Innovation Spillovers in Industrial Cities

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ABSTRACT

Older, industrial cities have suffered with the shift from manufacturing to services, but the increased importance of innovation as an economic driver may help industrial cities, which are often rich in the institutions that generate innovation. This paper studies how innovation is related to wages for different types of workers (e.g. more-educated versus less, and younger versus older) and to real estate prices for cities. We also study industrial and occupational employment shares. Our estimates indicate that innovation and aggregate education are associated with greater productivity in cities. They indicate that innovation and aggregate education impact wages less in industrial cities, but that they impact real estate prices more. We also find greater effects of innovation and aggregate education for more-educated and prime-aged workers. We pay particular attention to controlling for causality and adjustments of factor inputs.

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I. Introduction

Manufacturing's share of employment peaked in the middle of the 20th century. As service jobs replaced manufacturing jobs, many industrial cities experienced large, protracted declines. Now innovation is increasingly driving regional economic growth, with innovations spilling over to local firms. The shift to an innovation-driven economy is significant for older, industrial cities because innovation cuts across industrial sectors. For example, the big three car companies in Detroit are all among the top patent assignees in the United States. Moreover, many major scientific research institutions were founded by industrialists and are located in industrial cities – Baltimore, Cleveland, Pittsburgh, and St. Louis are all homes to major research hospitals and universities. Because local firms are often best positioned to exploit recent innovations, the emerging innovation-based economy may mark a turning point for industrial cities. This possibility has not been lost on policy makers (e.g. Pianalto [2006]), but it has not been examined in the scholarly literature.

This paper studies the prospects of industrial cities in the new innovation-based era. We study how wages and real estate prices vary across cities and change over time as functions of academic and industrial innovation, measured by academic R&D and patenting per capita. We also consider aggregate education, measured by the college graduate populations share. Analyzing the effect of innovation on older, industrial cities is critical because they differ markedly from the cities that have relied most conspicuously on innovation for growth (e.g. San Francisco, Boston, Austin, and the

Research Triangle[1]) in terms of growth trends, demographics, and sectoral composition. Our analysis addresses these three differences.

We estimate local productivity spillovers from innovation from the relationship between wages and real estate prices and measures of innovation that vary across cities and over time, which poses two formidable challenges. First, innovation intensive cities may differ from those where little important innovation occurs in ways that are not observed to the researcher. We refer to this challenge as *unobserved differences in cities*.

A second concern is the adjustment of factor inputs. If innovation (or other features of a city) raise productivity, firms will locate there and the city will expand. Disentangling the direct effects of innovation and aggregate education on productivity from the indirect effects through factor input utilization without explicit data on inputs and output, requires a formal framework.[2] It is particularly important to address factor input adjustment when studying older, industrial cities because many of them have large stocks of real estate that are inelastically supplied (see Glaeser and Gourko [2005]).

To address these concerns, we develop a simple, formal model of wage and rental rate determination in the presence of production and consumption amenities and varying real estate supply elasticities, a topic of recent interest (e.g. Glaeser, Gyourko, and Saks [2005]; Saks [2008]; and Saiz [2010]). Our model provides reduced-form implications that enable us to address factor input adjustment. It indicates that a sufficient condition to conclude that innovation and aggregate education raise productivity is that both wages and real estate costs are non-decreasing in innovation and aggregate education and that at

[1] For discussions, see Dorfman [1983]; Saxenian [1996]; Feldman and Desrochers [2003]; Zucker, Darby, and Brewer [1998]; and Bauer, Schweitzer, and Shane [2006].
[2] Henderson [2003] estimates the effect of agglomeration on productivity directly but, as Rosenthal and Strange [2004] argue, this approach has a number of limitations, including strong data requirements.

least one of them is increasing. Our model indicates that if the supply of real estate is less elastic in industrial cities then innovation and aggregate education should have a larger effect on real estate prices but a smaller effect on wages in industrial cities than in other cities. Lastly, our model provides a formal framework for thinking about how unobserved differences across cities are likely to bias estimates of the effects of innovation and aggregate education.

Our estimates indicate that innovation and aggregate education are associated with both higher wages and higher real estate prices in cities, indicating that innovation and aggregate education increase productivity. In keeping with our model, we find that innovation and aggregate education impact wages less in industrial cities, but that they impact real estate prices more. To address unobserved heterogeneity across cities, we employ two strategies. We begin by including metropolitan area fixed effects, which will eliminate time-invariant differences across cities in innovation and aggregate education that may be correlated with wages and real estate prices. We then turn to instrumental variables, exploiting historic variations across metropolitan areas in both scientific research and university enrollments. To instrument for academic R&D, we develop a share-shift index that interacts initial variations in the types of research performed in different metropolitan areas with national trends in funding by field. To instrument for patenting, we use data on the locations where highly-cited papers were published between 1900 and 1945. To instrument for the population share of college graduates, we use data on enrollments at colleges and universities in 1925. Deep lags are often used as instruments and seem well justified in this context. As discussed, many research institutions were established during industrialization and are located in industrial cities.

Insofar as our economic outcomes cover a period of de-industrialization, and many of the areas where research institutions were founded during industrialization have experienced adverse shocks during deindustrialization, our estimates will, if anything, be conservative, but our instrumental variables estimates are frequently in the middle of our other estimates.

A substantial amount of innovation occurs in or around universities, and these universities also produce students that may themselves generate substantial spillovers (e.g. Moretti [2004a]). Thus, it is important to distinguish the effects of innovation from those of a highly-educated population, which we do by including controls for the share of the population that completed college (which we refer to as the college graduate population share and aggregate education).

This paper relates to a small literature on the benefits of innovation that obtains mixed results. Beeson and Montgomery [1993] find that university research is weakly related to wages, employment, and migration (although it is related to the probability of being employed in a knowledge occupation or industry). Bania, Eberts, and Fogarty [1993] find mixed evidence for the relationship between university research and startups in high-technology industries. By contrast, Zucker, Darby, and Brewer [1998] find a strong relationship between biotechnology startups and the presence of star scientists. Carlino and Hunt [2009] find a relationship between patenting and academic research and development. Bauer, Schweitzer, and Shane [2006] find that the local knowledge foundation, as measured by patenting and the education distribution, are key determinants of long-run growth. Lastly, Saha [2008] finds a strong relationship between academic R&D and income, controlling for education variables. There are also more distantly related bodies of work emerging on human capital spillovers and agglomeration economies (Rosenthal and Strange [2004] and Moretti [2004b] provide reviews and individual studies include Rauch [1993]; Glaeser and Mare [2001]; and Shapiro [2006]).[3]

We contribute to this work in two ways. First, we focus specifically on the extent to which innovation can revive industrial cities. Second, we pay close attention to causality and factor input adjustments, which have received little attention in existing work on the local economic impacts of innovation. We do this by developing a theoretical framework that specifically addresses differences between cities and factor input adjustments (see Glaeser, Gyourko, and Saks [2006] for an alternative approach).

As indicated, many industrial cities have less-educated and older workforces than the cities known for their knowledge economies. We explore models that allow for the effects of innovation and aggregate education to vary with a person's education and age. These models show the largest effects for more educated and middle-aged workers.

It is worth stating at the outset that our analysis only captures the economic spillovers from innovation that accrue differentially to the local economy. Presumably, the majority of the benefits of innovation accrue to consumers across the country and world. Other spillovers likely flow across local, state, and national boundaries. Still, there are reasons to believe that recently-produced, tacit knowledge diffuses geographically, having large benefits for the local economy. Similarly, academic R&D may benefit the local economy by improving student training, providing experts to industry, building infrastructure, including equipment and facilities, or providing a hub for industrial

[3] There is also a line of work that seeks to estimate knowledge spillovers from geographic concentration of patents (see Jaffe, Trajtenberg, and Henderson [1993] and Thompson and Fox-Kean [2005]) or the geographic concentration of industries (Glaeser, Kallal, Scheinkman, and Schleifer [1992] and Glaeser and Ellison [1997]).

innovation. Our estimates only capture the effects on the local economy over and above those experienced in other parts of the country. Our focus on the differential local benefits should not be taken as an indication that we believe that all or even most of the benefits of innovation accrue locally. Yet, to the extent that a large portion of the benefits accrue more broadly, our estimates will be a lower bound on the benefits of innovation. At the same time, these estimates are relevant for local authorities considering investing in innovation.

Theoretical Framework

This section sketches a simple model to illustrate how changes in productivity affect wages and real estate prices in older, industrial cities versus newer, non-industrial cities. We also use our model to think about how factor input utilization impacts our estimates and the extent to which we can make rigorous statements about how innovation and aggregate education are related to productivity.

To illustrate how innovation and aggregate education in cities will affect wages and rental rates of real estate, we develop a general equilibrium model of the labor and real estate markets in a city.

