Estimating the Local Productivity Spillovers from Science

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ABSTRACT

We estimate the local productivity spillovers from science by relating wages and real estate prices across metros to measures of scientific activity in those metros. We address three fundamental challenges: (1) *unobserved differences in metros / causality* using a share shift index that exploits historic variation in the mix of research in metros interacted with trends in federal funding for specific fields as an instrument; (2) *unobserved differences in workers* using data on the states in which people are born; and (3) *factor input adjustments*, using wages and real estate prices, along with Shepard's Lemma, to estimate changes metros' productivity, which much equal changes in unit production cost. Our estimates show a strong positive relationship between wages and scientific research and a weak positive relationship for real estate prices. Overall, we estimate, high rate of return to research.

JEL Codes: J3, R11, O33

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Estimating the Local Economic Spillovers from Science

I. Introduction

National, regional, and local governments provide substantial support for science, directly, through support for higher education, and through tax benefits. Since 2003, the United States Federal government alone has spent roughly $60 billion annually (in 2009 dollars) on basic and applied research (Clemins [2009]). Supporters point to Silicon Valley, the Route 128 corridor in Boston, and the Research Triangle Park to justify this support (see, for instance, Dorfman [1983]; Saxenian [1996]; and Feldman and Desrochers [2003]), but science is often viewed as being “ivory tower,” with limited practical value (Prager and Omenn [1980]).[1] Even in the scientific community, the economic benefits from research are disputed (Macilwain [2010]).

This paper estimates the local economic spillovers from science, which arise when ideas diffuse to the local economy through trainees, consulting, technology transfer, and infrastructure sharing. While policy makers have frequently focused on “job creation”, basic economic logic indicates that the local economic spillovers from science should be measured in terms of the effects on productivity, which in turn, may lead to employment growth (depending on, among other things, the labor supply elasticity). As described below, we infer how scientific activity affects productivity from how it affects wages and real estate prices using panel data on U.S. Metropolitan areas (“metros”) from 1980 to 2011.

There are three (sometimes interrelated) challenges to estimating the local economic spillovers from science using variation across metropolitan areas, which must be addressed. Specifically:

1. Unobserved Differences in Metros (Causality). The metros where a large amount of scientific activity occurs may be different from those producing little science. Universities may generate

[1] A blue-ribbon panel convened by the Office of Science and Technology Policy to enhance university-industry technology transfer concluded that, "University research is viewed by industry as ivory-tower with little thought to applicability... (Prager and Omenn [1980])."

desirable cultural amenities. If scientific activity is positively correlated with attractive amenities, then, all else equal, we would expect workers to move to these metros, depressing wages and reducing the estimated spillovers from science. Moreover, universities produce students, making it interesting to separate the research aspect of universities from their educational component.

2. Differences in Worker Skill (Selection). Science organizations produce highly productive workers and the amenities they generate for their communities may be attractive to the most productive workers. If so, the average worker in a metro with a large amount of science may be more productive than observationally equivalent workers in other metros, inflating the estimated spillovers from science.

3. Factor Input Adjustment. We seek to estimate the effect of science on productivity in the metros in which it is produced. It would be natural to relate wages in a metro to measures of innovation to capture the effect on productivity. But, if innovative activity in a metro raises wages, one would expect workers to move to that metro, which would at least partially offset any increase in wages.[2] Thus, failure to correct for changes in labor inputs is likely to lead to underestimates of the effect of science on productivity. Alternatively, if science raises productivity in a metro, it would be natural to expect firms to locate there and for the metro to expand, which would raise wages. Thus, failure to account for firm location decisions may lead to overestimates of the effect of science on productivity. To estimate the spillovers from science, one must address adjustments of factor inputs such as capital, real estate, and labor.

We address each of these challenges. We address the first challenge, unobserved differences in metros (causality), using metro fixed effects and a share shift instrumental variables strategy, which exploits historic variations across metros in the amount of research conducted in different fields. For instance, federal funding for medical research has grown relative to that for physical sciences. Under the assumption that metros that were initially more specialized in medical research will be better positioned to capture this increase in spending, this shift will tend to favor metros that were initially stronger in medical research. We address the second challenge, unobserved differences in worker ability (selection), using data on science in the states where people were born.

To address the third challenge, factor input adjustments, we rely on a standard economic cost function framework. Our approach is based on the principle that optimal firm locations imply that the cost of producing a unit of a traded good must be equal in all metros. Thus, the effect of science on productivity can be estimated from the effect of science on production costs – if science raises productivity in a metro, firms will drive up costs to the point that higher costs offset the productivity advantage. This framework is both powerful and quite general; it can be applied using readily-available data; and it can be used to address other questions.

