings, and is used to compute the denominator of equation (25).

Data for Earnings Weights, $w^i_{t,j}$ Regional Accounts Table CA05, 1969-2000		Data for Growth in Prices, $g^p_{t,j}$ Industry Accounts, 1969-2001	
Line	Label	Line	Label
100	Agricultural services, forestry fishing and other	3	Agriculture, forestry, fishing and hunting
200	Mining	6	Mining
300	Construction	11	Construction
400	Manufacturing	12	Manufacturing
500*	Transportation and public utilities less electric, gas, and sanitary services	36	Transportation and warehousing
570	Electric, gas, and sanitary services	10	Utilities
610	Wholesale trade	34	Wholesale trade
620	Retail trade	35	Retail trade
700	Finance, insurance and real estate	50	Finance, insurance, real estate, rental and leasing
800	Services	59	Professional and business services

* See text for details.

[7] The three reasons that are listed for omission are (a) avoid disclosure of confidential information (code D), (b) earnings are less than $50,000 (code L), or (c) data not available for this year (code N). These omissions occur in approximately six percent of industry-MSA-year cells from 1969 to the mid-1990s and about thirteen percent of cells from the mid-1990s through 2006.

Data for Earnings Weights, $w^i_{t,j}$ Regional Accounts Table CA05N, 2001-2005		Data for Growth in Prices, $g^p_{t,j}$ Industry Accounts, 2001-2006	
Line	Label	Line	Label
100	Forestry, fishing, related activities and other	5	Forestry, fishing and related activities
200	Mining	6	Mining
300	Utilities	10	Utilities
400	Construction	11	Construction
500	Manufacturing	12	Manufacturing
600	Wholesale trade	34	Wholesale trade
700	Retail trade	35	Retail trade
800	Transportation and warehousing	36	Transportation and warehousing
900	Information	45	Information
1000	Finance and insurance	51	Finance and insurance
1100	Real estate and rental and leasing	56	Real estate and rental and leasing
1200	Professional, scientific and technical services	60	Professional, scientific and technical services
1300	Management of companies and enterprises	64	Management of companies and enterprises
1400	Administrative and waste services	65	Administrative and waste management services
1500	Educational services	69	Educational services
1600	Health care and social assistance	70	Health care and social assistance
1700	Arts, entertainment and recreation	75	Arts, entertainment and recreation
1800	Accommodation and food services	78	Accommodation and food services
1900	Other services except public administration	81	Other services except government

In all cases except one, there is an exact correspondence of earnings estimates from Tables CA05 and CA05N to prices from the Annual Industry Accounts. For the SIC category of "Transportation and public utilities," line 500 of Table CA05, there is no clean analogous price index in the Annual Industry Accounts. Instead, the Annual Industry Accounts includes separate price indexes for "Transportation and warehousing" and "Utilities." In Table CA05, we therefore separate earnings of the single Transportation and public utilities into earnings in two categories: Earnings from utilities ("electric, gas, and sanitary services", line 570) and earnings from transportation and public utilities less earnings from utilities (i.e. line 500 less line

570).

A.1.3 Davis and Palumbo Data (Land Prices)

Davis and Palumbo (2008) report the quarterly value of land on a typical owner-occupied single-family lot for 46 MSAs over the 1984:4 - 2004:4 period. We directly use their data, but define the annual estimate as the average of the quarterly readings. Davis and Palumbo (2008) estimate the value of land as the market value of housing units less an estimate of the replacement cost of the structure (after accounting for depreciation) – see their paper for details.

A.1.4 OFHEO Data and 1990 Decennial Census of Housing (House Prices)

We create annual estimates over the 1985-2006 period of the average price of single-family owner-occupied housing units, by MSA, using a two-step procedure.

In the first step, we estimate the average price of single-family owner-occupied housing units in 1990 using household-level data from the 1990 Decennial Census of Housing (DCH). These data are available for download at *http://usa.ipums.org/usa/* as part of the Integrated Public Use Microdata Series (IPUMS-USA) project at the University of Minnesota Population Center. We use data from the 1990 DCH, rather than the 2000 Census of Housing, because more 1990 DCH reports more areas.

With IPUMS-USA variables in italics, we restrict the 1990 DCH sample to owner-occupied non-farm households living in single-unit residences in an identifiable MSA ($metarea > 0$, $ownershg = 1$, $farm \neq 1$, and $unitsstr \in \{3, 4\}$) who live in households and do not live in group quarters ($gq \in \{3, 4, 6\}$) and where the reported value of the house is not missing and is nonzero ($valueh > 0$ and $valueh < 999999$). The reported value of housing units, $valueh$, is top-coded at \$400,000 in 1990; we replace this top-coded value with \$662,000, which is the value of housing units worth more than \$400,000 in 1990.[8] Conditional on these restrictions, we compute the weighted average value of units by MSA using the sampling weight variable $hhwt$. These calculations yield estimates of the average price of housing for 272 metro areas as identified

[8]This estimate was first reported by Davis and Heathcote (2007) and is based on proprietary data in the 1989 Survey of Consumer Finances.

in the 1990 DCH.