Let w denote the (nominal) wage and r^R give the rental rate of real estate in a city. We assume that each worker works for 1 unit of time, earning w and consumes 1 unit of real estate, paying r^R. To capture differences in amenities across cities and differences in the extent to which each worker values those amenities, we assume that a worker's utility depends linearly on consumption and his taste for living in the city, equal to $\theta_0 + \theta_i$, measured as the difference from the best alternative. Here θ_0 gives a common component to the amenity level in the city and θ_i, an individual shock, which is exponentially distributed with parameter, λ. In this structure, θ_0 denotes the minimum of the taste for living in the city. We model across-the-board changes in the desirability of living in the city from changes in innovation and aggregate education through changes in θ_0. If worker *i* resides in the city she receives utility of $u_i = \theta_0 + \theta_i + w - r^R$.

We assume that there are a unit measure of workers. The supply of labor is determined by the value of θ_i, at which a worker is indifferent between living in the city versus another city, θ^*. Formally, $\theta^* = -\theta_0 - w + r^R$, so the supply of labor to the city is $n^s = \exp\{-\lambda(-\theta_0 - w + r^R)\}$.

Firms are each assumed to hire 1 worker and to require $\alpha \geq 0$ units of real estate. All firms located in the city produce *A* units of output, which sells at a price of 1. Productive effects of innovation and aggregate education enter through *A*. A firm's profits from locating in the city are $\pi = A - w - \alpha r^R$. Free entry of firms drives economic profits to zero, so in equilibrium, $w = A - \alpha r^R$.

In equilibrium, the number of firms and workers in the city must be equal and the supply of real estate must equal the demand. With *n* firms and workers in the city, total real estate demand is $R^D = (1 + \alpha)n$. We specify the real estate supply equation, $R^S = (1 + \alpha)\exp\{\gamma r^R\}$. This specification can capture an elastic supply of real estate (if γ is high) as well as an inelastic supply (if γ is low).

To solve for an equilibrium, we substitute the firms' zero profit condition into the labor supply equation and equate the demand and supply for real estate. Using the conditions for the number of workers and firms and the supply of land, it is possible to show that in equilibrium,

$$r^R = \frac{\lambda(A+\theta_0)}{\gamma+\lambda(1+\alpha)} \tag{1}$$

$$w = \frac{(\gamma+\lambda)A - \alpha\lambda\theta_0}{\gamma+\lambda(1+\alpha)} \tag{2}$$

and that $n = \exp\{\gamma\lambda(\theta_0 + A)/\gamma + \lambda(1+\alpha)\}$.

This solution is intuitive and consistent with exiting work (e.g. Haurin [1980] and Roback [1982]). Increases in A increase wages, the size of the city, and real estate prices. Increases in θ_0 increase the size of the city and real estate prices, but decrease wages.

Figure 1 illustrates the operation of the model. Panels A and B assume low and high elasticities of real estate supply. The solid lines show the contour of the (unit) iso-cost line for firms and the indirect utility function for the marginal worker in a baseline case. The contour of the indirect utility function slope up because any given worker requires higher wages to compensate for higher real estate prices, while the firms' iso-cost line slopes down because higher rents must be offset by lower wages to maintain the same unit costs. The implied equilibrium is given by (a).

We now consider the effect of an amenity that raises productivity in the city. An increase in productivity shifts out the firms' (unit) iso-cost line, as represented by the dashed line. Intuitively, with higher productivity, firms achieve the same unit cost at higher wages and rents. Workers will be attracted to the city. The marginal worker to move to the city will have a lower taste for living in the city than the previous workers and require either higher wages or lower rental rates. The contours of the new marginal worker's indirect utility function are given by the dotted line. In equilibrium, at (b), wages and real estate rental rates are higher than in the original equilibrium (a). With a low elasticity of real estate supply, real estate rental rates increase substantially. Wages increase enough to attract workers and compensate them for higher real estate rental rates.

Panel B shows the equilibrium with a highly elastic supply of real estate. The original equilibrium (a) and the shifted out, dotted iso-cost curve are the same as in panel A. If the supply of real estate is highly elastic, then real estate rental rates increase little relative to the original equilibrium price, which induces more firms and more workers to enter the city than with an inelastic supply of land. With a large number of workers entering, the new marginal worker to live in the city has a much lower taste for living in the city and requires substantially higher wages or substantially lower real estate rental rates to enter. The new equilibrium at (b) has higher wages than the original equilibrium at (a), but only slightly higher real estate rental rates. Not surprisingly, real estate rental rates adjust much less and wages adjust much more when the supply of real estate is highly elastic.

While our model is similar in spirit to Roback's [1982] well-known model, it points to an important limitation of her analysis. Specifically, Roback's analysis is akin to the comparison of the original and new equilibria in the figure, but her model is driven completely from the effects of amenities on productivity and worker utility – technology and utility parameters – with no role for the elasticity of supply of real estate. Any amenity that affects utility or productivity will change the equilibrium, but in Roback's analysis, the implied change in the demand for real estate must equal the change in supply, which imposes strong, arbitrary, and unspecified assumptions about the supply elasticity of real estate. This problem is particularly significant as research increasingly emphasizes a variety of sources of differences in the supply elasticity of real estate across cities.

As indicated, we model older, industrial cities as having less elastic real estate supplies because of sunk investments in real estate. Older, industrial cities have large stocks of housing, with people remaining in them in part because of low housing prices. If demand for housing in these cities falls, prices decline and the housing stock slowly deteriorates. An increase in demand for real estate in these cities drives up prices. In expanding, non-industrial cities, real estate is being developed and is supplied relatively elastically (Glaeser and Gyourko [2005]). Thus, we expect real estate prices to adjust more in response to innovation and aggregate education in older, industrial cities than in younger, non-industrial cities. By contrast, wages are expected to adjust less in older, industrial cities than in younger, non-industrial cities.

Empirical Implications

As indicated, adjustments in factor inputs will impact how productive amenities affect wages and real estate rental rates. Moreover, innovation and aggregate education may affect workers' utility directly (e.g. they may lead to "greener" cities). Fortunately, equations (1) and (2) imply that if innovation or aggregate education are associated with an increase in wages (and no change in real estate rental rates), an increase in real estate rental rates (and no change in wages), or an increase in both wages and real estate rental rates then they must raise productivity. This is a sufficient, but not necessary, test for a productivity increase. If, for instance, innovation or aggregate education are also consumption amenities then they may be associated with lower wages even though they raise productivity.

Our model also provides a structured way of thinking about how unobserved differences across cities will affect the estimated relationship between innovation and aggregate education and wages and real estate prices. These implications are discussed in the next section.

Estimation

To estimate the relationship between innovation and aggregate education and wages and real estate prices, we run reduced-form cross-city regressions. Our models are of the form,

$$\ln w_{cti} = IE_{ct}\beta^W + Z_{ct}\gamma^W + x_{cti}\theta^W + \nu_t^W + \eta_c^W + \varepsilon_{ct}^W + \xi_{cti}^W \qquad (3)$$

$$\ln r_{ct}^R = IE_{ct}\beta^R + Z_{ct}\gamma^R + \nu_t^R + \eta_c^R + \varepsilon_{ct}^R. \qquad (4)$$

Here $\ln w_{cti}$ denotes the log wage of person *i* in city *c* at time *t*; $\ln r_{ct}^R$ denotes the log rental rate in city *c* at time *t*; IE_{ct} denotes the innovation and aggregate education variables in city *c* at time *t*; Z_{ct} denotes other characteristics of city *c* at time *t*; x_{cti} denotes characteristics of person *i* in city *c* at time *t*; and the ν_t, η_c, ε_{ct}, and ξ_{cti}^W denote time, city, city-time, and individual level effects, which can be treated as fixed or random effects. It is worth noting that we estimate our wage equation at the individual level, adjusting our standard errors for the presence of metropolitan area effects. Our data on real estate prices are at the metropolitan area level, so equation (4) is estimated at that level.

Uncontrolled differences in productivity or amenities will bias both $\hat{\beta}^W$ and $\hat{\beta}^R$. If, for instance, universities tend to be sited in places where productivity would otherwise be low (e.g. because of the lower opportunity cost of real estate), both $\hat{\beta}^W$ and $\hat{\beta}^R$ will be biased downward. (The opposite is true if innovation and aggregate education are highest in places where productivity would otherwise be high.) Interestingly, if innovation and aggregate education are highest in places with desirable consumption amenities then $\hat{\beta}^W$ will be biased downward and $\hat{\beta}^R$ upward. (A negative correlation between consumption amenities and IE_{ct} will generate the opposite bias). It is also possible that cities with higher IE_{ct} will attract the most skilled workers. If so, we would expect $\hat{\beta}^W$ to be biased upward ($\hat{\beta}^R$ may also be biased upward, but this bias is less clear).

To address these biases, we estimate (3) and (4) with fixed effects and with instrumental variables. The fixed effects estimates control for time-invariant differences in production and/or consumption amenities across cities, but not time-varying differences, including changes in innovation and aggregate education that are driven by changes in wages or real estate prices.

Instrumental Variables Strategy

To address these time-varying differences across cities, we turn to an instrumental variables strategy, relying on historic variations in innovation and education. We employ three sets of instruments. The first set of instruments is the enrollment rate of students in the metropolitan area in 1925, which was chosen to be late in the establishment of American universities but before the Great Depression and Second World War. Our expectation is that metropolitan areas with higher historic enrollments will have more educated populations in recent years, although the strength of that relationship may vary over time as education levels increase. The second instrument is the number of highly-cited papers published between 1900 and 1945 in each city, which is expected to be associated with higher patenting. Because our sample pools data for three years and the relationship between historic enrollments and important papers and later education levels and patenting may vary over time, we interact these instruments with year dummy variables.

The third instrument is a "share-shift" index for R&D funding. Intuitively, these instruments exploit regional variations in research foci interacted with trends in support for various fields. To illustrate our approach, consider a simple, stylized example with two sectors – information and computing technology and bio-medical technology. The San Francisco Bay area and Boston both have considerable academic R&D, but R&D in San Francisco is more focused on information and computing technology while Boston is more heavily focused on bio-medical technology. An increase in the share of bio-medical R&D will likely raise R&D in the Boston area more than in the San Francisco Bay.

Formally, Let e_{fnt} and e_{fct} denote spending on field *f* in year *t* nationally and in city *c*. Total spending in year *t* in city *c* is $e_{ct} = \sum_f e_{fct}$. Field *f*'s share of all spending in city *c* in year *t* is $s_{f|ct} = \frac{e_{fct}}{e_{ct}} = \frac{e_{fct}}{\sum_f e_{fct}}$. The share shift index starts with the shares in some base year, *t=0*, which we take to be 1973. Then for each city *c* the imputed growth (where 1 equates to no change) in spending between 0 and year *t* is,

$$\frac{e_{ct}}{e_{c0}} = \left(\sum_f s_{f|c0} \frac{e_{fnt}}{e_{fn0}} \right) = \left(\sum_f \frac{e_{fc0}}{\sum_f e_{fc0}} \frac{e_{fnt}}{e_{fn0}} \right) \qquad (5)$$

For each city, the implied growth is a weighted average of the growth in academic R&D spending in each field where the weights for each city correspond to the share of spending in that city in field *f*. We then interact these growth rates with per capital spending in the base year (e_{c0}^{PC}) to get

$$\%\Delta e_{ct} e_{c0}^{PC} = \left(\sum_f s_{f|c0} \frac{e_{fnt}}{e_{fn0}} \right) e_{c0}^{PC} = \left(\sum_f \frac{e_{fc0}}{\sum_f e_{fc0}} \frac{e_{fnt}}{e_{fn0}} \right) e_{c0}^{PC} . \qquad (6)$$

These are our estimates of predicted academic R&D spending, which vary across cities and over time within cities.

Instrumental Variables Estimation

In our individual-level wage regressions, (3) we instrument for the metropolitan area-level innovation and aggregate education variables, IE_{ct}. Our first stage equation contains individual characteristics, x_{cti} and, insofar as there is selection into cities, these characteristics may themselves be endogenous. To address this concern, we estimate the mean of the individual characteristics in city *c* in year *t*, $\bar{x}_{ct}$, and use the deviation of the characteristics from the city-time mean, $\Delta x_{cti} = x_{cti} - \bar{x}_{ct}$ as instruments for x_{cti}. Formally, the first stage equations for our wage regression (3) are of the form,

$$IE_{ct} = H_{ct}\pi^{IE} + Z_{ct}\gamma^{IE} + \Delta x_{cti}\theta^{IE} + \nu_t^{IE} + \eta_c^{IE} + \varepsilon_{ct}^{IE} + \xi_{cti}^{IE} \qquad (7a)$$

$$x_{cti} = H_{ct}\pi^{x} + Z_{ct}\gamma^{x} + \Delta x_{cti}\theta^{x} + \nu_t^{x} + \eta_c^{x} + \varepsilon_{ct}^{x} + \xi_{cti}^{x} \qquad (7b)$$

where H_{ct} denotes the historic instruments. In both (7a) and (7b) the unit of observation is an individual *i* in city *c* at time *t*, with all people in the city in that year being assigned common values for the city-time variables, IE_{ct}, H_{ct}, and Z_{ct}. Instrumenting for x_{cti} with Δx_{cti} eliminates any bias from selective migration and eliminates noise in the predicted values of IE_{ct} generated by the inclusion of individual level variables in the first stage (because in (7a), $\hat{\theta}^{IE} = 0$ by construction). The first stage regressions for the real estate price equation (4) are straightforward because this model is estimated at the metropolitan area-level without individual controls.

Comparison of Estimates from the Different Strategies

The various strategies emphasize different sources of variation in innovation and aggregate education. In particular, the fixed effects estimates place more weight on the high- to middle-frequency variation compared to models without fixed effects, including our instrumental variables estimates. For a given magnitude of change, higher-frequency shocks should have smaller effects on the supply of both labor and real estate, consequently the variations in current "rental rates" should be greater for both. In the case of labor, the wage gives the current "rental rate," so wages should be more affected by higher-frequency variations than lower-frequency variations. Our real estate prices capitalize future rental rates. If the high- to middle-frequency shocks emphasized by the fixed effects estimates are expected to persist, then fixed effects estimates should yield larger estimates than the other strategies for real estate prices.

There may be measurement error in the innovation and aggregate education variables. Insofar as there is time-varying measurement error, fixed effects estimates are likely to suffer most from attenuation bias. On the other hand, the instrumental variables estimates will correct for attenuation bias.

Data

We draw together data from a variety of sources. Our main independent variables are contemporaneous data (for 1980, 1990, and 2000) on innovation and aggregate education. We use historic data as instruments. Our outcomes are wages, which are drawn from the 1980, 1990, and 2000 Censuses and real estate price indexes. Our data draw on and extend Saha [2008].

Main Independent Variables: Contemporaneous Innovation and Aggregate Education Variables

Innovation is measured using academic R&D and patenting within a metropolitan area. We view local academic R&D and patents as related but distinct. While academic R&D may underlie many technological advances, many technological advances do not depend on academic R&D or draw on academic R&D performed outside the local area. Some academic R&D leads to local patents, but other academic R&D generates innovations that are not patentable (or are patented elsewhere). Innovation may also affect outcomes with a lag, but our estimates are more precise when we use contemporaneous measures of innovation. Here and elsewhere we use the term innovation to encompass scientific advances as well as technological innovations and do not make the Schumpeterian distinction between invention and innovation.

Data for academic R&D expenditures for individual colleges and universities are obtained from the National Science Foundation's *Survey of Research and Development Expenditures at Universities and Colleges*. Spending is reported by field (physical sciences, life sciences, math, engineering, geology, psychology, and social science, which includes the humanities) and source (e.g. federal, state, local, and industrial) for 1980, 1990 and 2000.[4] Matching these schools to the Carnegie Classification [2002], about 93% of universities and colleges that have positive R&D are Ph.D. granting research schools, or mining engineering schools.[5] The national observatories and national laboratories, which are large producers of scientific research, are excluded from this sample. R&D is

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[4] A limitation of the data is that it does not include information on subcontracts to other organizations or from other organizations. This is only a problem for subcontracts that are to or from organizations that are outside of the lead institution's metropolitan area.
[5] Metropolitan areas without academic R&D for any institution were imputed to be at the 5th percentile of the distribution of academic R&D per capita.

measured in thousands of dollars. Total R&D from all universities and colleges is 64.3 billion in 1980 rising to 110.5 billion in 1990 and to 158.2 billion in 2000. The data is aggregated to a metropolitan area level by matching the schools to IPUMS metropolitan area codes. The New York, Boston, San Francisco, Chicago, and Los Angeles metros have the most R&D but, not surprisingly, university towns like College Station, TX; State College, PA; Iowa City, IA; Lafayette, IN; and Champaign, IL all have the most R&D in per capita terms.

Data on patents for individual metropolitan areas were generously provided by Mark Schweitzer and Paul Bauer of the Federal Reserve Bank of Cleveland. Patent data was extracted from government patent files. See Bauer, Schweitzer, and Shane [2006] for additional details. Data on the education distribution in cities was estimated from the census.

Historic Instruments for Enrollments, Publications, and Patenting

We have hand-collected data on enrollments in higher education in 1925 from Biennial Survey of Education, 1924-1926. The data is available by school and field. We match schools to their metropolitan areas and aggregate over fields and schools to obtain the total enrollment of a metropolitan area. Tallahassee, Dallas, Los Angeles, Raleigh, and Greensborough had the highest per capita enrollment in 1925. These data are used as instruments for the current share of the population with a college education.