In the second step, we extrapolate the price of housing in each metro area forward from 1990 to 2006 and backwards from 1990 to 1985 using MSA-specific constant-quality price indexes for owner-occupied single-family existing homes. These price indexes are published by the Office of Federal Housing Enterprise Oversight (OFHEO), until recently the regulator of the Fannie Mae and Freddie Mac organizations, and are available at *http://www.ofheo.gov/hpi_download.aspx*. The reported price indexes are quarterly; we convert to annual using a simple average of the quarterly readings.

For most metropolitan areas, OFHEO reports the price index for the MSA that are given by the list in the November, 2007 report of the Office of Management and Budget,[9] and so the mapping of MSAs from the IPUMS *metarea* variable to the OFHEO *cbsa* variable is one-to-one. For a few of the larger MSAs – Boston, Chicago, Dallas, Detroit, Los Angeles, Miami, New York, Philadelphia, San Francisco, Seattle, and Washington, DC – OFHEO reports the price indexes for metropolitan divisions within the MSA. In these cases, we set the growth rate of house prices of the entire MSA as the simple average of the growth rate of the underlying metropolitan divisions in the MSA.

In the OFHEO data, quite a few MSAs do not have a price index that extend back to 1985. After merging the 1990 DCH with the OFHEO price indexes, and eliminating the MSAs for which price indexes are not available back to 1985, we are left with annual estimates of house prices over the 1985-2006 period for 178 MSAs.

A.1.5 Decennial Data on Wages, Employment, House Prices, 1970-2000

We use decennial IPUMS data from 1970 to 2000 available at *http://usa.ipums.org/usa/*. Specifically, we use the 1% Metro sample for 1970[10], 1980, 1990, and 2000. In each year, we use the same respondent criteria as with the March CPS data described in section A.1.1. Note also the added requirement that the respondent is an employed, non-military civilian. The resulting sample restrictions are:

[9] For a complete list of the counties comprising each MSA, go to *http://www.census.gov/population/www/metroareas/metrodef.html*.

[10] The Form 2 version.

- Respondent is aged 20 to 65 ($age \geq 20$ and $age \leq 65$)
- Lives in a household, not in group quarters or vacant units ($gq = 1$)
- Has an identified metro area of residence ($metarea$ non-zero, non-missing)
- Educational attainment is recorded ($educrec \geq 1$ and $educrec \leq 9$)
- Wage and salary income in the previous calendar year is identified and is nonzero ($incwage > 0$ and $incewage < 999998$)
- Is an employed, non-military civilian ($empstatd = 10$ or $empstatd = 12$)

We create the following three variables for each MSA:

1. Ratio of labor input of high skill to labor input of low skill, e_i/u_i
2. Ratio of total wages paid to total wages paid to low skill workers, χ_i
3. Average hourly wage of high skill workers, $w_{e,i}$

We use the *educrec* categorical variable to label respondents as either "low" or "high" skill workers. High skill workers are assumed to have completed 1+ years of college. Everyone else in the sample is assumed to be a low skill worker.

e_i and u_i are the total number of hours worked by skilled and unskilled workers, respectively, in the previous calendar year for MSA i. It is calculated as the sum of hours worked last year (IPUMS variables $uhrswork_j \times wkswork1_j$, i.e. respondent j's usual hours worked last year multiplied by weeks worked last year) weighted by each respondent's sample weight, $perwt_j$. Since the 1970 sample only contains categorical codes for weeks and hours worked (IPUMS variables $wkswork2$ and $hrswork2$), we impute the 1970 values for $uhrswork$ and $wkswork1$ by using the national weighted average of $uhrswork$ and $wkswork1$ within each $hrswork2$ and $wkswork2$ category in 1980. For example, if a person belonged to the "50-52 weeks" category in 1970, then that person was assigned the national average among respondents in the "50-52 weeks" category in 1980, which was 51.7945.

The variables χ_i and $w_{e,i}$ are computed using the same proceudre as with the CPS data, described in section A.1.1. The average house price variable was created

from *valueh*, whose top codes have been set to according to the scheme in Davis and Heathcote (2007):

- 2000: replace \$999,998 with \$1,860,000
- 1990: replace \$400,000 with \$662,000
- 1980: replace \$200,000 with \$350,000
- 1970: replace \$50,000 with \$87,500

In addition, for consistency in the *valueh* variable across years, we include only single-family housing units ($unitsstr = 3$ or $unitsstr = 4$).