We identify important scientific publications between 1900 and 1945 using Thomson-Reuter's Century of Science, which is the predecessor to the well-known Science Citation Index. The Century of Science contains data on the institutional affiliations of the authors of all articles (but not books) and the cities where those institutions are located. To focus on the most important contributions, we focus on the

250 most cited indexed publications on which at least one author was located in the United States in each year. Multiauthored publications were prorated by author. Cities with more highly cited papers historically are expected to have higher patenting. Our third instrument is the share shift index described above.

Outcomes: Census Micro Data

We measure labor market activities, including earnings and the demographic and sectoral composition of the workforce, using Census data from the Integrated Public Use Microdata Series (IPUMS; see Ruggles; Alexander; Genadek; Goeken; Schroeder; and Sobek [2010]). We use the 1980 1% unweighted metro sample, the 1990 1% weighted sample, and the 2000 1% unweighted sample from IPUMS. These samples were chosen to maximize identification of metropolitan areas. These data contain a range of individual characteristics including education, gender, race, ethnicity, marital status as well as city of residence, earnings, weeks worked and the industry and occupation of employment. The switch from the SIC to the NAISC classification limits our ability to compare industries in 2000 to the earlier years.

The sample is limited to non-institutionalized civilians not currently enrolled in school living in metropolitan areas between age 18 and 65. Earnings are measured in real weekly wages (deflated to 1982-1984=100 dollars). Individuals whose real weekly wages were below 40 dollars and above 4000 are excluded from the sample. Lastly, to ensure that our estimates capture spillover of academic R&D on the local economy, we discard people who are post-secondary teachers or who work in universities or colleges. Our wage sample includes 402,283 individuals in 1980, 441,115 individuals in 1990, and 470,707 individuals in 2000.

The education level in a city may generate spillovers. Our use of micro-data enables us to distinguish spillovers from an educated population from the direct effect of the education of the individuals in a city.

Constant Mortgage Home Price Index Data

We obtain real estate costs using the Constant Mortgage Home Price Index (CMHPI) from Freddie Mac. There are three sources of slippage using these data. First, the ideal measure of real estate costs would include both commercial land and structures. Standard urban theory implies that the costs of residential real estate and commercial real estate are equal at the point where developers are indifferent between using land in residential and commercial uses, but only at that point. Unfortunately, systematic data on commercial real estates prices are not available for the number of cities and years that we study.[6] Second, our data are not on current rental rates, but on sale prices, which capitalize future expectations. As discussed, using prices is likely to have the greatest impact on the fixed effects estimates. Lastly, there are variations in the quality of real estate. The Constant Mortgage Home Price Index is calculated for metropolitan areas on a quarterly basis, with many areas having data back to 1975. The index is calculated using the "repeated sales method", which exploits the change in prices for the same house at two points in time to create a "constant-quality housing price index" [Stephens, et al, 1995]. The data that we are using is the First Quarter index for years 1980, 1990 and 2000, obtained from the MSA-series available on Freddie Mac's website[7].

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[6] For instance the CB Richard Ellis data on commercial real estate prices derived from the work of Torto and Wheaton is available for most categories for only 53 cities and for the last 15 years. Our data date back 35 years and cover 108 metropolitan areas in 1980 rising to 157 in 2000.
[7] For more information and a full description and discussion of the index, see Stephens et al [1995] and http://www.freddiemac.com/finance/cmhpi/.

Other Metropolitan Area Characteristics

We also obtained data on a range of control variables for metropolitan areas like population, crime rates and public school attendance from the *State and Metropolitan Data Set* 1980, 1990 and 2000 from ICPSR. To measure the cost of living in each metropolitan area, we obtained data for utilities, mortgages, and taxes, from the *Places Rated Almanac* of 1972, 1980, 1990 and 2000. We do not include these variables in the estimates we report here because they are likely to be endogenous, but our results are robust to including these variables as controls.

Aggregation

Metropolitan areas are aggregated to Consolidated Metropolitan Statistical Areas (CMSA), New England Consolidated Metropolitan Areas, (NECMA) and Metropolitan Statistical Areas (MSA). The constituent metropolitan areas in CMSAs and NECMAs change from year to year. For consistency, we use the CMSA, NECMA and MSA classification in the *State and Metropolitan Area Data Book 1997-1998* (U.S. Bureau of Census [1998]).

Descriptive Statistics

Table 1 reports descriptive statistics for our wage sample. On average academic R&D spending is $55 per person in 1982-1984 dollars, with a standard deviation of $82. R&D effectively doubles over the period, increasing from $36 in 1980 to $56 in 1990 to $70 in 2000. Patenting is infrequent, with just under .0003 patents per person (roughly 1 patent per 3600 people) with a standard deviation of .0006 patents per person over all years. Patenting increases substantially over time, increasing by 31% between 1980 and 1990 and virtually doubling between 1990 and 2000. Roughly 27% of the workers in the cities in our sample have a college degree, with a standard deviation of 8%. The college graduate population share increases by more than 50% from 21% in 1980 to 27% in 1990 and to 33% in 2000. Lastly, housing prices also increase over time.

It is also worth noting that the innovation and aggregate education variables are relatively weakly correlated with each other. The main exception is academic R&D and the college graduate population share, which frequently have correlations in the range of .25-.4. By contrast the other correlations are beneath .1, frequently considerably lower.

We have also explored the extent to which academic R&D and a large college graduate population share drive patenting. Our estimates are reported in Appendix Table 1 and show that there is a tendency for patenting to be higher in metropolitan areas with higher academic R&D. Based on the random effects and fixed effects estimates, a 1 standard deviation change in either academic R&D or the college graduate population share "explains" roughly 14-26% of a standard deviation in per capita patenting. The share is considerably higher in the instrumental variables regressions. Thus, both academic R&D and an educated workforce are related to patenting, but much of the variation in patenting is not explained by academic R&D and aggregate education.

Results

Wage Estimates

The top panel of Table 2 reports generalized least squares random effects estimates of the relationship between academic R&D, patenting, and the share of college graduates in a metropolitan area and wages. The primary source of identification in these estimates comes from variation across metropolitan areas, with additional identification from changes over time within metropolitan areas. There is a positive relationship between patenting and the college graduate population share and wages, but there is no relationship between academic R&D and wages. (A negative relationship between academic R&D and wages arises when the college employment share is included because these two variables are relatively strongly correlated.)

The middle panel includes fixed effects. These estimates are consistently larger than the random effects estimates. This finding is consistent with innovation and aggregate education being associated with fewer productive amenities and/or higher consumption amenities (it is also consistent with a greater wage responses to high-frequency shocks because of slow labor adjustment). Using the estimates in columns (1)-(3), a 1 standard deviation increase in academic R&D is associated with a 1.4% increase in wages, a 1 standard deviation increase in patenting is associated with a 1.8% increase in wages, and a 1 standard deviation increase in the college graduate population share is associated with a 5.8% increase in wages.

To directly address causality, the bottom panel reports two-stage least squares estimates. The corresponding first stage regressions are reported in Appendix Table 2. (The specifications used are in columns (4)-(6).) They show that the share shift index is quite powerful, predicting academic R&D extremely well. The share shift index also predicts the college graduate population share, but less well. College enrollments in 1925 predict the contemporaneous college graduate population share. Highly cited papers are weakly related to patenting, as are the other instruments.[8]

The instrumental variables estimates with each variable included separately show that academic R&D and the college-graduate population share are both significant economically and statistically (at the 10% level). The coefficient for academic R&D lies

[8] We have also used the number of patents issued to Fortune 100 companies headquartered in each city between 1969 and 1973 as an instrument for patenting controlling for the total revenue of these companies. This instrument also yielded weak results.

between the random effects and fixed effects coefficients, while the coefficient on the college graduate population share is lower than either the random effects or fixed effects coefficients. The coefficient on patenting is large but imprecise, but this result is not surprising given that the first stage equation for patenting is relatively weak. Not surprisingly, including all of the variables together reduces their precision. Based on the estimates in columns (1)-(3), a 1 standard deviation increase in academic R&D would raise wages by .7%, a 1 standard deviation increase in patenting would raise wages by 4.6%, and a 1 standard deviation increase in the college graduate population share would raise wages by 2.6%. These estimates are economically large, although not implausibly large (in the case of the college graduate population share, they are smaller than Moretti's estimates). The fact that the estimates increase when moving from random effects to both fixed effects and instrumental variables suggests that innovation and aggregate education are associated with fewer productive amenities and/or higher consumption amenities.

Changes over Time

Both academic R&D and patenting are increasing over time. To assess whether they are also becoming more important determinants of wages, Table 3 reports cross-sectional estimates for each year. The patterns are imprecise, but striking. The relationship between each of the variables and log wages is negative in 1980, but the coefficients increase steadily over time. By 1990 all three coefficients are positive and by 2000, academic R&D and the college graduate population share are both statistically significant. Thus, it appears that innovation and aggregate education are becoming more important over time.

Wage Estimates for Different Groups

This section explores how innovation is related to wages for different types of workers. Innovation is often seen to benefit highly-skilled, knowledge workers, but it may have substantial benefits for workers in the middle of the education or skill distribution. Such benefits might arise because spillovers benefit mid- or low-skilled workers directly; because better markets for the most skilled workers trickle down to less skilled workers in support positions; or because innovation increases the supply of high-skilled workers. We address these issues in three ways. First, we estimate interactions between innovation and aggregate education and an individual's education (a dummy variable for whether the person completed college). Second, we estimate interactions between innovation and age. Third, we estimate interactions between innovation and both education and age.

Table 4 reports estimates with interactions between the innovation and aggregate education variables and whether a person has completed college. The estimates indicate that the relationship between wages and academic R&D, patenting, and the college graduate population share is considerably stronger – between two thirds higher and double - for college graduates than for other workers. These results contrast with Moretti, who reports larger effects on people who have less education.[9]

Young workers may be more familiar with or better able to utilize new technologies than older workers (Weinberg [2006]). On the other hand, older workers have more human capital than younger workers, which our previous estimates suggest would lead them to benefit more from innovation. Younger workers are also likely to be more geographically mobile, in which case any wage impacts on younger workers are likely to be muted because they are offset by employment changes. Similarly, many older

[9] The difference in results does not appear to be due to the difference in strategies. Saha [2010] finds weak effects of the presence of a land grant college even in specifications that are similar to Moretti [2004].

workers may be close to the margin to retire. Table 5 explores how age mediates the relationship between innovation and aggregate education and wages. The estimates indicate that the relationship between innovation and aggregate education and wages is positive for all workers, but it is stronger for prime-aged workers than for younger or older workers. Although these estimates do not allow us to identify specific mechanisms, they are consistent with prime-age workers being less mobile than young workers and further from the margin to retire than older workers and/or having more (relevant) human capital than younger and older workers.

We have also estimated models that interact both education and age with the innovation and aggregate education variables. These estimates generally show small relationships for young workers without a college education.

City Characteristics and Shape of Relationships

This section probes the previous estimates in a number of ways, by looking at the types of cities where the relationship between wages and innovation is strongest and the curvature of the relationship. Are the marginal benefits of innovation and aggregate education greatest in cities where they are already concentrated or greatest starting at low levels? To address this question, Table 6 contains higher order terms in the innovation and aggregate education variables. The estimates for innovation show positive linear terms and negative squared terms, so that the marginal benefits of academic R&D and patents are greatest at low levels, declining at higher levels. The college graduate population share has a convex relationship with wages. This convex relationship is consistent with the greater benefits of aggregate education for college graduates found above.[10]

As indicated, many leading research institutions are located in older, industrial cities (at least in part because they were founded by industrialists or during industrialization). This pattern has lead many cities to view innovation as a route to renewed growth (e.g. Pittsburgh and Cleveland). To directly assess the potential for innovation to perform this role, Table 7 studies how innovation and the education distribution interact with the share of employment in manufacturing in 1980. The coefficient on the interaction between the employment share in manufacturing in 1980 and academic R&D and the college graduate population share are both negative and larger in magnitude than the positive main effect, indicating that wages are more weakly related to wages in a metropolitan area with higher manufacturing employment. These estimates are consistent with the model, indicating that wages respond less to productivity shocks in cities with a less elastic supply of land.

To further probe how manufacturing intensity interacts with the innovation and aggregate education variables, we estimated wage models for sets of industries. These estimates do not show large differences across industries, although precision is reduced when the sample is stratified.

Summary of Wage Results

Taken together, these estimates indicate that innovation and aggregate education raise wages. If anything the strength of this relationship has increased over time. Yet our

[10] It is natural to consider whether our estimates are being driven by "college towns," with relatively small populations and large universities. To address this possibility, we have excluded metropolitan areas with fewer than 500,000 people. These estimates are similar to those in Table 6 for patenting and the college graduate population share, indicating that college towns do not drive these estimates. We find an imprecise convex relationship for academic R&D indicating that college towns may be responsible for the (imprecise) concavity in academic R&D in Table 6.

estimates indicate that the wage benefits of innovation and aggregate education are lower in industrial cities for two reasons. First, as predicted by the model, wages respond less in cities with less elastically supplied real estate. Second, the benefits of innovation and aggregate education are lower for people who have not completed college, who are overrepresented in industrial cities.

Real Estate Price Results

Our wage results indicate that innovation and aggregate education are associated with higher wages. While this finding suggests that innovation and aggregate education raise productivity, the same pattern would arise if innovation and aggregate education are consumption disamenities. The model indicates that it is possible to distinguish these explanations by looking at real estate prices – if innovation and aggregate education are associated with higher real estate prices, then it would indicate that they raise productivity. Our analysis of real estate prices follows the same overall structure as our analysis of wages.

The top panel of Table 8 reports regressions of the CMPHI on the innovation and aggregate education variables using generalized least squares random effects. The estimates indicate that innovation and aggregate education are associated with higher real estate prices, although the estimates are frequently imprecise.

The middle table reports fixed effects estimates. These estimates are all positive and considerably larger than the random effects estimates. The fact that they are larger than the random effects estimates (and the instrumental variables estimates discussed below) suggests that the high- to middle-frequency shocks that are emphasized by the fixed effects estimates are believed to be persistent. Using these estimates, a 1 standard deviation increase in academic R&D is associated with a 4.8% increase in real estate prices, a 1 standard deviation increase in patenting is associated with a 6% increase in real estate prices, and a 1 standard deviation increase in the college graduate population is associated with a 29% increase in real estate prices.

The bottom panel reports instrumental variables estimates. First stage equations are reported in Appendix Table 3. (The specifications used are in columns (4)-(6).) Although these estimates are imprecise, they all lie between the random effects and fixed effects estimates. They are also economically sizable. A 1 standard deviation increase in academic R&D raises real estate prices by .7%, a 1 standard deviation increase in patenting raises real estate prices by 4.2%, and a 1 standard deviation increase in the college graduate population share raises real estate prices by 3.1%.

Effect of Real Estate Prices on Real Wages

It is possible to use our wage and real estate price estimates to impute the effect of innovation and aggregate education on real wages. People who already own their homes receive windfall gains from increases in real estate prices, while people planning to purchase homes must pay more, but obtain more valuable assets. For renters, increases in housing prices reduce real wages. The magnitudes of two-stage least squares estimates for wages and real estate prices are remarkably similar. Expenditures on shelter are roughly 20% of consumer expenditures (U.S. Bureau of Labor Statistics [2008]). Thus, for renters roughly 80% of the increase in nominal wages from increases in innovation and aggregate education represent increases in real wages.[11]

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[11] The fixed effects real estate estimates are considerably higher than the wage estimates – 3.3 to 5 times higher. Thus, for renters, most of the increase in nominal wages from high- to middle-frequency changes in innovation and aggregate education are offset by increases in real estate prices.

Changes over Time

Table 9 builds on these results looking at changes over time in the relationship between innovation and aggregate education and real estate prices. Although these estimates are less precise, they echo the wage results, showing a tendency for the relationship between innovation and aggregate education and real estate prices to increase over time. Thus, all of the innovation and aggregate education variables have negative coefficients in 1980. The coefficients are positive or less negative by 1990, and by 2000 all of them are positively related to wages and of a magnitude that is economically significant.

The fact that the both wages and real estate prices are increasing in innovation and aggregate education indicates that they increase productivity in a metropolitan area. (As discussed, it is impossible to say whether they generate consumption amenities too.)

Industrial Cities

Table 10 interacts the innovation and aggregate education variables with the initial manufacturing share. These estimates indicate that the relationship between innovation and aggregate education is strongest in manufacturing-intensive metropolitan areas. Again, this result is consistent with the model in that real estate is less elastically supplied in older, manufacturing-intensive metropolitan areas. At a practical level, it implies that while innovation and aggregate education have the potential to benefit older, industrial cities, more of the benefits from innovation and aggregate education accrue to real estate owners in these metropolitan areas.

Employment Shares

While work on the benefits of academic research has focused on high-technology industries (see Saxenian [1997] on electronics and Zucker, Darby, and Brewer [1998] on biotechnology), one of the original missions of research universities (especially land-grant universities) was to benefit agriculture. Thus, some research may benefit agriculture and engineering research may benefit manufacturing. This section estimates the relationship between innovation and aggregate education and employment in occupations and industries.