A.2 Merging the Data

A.2.1 Annual Data Set with Land Prices, 1985-2004

Our first data set we use in estimation contains annual data with land prices over the 1985-2004 period. To create this data set, we merge the CPS data on wages and employment (section A.1.1) with the BEA data on output prices (A.1.2) and the Davis and Palumbo (2008) data on land prices (section A.1.3), which yields annual data on 42 MSAs.[11] In every MSA and date, the minimum number of respondents from the CPS is never less than 100. The median number of respondents is about 420 until about 2000, at which point the median jumps to about 650. The maximum number of respondents is typically over 4,000.

We merge these data by MSA. Note that the MSA definitions may not be completely consistent. In the BEA data, MSAs definitions are given by the list in the November, 2007 report of the Office of Management and Budget.[12] The MSA definitions in the CPS data are consistent with the definitions as of the 1990 Census. The Davis and Palumbo (2008) data are created by merging data from various sources, and

[11] We discard information on four areas reported by Davis and Palumbo (2008) because information on these areas is not available in the CPS.

[12] For a complete list of the counties comprising each MSA, go to *http://www.census.gov/population/www/metroareas/metrodef.html*.

the MSA definition of one of the key sources (data from the R.S. Means corporation) is not known.

A.2.2 Annual Data Set with House Prices, 1985-2006

Our second data set we use in estimation contains annual data with house prices over the 1985-2006 period. To create this data set, we merge the CPS data on wages and employment (section A.1.1) with the BEA data on output prices (A.1.2) and the annual data we construct on house prices by merging the OFHEO price indexes with information on house prices in the 1990 Decennial Census of Housing (section A.1.4). After all data are merged, we are left with a balanced panel of 146 MSAs.

Since we include many more relatively small MSAs in our sample than the first data set described in the previous section (A.2.1), the typical number of observations we use to compute our wage and employment variables is lower than the first data set. Across our 146 MSAs, the median number of observations in the CPS data is about 130 until about the year 2001, at which point the median number of observations jumps to approximately 170.[13] Until 2001, about 12 percent of our MSAs (around 18 MSAs) have less than 50 observations per year in the CPS data; after 2001, only 4 percent of our MSAs (6 MSAs) have less than 50 observations per year.

All data files are merged by MSA, and the caveat from the previous section – that the MSA definitions may not be completely consistent across data sets – applies.

A.2.3 Decennial Data Set with House Prices, 1970-2000

Our third data set in estimation contains data from the 1970, 1980, 1990, and 2000 Decennial Census of housing on wages, employment, and house prices. To create this data set, we merge the Decennial Census data on wages, employment, and house prices (section A.1.5) with the BEA data on output prices (A.1.2). After all data are merged, we are left with a balanced panel of 83 MSAs. As noted earlier, the MSA definitions from the Decennial Census files may not be completely consistent with the

[13] About 35 percent of our MSAs have more than 200 CPS observations in any year up through 2001; after 2001, the fraction of MSAs with more at least 200 CPS observations in any year rises to 45 percent.

MSA definitions from the BEA data.

Table 1: Summary of Data

Variable	Standard Deviations: Data Set 1	Data Set 2	Data Set 3
$\hat{w}_{ei,t}$	0.105	0.164	0.096
$\hat{p}_{i,t}$	0.961	0.406	0.319
$\hat{q}_{i,t}$	0.053	0.072	0.051
$\hat{\chi}_{i,t}$	0.195	0.288	0.135
$\frac{\hat{e_{i,t}}}{u_{i,t}}$	0.255	0.399	0.281

Data set 1:
Annual data, 1985-2004, 42 MSAs: $\hat{w}_{ei,t}$, $\hat{\chi}_{i,t}$, $\frac{\hat{e_{i,t}}}{u_{i,t}}$ from CPS, $\hat{p}_{i,t}$ from Davis and Palumbo (2008), $\hat{q}_{i,t}$ from BEA.

Data set 2:
Annual data, 1985-2006, 149 MSAs: $\hat{w}_{ei,t}$, $\hat{\chi}_{i,t}$, $\frac{\hat{e_{i,t}}}{u_{i,t}}$ from CPS, $\hat{p}_{i,t}$ constructed from 1990 DCH and OFHEO house price indexes, $\hat{q}_{i,t}$ from BEA.

Data set 3:
Decennial data, 1970-2000, 83 MSAs: $\hat{w}_{ei,t}$, $\hat{\chi}_{i,t}$, $\frac{\hat{e_{i,t}}}{u_{i,t}}$, $\hat{p}_{i,t}$ from 1970-2000 DCH, $\hat{q}_{i,t}$ from BEA.