Table 11 presents results for occupations for 1980, 1990, and 2000. Column (1) gives the mean employment shares (and their standard deviations across cities). Managerial occupations have the largest shares followed by administrative support occupations. Technical occupations have the lowest share. Column (2) reports the share of workers in each occupation that are college graduates, with 62% of managerial workers and 36% of technical workers being college graduates. The estimates in columns (3) through (5) show the relationship between the three innovation and aggregate education variables and the employment in each of the occupations from seemingly unrelated regression models with metropolitan area fixed effects. Each column is from a separate model. The estimates show that innovation and aggregate education are associated with higher employment in managerial and technical occupations and lower employment in administrative support and service occupations.[12] The occupations that grow as innovation and aggregate education increase have the highest employment shares of college graduates, while the occupations that shrink have among the least educated workforces. Thus, there is a clear pattern of skill upgrading across occupations associated with innovation and aggregated education.

[12] In interpreting the estimates where the college graduate employment share is taken as the independent variable, it is important to note that an increase in the share of college graduates should lower their relative wages inducing growth in the sectors that employ many college graduates.

Table 12 presents results for industry employment for 1980 and 1990. Again, the first column gives the mean employment shares (and their standard deviations across cities) for each industry and the second column reports the share of employees in each industry that are college graduates. Column (3) presents results for academic R&D per capita. The employment share in manufacturing is strongly, positively related to R&D. Employment in public administration is negatively related to R&D. Column (4) shows that employment in agriculture, construction, and wholesale trade are all positively related to patenting. Employment in transportation and retail are negatively related to patenting. Lastly, in Column (5), the share of college graduates in the city is associated with higher employment in professional services, business and related services, and finance, but lower employment in public administration and transportation. Thus, there is less evidence of skill upgrading across industries than occupations. Results (not reported here), show broadly similar results when all three innovation and aggregate education variables are included together, but the coefficients are lower.

Conclusion

Innovation is increasingly viewed as an economic driver, especially in rapidly growing cities. Many industrial cities are rich in research institutions, making innovation-driven growth a possible route to recovery for industrial cities. This paper studies how innovation is related to outcomes for different types of workers (e.g. more-educated versus less, and younger versus older) and for industrial cities. Our estimates indicate that innovation and aggregate education are associated with greater productivity in cities. They indicate that innovation and aggregate education impact wages less in industrial cities, but that they impact real estate prices more. The stronger effect on real estate prices is consistent with sunk investments leading to a less elastic supply of real estate in industrial cities.

Our estimates indicate that the benefits of innovation and aggregate education are increasing over time. We also find greater effects of innovation and aggregate education for prime aged workers and for college graduates, which may not favor industrial cities. Overall, it appears that innovation-driven growth can benefit industrial cities, especially in the form of higher returns for real estate owners. At a practical level, increases in real estate prices benefit homeowners, but are costly to renters. Insofar as local governments rely heavily on real estate taxes, our estimates indicate that investments in innovation and aggregate education by local governments in older, industrial cities may be repaid (at least in part) in the form of higher tax bases.

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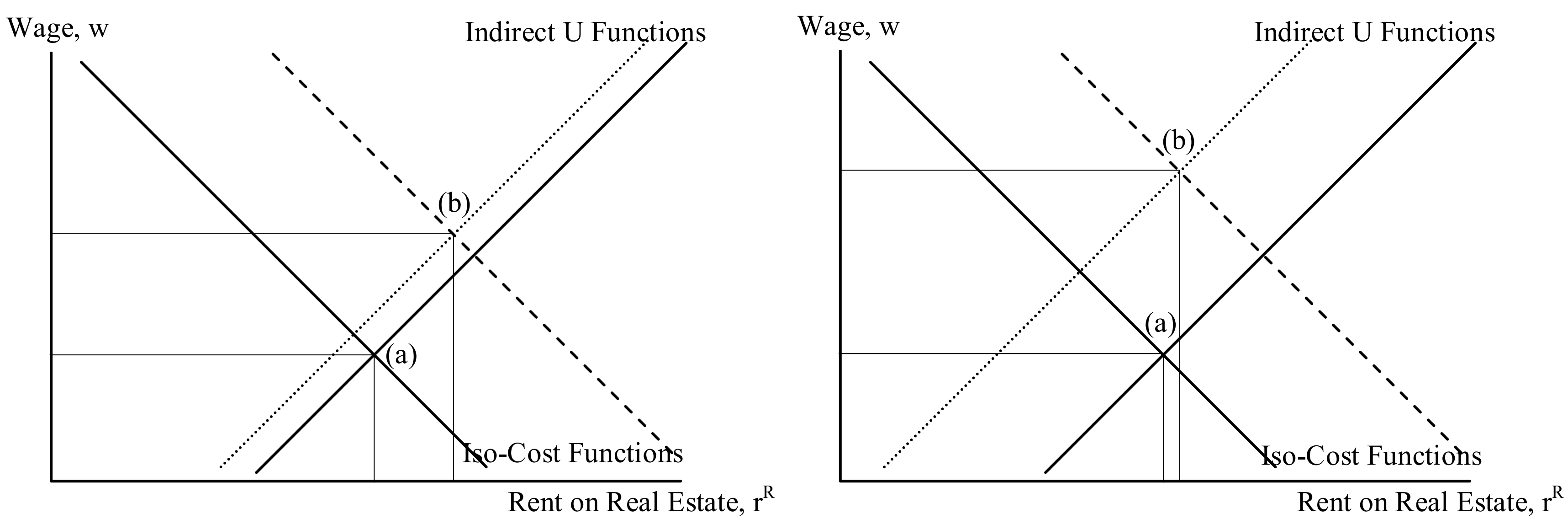
Figure 1. The Effect of an Increase in Productivity on Wages and Real Estate Rental Rates.

A. Low Elasticity of Real Estate Supply. B. Highly Elastic Supply of Real Estate.



Note. The solid lines give the contours of the indirect utility function for the marginal worker to live a city and the unit iso-cost lines for the marginal firm to locate in the city in an initial equilibrium, given by (a). The dashed lines give the unit iso-cost line after a positive productivity shock. As workers enter the city, the marginal worker to live in the city has a lower taste for living in the city. The dotted indirect utility function contour corresponds to the new marginal worker to live in the city (i.e. after entry) in the new equilibrium (b).

Table 1. Descriptive Statistics.

	All years	1980	1990	2000	Units / Measurement
Academic R&D Per Capita	0.055	0.036	0.056	0.070	Thousands of Current Dollars per person.
	(0.082)	(0.054)	(0.087)	(0.093)	
Patenting Per Capita	0.000281	0.000173	0.000227	0.000429	Patents per person.
	(0.000598)	(0.000355)	(0.000496)	(0.000797)	
Col. Grad. Pop. Share	0.274	0.211	0.268	0.334	
	(0.078)	(0.045)	(0.059)	(0.071)	
Log(Wage)	5.851	5.811	5.829	5.907	Current Dollars
	(0.727)	(0.695)	(0.729)	(0.748)	
Individuals	1,314,105	402,283	441,115	470,707	
Log(Housing Price Index)	4.711	4.196	4.786	5.119	1987 Q1=100
	(.434)	(.277)	(.164)	(.180)	
Metropolitan Area Years	509	132	188	189	

Note. Table reports means and standard deviations in parentheses.

Table 2. Relationship between Innovation and Aggregate Education and Wages.

Dep. Var: Log Wages	(1)	(2)	(3)	(4)
		GLS Random Effects		
Academic R&D Per capita	0.035			-0.047
	(0.035)			(0.029)
Patenting Per Capita		19.599+		15.921
		(11.127)		(9.991)
Col. Grad. Pop. Share			0.518***	0.512***
			(0.150)	(0.146)
		Fixed Effects		
Academic R&D Per Capita	0.179			0.065
	(0.118)			(0.092)
Patenting Per Capita		29.287+		22.078+
		(14.873)		(13.186)
Col. Grad. Pop. Share			0.745***	0.675***
			(0.198)	(0.185)
		Two-Stage Least Squares		
Academic R&D Per Capita	0.084+			-0.230*
	(0.046)			(0.106)
Patenting Per Capita		76.696		64.145
		(59.608)		(105.580)
Col. Grad. Pop. Share			0.332**	0.813***
			(0.105)	(0.160)

Note. Sample includes 1,314,105 observations on 217 metropolitan areas for 1980, 1990, and 2000. Individual-level controls include education, a quartic in potential experience, race (dummies for black and other race), Hispanic background, citizenship, and marital status. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates weighted by population weights. Fixed effects estimates include metropolitan area fixed effects. In the two-stage least squares estimates, the instruments are (1) a share shift index for academic R&D; (2) college enrollments in 1925 per capita; and (3) the number of highly cited papers published between 1900 and 1945 by people in the city. Enrollments and highly cited papers are interacted with year dummy variable. The individual characteristics are also treated as endogenous. We include the deviation of each individual variable from its mean in each metropolitan area in each year as instruments. First stage regressions are reported in Appendix Table 2. (The specifications used are in columns (4)-(6).) Standard errors, which are clustered at the metropolitan area level for fixed effects and two-stage least squares, are reported in parentheses. Significance given by: *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.10$.

Table 3. Relationship between Innovation and Aggregate Education and Wages, By Year.

Dep. Var: Log Wages	(1)	(2)	(3)	(4)
	1980 (402,283 Obs.)			
Academic R&D Per capita	-0.073			-0.065
	(0.071)			(0.096)
Patenting Per Capita		-6.588		-6.296
		(10.435)		(10.011)
Col. Grad. Pop. Share			-0.081	-0.023
			(0.229)	(0.278)
	1990 (441,115 Obs.)			
Academic R&D Per capita	0.049			-0.048
	(0.041)			(0.031)
Patenting Per Capita		5.580		2.176
		(5.713)		(4.461)
Col. Grad. Pop. Share			0.340**	0.381**
			(0.104)	(0.118)
	2000 (470,707 Obs.)			
Academic R&D Per capita	0.073+			-0.052
	(0.041)			(0.032)
Patenting Per Capita		15.650		10.081
		(12.094)		(8.714)
Col. Grad. Pop. Share			0.421***	0.434***
			(0.118)	(0.103)

Note. Sample includes 217 metropolitan areas. Individual-level controls include education, a quartic in potential experience, race (dummies for black and other race), Hispanic background, citizenship, and marital status. Regressions also include the log of population and its square. Estimates weighted by population weights. Standard errors, clustered at the metropolitan area level, are reported in parentheses. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Table 4. Individual Education and the Relationship between Innovation and Aggregate Education and Wages, Fixed Effects Estimates.

Dep. Var: Log Wages	(1)	(2)	(3)	(4)
Academic R&D Per Capita	0.125			0.080
	(0.112)			(0.094)
* Col. Grad. or Higher	0.078*			-0.107**
	(0.037)			(0.036)
Patenting Per Capita		21.282+		16.833
		(12.682)		(12.151)
* Col. Grad. or Higher		14.968*		4.755
		(6.928)		(4.068)
Col. Grad. Pop. Share			0.485**	0.423*
			(0.181)	(0.169)
* Col. Grad. or Higher			0.496***	0.529***
			(0.055)	(0.056)

Note. Sample includes 1,314,105 observations on 217 metropolitan areas for 1980, 1990, and 2000. Individual-level controls include education, a quartic in potential experience, race (dummies for black and other race), Hispanic background, citizenship, and marital status. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates include metropolitan area fixed effects. Estimates weighted by population weights. Standard errors, clustered at the metropolitan area level, are reported in parentheses. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Table 5. Age and the Relationship between Innovation and Aggregate Education and Wages, Fixed Effects Estimates.

Dep. Var: Log Wages	(1)	(2)	(3)	(4)
Academic R&D Per Capita	0.157			0.110
	(0.114)			(0.100)
* Age>35 and Age<55	0.034			-0.049+
	(0.025)			(0.026)
* Age≤35	-0.007			-0.066*
	(0.029)			(0.029)
Patenting Per Capita		20.379+		16.120
		(12.059)		(11.921)
* Age>35 and Age<55		9.460+		5.696
		(5.322)		(3.865)
* Age≤35		10.393		7.643
		(7.145)		(6.118)
Col. Grad. Pop. Share			0.592**	0.511**
			(0.199)	(0.192)
* Age>35 and Age<55			0.188***	0.198***
			(0.048)	(0.053)
* Age≤35			0.125**	0.143***
			(0.044)	(0.042)

Note. Sample includes 1,314,105 observations on 217 metropolitan areas for 1980, 1990, and 2000. Individual-level controls include education, a quartic in potential experience, race (dummies for black and other race), Hispanic background, citizenship, and marital status. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates include metropolitan area fixed effects. Estimates weighted by population weights. Standard errors, clustered at the metropolitan area level, are reported in parentheses. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Table 6. Curvature of the Relationship between Innovation and Aggregate Education and Wages, Fixed Effects Estimates.

Dep. Var: Log Wages	(1)	(2)	(3)	(4)
Academic R&D Per Capita	0.349			-0.030
	(0.268)			(0.205)
Squared	-0.119			0.008
	(0.115)			(0.090)
Patenting Per Capita		58.340**		29.258*
		(20.773)		(13.387)
Squared		-4,588.013*		-2,698.172*
		(1,917.081)		(1,302.607)
Col. Grad. Pop. Share			-0.985**	-0.878**
			(0.373)	(0.330)
Squared			2.496***	2.286***
	0.349			-0.030

Note. Sample includes 1,314,105 observations on 217 metropolitan areas for 1980, 1990, and 2000. Individual-level controls include education, a quartic in potential experience, race (dummies for black and other race), Hispanic background, citizenship, and marital status. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates include metropolitan area fixed effects. Estimates weighted by population weights. Standard errors, clustered at the metropolitan area level, are reported in parentheses. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Table 7. Manufacturing Intensity and the Relationship between Innovation and Aggregate Education and Wages, Fixed Effects Estimates.

Dep. Var: Log Wages	(1)	(2)	(3)	(4)
Academic R&D Per Capita	0.872*			0.689*
	(0.343)			(0.317)
* 1980 Manufacturing Share	-3.515+			-3.496*
	(1.794)			(1.692)
Patenting Per Capita		29.364		-12.299
		(28.812)		(25.376)
* 1980 Manufacturing Share		2.313		157.557
		(106.932)		(109.187)
Col. Grad. Pop. Share			1.144***	0.986***
			(0.269)	(0.274)
* 1980 Manufacturing Share			-1.637*	-1.184
			(0.687)	(0.746)

Note. Sample includes 1,314,105 observations on 217 metropolitan areas for 1980, 1990, and 2000. Individual-level controls include education, a quartic in potential experience, race (dummies for black and other race), Hispanic background, citizenship, and marital status. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates include metropolitan area fixed effects. Estimates weighted by population weights. Standard errors, clustered at the metropolitan area level, are reported in parentheses. Significance given by: *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.10$.

Table 8. Relationship between Innovation and Aggregate Education and Real Estate Prices.

Dep. Var: Log Real Estate Price	(1)	(2)	(3)
GLS Random Effects			
Academic R&D Per Capita	0.008		
	(0.102)		
Patenting Per Capita		34.643*	
		(14.336)	
Col. Grad. Pop. Share			0.270
			(0.197)
Fixed Effects			
Academic R&D Per Capita	0.583		
	(0.474)		
Patenting Per Capita		99.718*	
		(41.495)	
Col. Grad. Pop. Share			3.695***
			(0.726)
Two-Stage Least Squares			
Academic R&D Per Capita	0.088		
	(0.104)		
Patenting Per Capita		70.963	
		(242.108)	
Col. Grad. Pop. Share			0.394
			(0.255)

Note. Sample includes 509 observations for 1980, 1990, and 2000. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Fixed effects estimates include metropolitan area fixed effects. Instruments are (1) a share shift index for academic R&D; (2) college enrollments in 1925 per capita; and (3) the number of highly cited papers published between 1900 and 1945 by people in the city. Enrollments and highly cited papers are interacted with year dummy variables. First stage regressions are reported in Appendix Table 3. (The specifications used are in columns (4)-(6).) Standard errors reported in parentheses. Estimates weighted by the square root of population in 2000. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Table 9. Relationship between Innovation and Aggregate Education and Real Estate Prices, By Year.

Dep. Var: Real Estate Price	(1)	(2)	(3)	(4)
1980 (132 Obs.)				
Academic R&D Per capita	-0.691			-0.159
	(0.510)			(0.473)
Patenting Per Capita		-7.955		1.734
		(33.086)		(34.090)
Col. Grad. Pop. Share			-1.496+	-1.372
			(0.890)	(0.983)
1990 (188 Obs.)				
Academic R&D Per capita	0.017			0.143
	(0.088)			(0.120)
Patenting Per Capita		8.296		12.627
		(17.914)		(16.200)
Col. Grad. Pop. Share			-0.382	-0.539
			(0.527)	(0.596)
2000 (189 Obs.)				
Academic R&D Per capita	0.128			0.031
	(0.104)			(0.106)
Patenting Per Capita		45.614		41.845
		(32.270)		(28.324)
Col. Grad. Pop. Share			0.406	0.273
			(0.435)	(0.402)

Note. Regressions also include the log of population and its square. Standard errors reported in parentheses. Estimates weighted by the square root of population in 2000. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Table 10. Initial Manufacturing Intensity and the Relationship between Innovation and Aggregate Education and Real Estate Prices, Fixed Effects Estimates.