Table 2: Standard Deviations of the Data by Year

	Data Set 1:					Data Set 2:					Data Set 3:				
year	$\hat{w}_{ei,t}$	$\hat{p}_{i,t}$	$\hat{q}_{i,t}$	$\hat{\chi}_{i,t}$	$\frac{\hat{e_{i,t}}}{u_{i,t}}$	$\hat{w}_{ei,t}$	$\hat{p}_{i,t}$	$\hat{q}_{i,t}$	$\hat{\chi}_{i,t}$	$\frac{\hat{e_{i,t}}}{u_{i,t}}$	$\hat{w}_{ei,t}$	$\hat{p}_{i,t}$	$\hat{q}_{i,t}$	$\hat{\chi}_{i,t}$	$\frac{\hat{e_{i,t}}}{u_{i,t}}$
1970											0.087	0.214	0.003	0.194	0.322
1980											0.080	0.288	0.041	0.139	0.265
1985	0.080	1.078	0.043	0.171	0.294	0.144	0.327	0.056	0.231	0.407					
1986	0.097	1.063	0.039	0.194	0.292	0.152	0.350	0.050	0.232	0.399					
1987	0.085	1.074	0.043	0.180	0.281	0.161	0.380	0.055	0.254	0.415					
1988	0.105	1.155	0.042	0.184	0.286	0.151	0.407	0.055	0.258	0.418					
1989	0.101	1.201	0.042	0.188	0.301	0.158	0.428	0.054	0.249	0.416					
1990	0.098	1.210	0.042	0.162	0.240	0.144	0.428	0.055	0.240	0.392	0.101	0.416	0.052	0.099	0.273
1991	0.103	1.162	0.042	0.198	0.280	0.140	0.413	0.055	0.280	0.430					
1992	0.103	1.069	0.043	0.177	0.243	0.137	0.398	0.056	0.272	0.409					
1993	0.087	0.979	0.045	0.188	0.250	0.147	0.381	0.059	0.267	0.372					
1994	0.092	0.906	0.046	0.193	0.250	0.142	0.362	0.061	0.296	0.403					
1995	0.116	0.866	0.048	0.212	0.256	0.191	0.352	0.063	0.295	0.394					
1996	0.114	0.841	0.051	0.189	0.227	0.188	0.343	0.067	0.295	0.392					
1997	0.120	0.829	0.053	0.202	0.253	0.170	0.342	0.070	0.321	0.442					
1998	0.120	0.809	0.055	0.191	0.236	0.169	0.348	0.072	0.343	0.435					
1999	0.109	0.813	0.059	0.216	0.255	0.168	0.362	0.077	0.299	0.407					
2000	0.134	0.830	0.065	0.242	0.252	0.193	0.392	0.084	0.337	0.442	0.115	0.330	0.078	0.081	0.265
2001	0.116	0.823	0.067	0.202	0.204	0.190	0.411	0.087	0.307	0.386					
2002	0.090	0.830	0.070	0.192	0.220	0.154	0.428	0.090	0.268	0.352					
2003	0.129	0.834	0.073	0.232	0.263	0.184	0.446	0.094	0.285	0.360					
2004	0.112	0.860	0.075	0.215	0.244	0.172	0.485	0.097	0.300	0.367					
2005						0.163	0.531	0.100	0.314	0.363					
2006						0.185	0.548	0.102	0.361	0.382					

Table 3: Parameter Estimates (Standard Errors in Parentheses)

	Data Set 1:		Data Set 2:			
					42 MSAs	42 MSAs
	42 MSAs, 1985-2004		149 MSAs, 1985-2006		1985-2006	1985-2004
Parameter	Unrestricted	$\alpha = 0.30$	Unrestricted	$\alpha = 0.30$	$\alpha = 0.30$	$\alpha = 0.30$
	(1)	(2)	(3)	(4)	(5)	(6)
ρ	0.491	0.568	0.376	0.543	0.591	0.514
	(0.023)	(0.021)	(0.032)	(0.027)	(0.017)	(0.022)
α	-0.066		-0.492			
	(0.120)		(0.244)			
δ	1.026	1.012	1.106	1.075	1.037	1.072
	(0.007)	(0.004)	(0.045)	(0.022)	(0.011)	(0.015)
ξ	0.590	0.550	0.655	0.683	0.590	0.578
	(0.005)	(0.005)	(0.014)	(0.016)	(0.005)	(0.005)
J-test	57.892	58.190	115.609	116.117	61.225	58.914
p-value	1.000	1.000	0.999	0.999	1.000	1.000
d.o.f.	146	147	166	167	167	147