Dep. Var: Log Real Estate Price	(1)	(2)	(3)	(4)
Academic R&D Per Capita	-0.778			-0.404
	(0.903)			(0.831)
* 1980 Manufacturing Share	8.052			1.017
	(5.938)			(5.433)
Patenting Per Capita		52.685		81.902
		(97.544)		(90.285)
* 1980 Manufacturing Share		217.650		-94.066
		(378.530)		(343.215)
Col. Grad. Pop. Share			2.882**	2.829**
			(0.872)	(0.927)
* 1980 Manufacturing Share			3.734+	3.478
			(2.205)	(2.536)

Note. Sample includes 487 observations for 1980, 1990, and 2000. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Standard errors reported in parentheses. Estimates include metropolitan area fixed effects. Estimates weighted by the square root of population. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Table 11. Relationship between Innovation and Aggregate Education and Occupation Employment Shares, SUR Estimates.

	Summary Statistics				Regression Estimates					
Dep. Var: Employment Share in Occupation:	Mean Emp. Share (S.D.)		Col. Grad. Emp. Share	Academic R&D Per Capita		Patents Per Capita		College Graduate Share	
	(1)		(2)	(3)		(4)		(5)	
Managerial	0.30	(0.05)	0.62	0.095***	(0.027)	5.739**	(2.059)	0.555***	(0.025)
Technical	0.04	(0.01)	0.36	0.016	(0.010)	3.578***	(0.752)	0.090***	(0.012)
Sales	0.10	(0.01)	0.28	0.001	(0.015)	-1.952+	(1.102)	0.010	(0.018)
Administration	0.18	(0.02)	0.14	-0.102***	(0.021)	-3.329*	(1.604)	-0.211***	(0.024)
Precision	0.12	(0.02)	0.10	-0.007	(0.018)	0.001	(1.364)	-0.040+	(0.022)
Service	0.11	(0.02)	0.07	-0.052**	(0.017)	-3.800**	(1.293)	-0.149***	(0.020)
Operators	0.14	(0.04)	0.09	0.042+	(0.024)	-1.062	(1.805)	-0.229***	(0.027)

Note. Sample includes 621 observations for 1980, 1990 and 2000. Farming is the omitted occupation. Columns (3)-(5) report estimates from seemingly unrelated regressions, with the estimates in each column coming from separate models. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates include metropolitan area fixed effects. Estimates weighted by the square root of population. Standard errors are reported in parentheses. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Table 12. Relationship between Innovation and Aggregate Education and Industry Employment Shares, SUR Estimates.

	Summary Statistics			Regression Estimates					
Dep. Var: Employment Share in Industry:	Mean Emp. Share (S.D.)		Col. Grad. Emp. Share	Academic R&D Per Capita		Patents Per Capita		College Graduate Share	
	(1)		(2)	(3)		(4)		(5)	
Agriculture	0.020	(0.023)	0.16	-0.006	(0.009)	6.562**	(2.169)	0.003	(0.014)
Construction	0.064	(0.019)	0.10	0.017	(0.022)	12.602*	(5.499)	0.022	(0.034)
Manufacturing	0.226	(0.095)	0.16	0.129***	(0.039)	7.890	(9.664)	-0.077	(0.060)
Transportation	0.079	(0.021)	0.14	-0.023	(0.019)	-13.178**	(4.689)	-0.045	(0.029)
Wholesale	0.047	(0.016)	0.17	0.020	(0.016)	7.509+	(3.886)	-0.006	(0.024)
Retail	0.151	(0.025)	0.11	-0.007	(0.024)	-30.573***	(5.765)	-0.056	(0.037)
Finance	0.065	(0.025)	0.26	-0.018	(0.016)	3.265	(4.054)	0.084***	(0.025)
Business/Retail Services	0.038	(0.013)	0.15	0.008	(0.013)	2.650	(3.092)	0.054**	(0.019)
Personal Services	0.027	(0.019)	0.08	-0.006	(0.012)	-1.363	(2.848)	0.007	(0.018)
Entertainment	0.010	(0.011)	0.19	-0.008	(0.007)	1.196	(1.851)	0.015	(0.011)
Professional	0.208	(0.039)	0.44	0.008	(0.028)	4.326	(7.009)	0.129**	(0.043)
Public Admin.	0.056	(0.035)	0.29	-0.108***	(0.021)	-4.267	(5.278)	-0.206***	(0.031)

Note. Sample includes 396 observations for 189 metros in 1980 and 1990. Mining is the omitted industry. Columns (3)-(5) report estimates from seemingly unrelated regressions, with the estimates in each column coming from separate models. Regressions include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates include metropolitan area fixed effects. Estimates are weighted by the square root of population. Standard errors are reported in parentheses. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Appendix Table 1. Relationship between Academic R&D and Aggregate Education and Patenting.

Dep. Var: Patents Per Capita	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		RE			FE			2SLS	
Academic R&D Per Capita	0.001+		0.000	0.001		0.001	0.003+		0.001
	(0.000)		(0.000)	(0.001)		(0.001)	(0.002)		(0.001)
Col. Grad. Pop. Share		0.002***	0.002***		0.003+	0.003+		0.007	0.004
		(0.001)	(0.001)		(0.001)	(0.001)		(0.005)	(0.005)

Note. Sample includes 653 observations on 229 metropolitan areas for 1980, 1990, and 2000. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Fixed effects estimates include metropolitan area fixed effects. Instruments are (1) a share shift index for academic R&D and (2) college enrollments in 1925 per capita. Enrollments are interacted with year dummy variables. Estimates weighted by the square root of population. Standard errors are reported in. Significance given by: *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.10$.

Appendix Table 2. First Stage Regressions, Wage Sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Academic R&D Per Capita	Patenting Per Capita	Col. Grad. Pop. Share	Academic R&D Per Capita	Patenting Per Capita	Col. Grad. Pop. Share
Academic R&D Share Shift Index	1.116***			0.949***	0.001	0.235**
	(0.090)			(0.090)	(0.001)	(0.086)
Highly Cited Papers		0.002		7.121	-0.054	21.166
		(0.017)		(9.232)	(0.068)	(14.637)
Highly Cited Papers * 1990		0.010		-6.828	0.066+	19.880***
		(0.014)		(9.309)	(0.039)	(5.897)
Highly Cited Papers * 2000		0.036		-1.950	0.093	11.748+
		(0.086)		(15.804)	(0.107)	(6.049)
1925 Enrollments			1.549***	1.194***	0.000	0.857**
			(0.275)	(0.285)	(0.002)	(0.311)
1925 Enrollments * 1990			0.181	0.853**	-0.002*	-0.283
			(0.145)	(0.282)	(0.001)	(0.172)
1925 Enrollments * 2000			0.499**	-0.270	-0.003	-0.144
			(0.173)	(0.254)	(0.002)	(0.304)

Note. Sample includes 1,314,105 observations on 217 metropolitan areas for 1980, 1990, and 2000. Individual-level controls include education, a quartic in potential experience, race (dummies for black and other race), Hispanic background, citizenship, and marital status. These variables are also treated as endogenous. We use the deviation of each individual variable from its mean in each metropolitan area in each year as instruments. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates weighted by population weights. Standard errors, clustered at the metropolitan area level, are reported in parentheses. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Appendix Table 3. First Stage Regressions, Real Estate Price Sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Academic R&D Per Capita	Patenting Per Capita	Col. Grad. Pop. Share	Academic R&D Per Capita	Patenting Per Capita	Col. Grad. Pop. Share
Academic R&D Share Shift Index	1.160***			0.994***	0.001+	0.240***
	(0.082)			(0.084)	(0.000)	(0.055)
Highly Cited Papers		0.013		3.674	0.049	4.712
		(0.018)		(9.826)	(0.081)	(13.996)
Highly Cited Papers * 1990		-0.008		-7.839	-0.011	35.015+
		(0.028)		(15.130)	(0.093)	(18.259)
Highly Cited Papers * 2000		0.029		-1.716	0.012	29.225
		(0.085)		(17.107)	(0.123)	(20.230)
1925 Enrollments			1.878***	1.350***	-0.002	1.402***
			(0.260)	(0.352)	(0.003)	(0.365)
1925 Enrollments * 1990			-0.124	0.778	-0.001	-0.822+
			(0.452)	(0.628)	(0.003)	(0.486)
1925 Enrollments * 2000			0.186	-0.443	-0.001	-0.720
			(0.453)	(0.530)	(0.004)	(0.531)

Note. Sample includes 509 observations for 1980, 1990, and 2000. Regressions also include the log of population and its square, year dummy variables, and a full set of interactions between them. Estimates weighted by the square root of population in 2000. Standard errors are reported in parentheses. Significance given by: *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.