Our work relates to a small, but growing, line of research estimating the local impacts of science.[3] Beeson and Montgomery [1993] find that university research is weakly related to wages, employment, or 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. Abel and Deitz [2009] find that academic R&D is associated with more innovative and technical occupations. Bauer, Schweitzer, and Shane [2006] find that the local knowledge

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[2] Our procedure also adjusts for students educated in university towns leaving for other communities.
[3] There are also literatures looking at geographic concentration of patents (see Jaffe, Trajtenberg, and Henderson [1993] and Thompson and Fox-Kean [2005]) and the geographic concentration of industries (Glaeser, Kallal, Scheinkman, and Schleifer [1992] and Glaeser and Ellison [1997]). Another, more distantly related line of work looks at human capital spillovers and agglomeration economies (Rosenthal and Strange [2004] and Moretti [2004b] provide reviews and individual studies include

foundation, as measured by patenting and the education distribution, are key determinants of long-run growth. Hausman [2013] shows that university-related industries grow after Bayh-Dole Act especially in metros with higher initial research spending. Kantor and Whalley [2014] find that increases in university spending induced by stock market returns interacted with initial endowments increase labor income and employment. Lastly, in work that we will build upon, Saha [2010] finds a strong relationship between academic R&D and income controlling for education variables. Yet all of these studies leave one or more of the 3 challenges described above unaddressed.

There have been a few attempts to estimate the effects of spillovers on productivity accounting for adjustments in factor inputs (our third challenge). 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 very strong data requirements. Topel and Lange [2006] perform some "back of the envelope" calculations and criticize existing studies (e.g. Rauch [1993] and Moretti's [2004a]) for assuming free mobility of workers, but using strategies that violate that assumption. Our approach to estimating productivity can be implemented using data that are readily available and does not require contradictory assumptions about worker mobility.

Another larger line of work seeks to estimate the economic value of the innovations that develop from scientific work (examples include Mansfield [1991]; Higgins, Thusby, and Thursby [2010]; and Murphy and Topel [2006]). While we focus on the local economic spillovers, we recognize the importance of such "technological" (versus "spillover") benefits, which improve the quality of life and raise consumer surplus.

A study of the economic impact of science is particularly timely as Congress questions the value of science while the United States (and Europe) increasingly look to innovation as a way of preserving economic strength, especially in the face of rising economic strength in Asia (see, for

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Rauch [1993]; Glaeser and Mare [2001]; Shapiro [2006]; and Gould [2007]).

instance, HM Treasury [2004, 2006] and National Academies [2007]).

In estimating the local productivity spillovers from science, our estimates are circumscribed in at least two ways. First, we ignore any productivity spillovers accruing more broadly (e.g. nationally or globally). Second, as indicated, we ignore the technological benefits of science, which likely accrue broadly (even globally) too. Of course, the local economic spillovers are believed to be considerable and are particularly relevant for state and local policy makers.

II. Strategy to Address Challenges

Factor Inputs Adjustment

Let output in each metro c at time t, Y_{ct} , be produced according to the aggregate production function, $Y_{ct} = A_{ct} F(L_{ct}, R_{ct}, K_{ct})$. Here A_{ct} denotes (multifactor) productivity; L_{ct} denotes labor inputs (potentially a vector); R_{ct} denotes real estate inputs; and K_{ct} denotes capital inputs, all in metro c at time t. We assume that output is traded at no cost and that capital and the consumption good are produced according to the same production function. We are interested in estimating how scientific activity, S_{ct}, in metro c at time t affects productivity.

Without either explicit (and difficult-to-obtain) data on output and the use of inputs or unrealistic assumptions about factor input adjustments, there is no direct way to estimate how science affects these objects of interest. Faced with this challenge, it is natural to estimating how science (or other variables) affects the nominal wage, w_{ct}^{N} . But, as we show below, the nominal wage is of little interest in this setting.

Estimating the Effect on (Multifactor) Productivity

Here we propose a simple way to estimate these objects of interest from a standard cost minimization framework for firms. Assuming constant returns to scale (at the firm level), let $c(w_{ct}{}^{N}, r_{ct}{}^{R}, r_{ct}{}^{K})$ denote the cost per unit of output when multifactor productivity, $A_{ct}=1$, where w_{ct}^{N}

denotes the nominal wage; and r_{ct}^{R} and r_{ct}^{K} give the (nominal) rental rates on real estate and capital. Firms will arbitrage where they locate until $A_{ct}c\left(w_{ct}{}^{N}, r_{ct}{}^{R}, r_{ct}{}^{K}\right) = C_t^*$ in all metros. Applying Shepard's lemma and manipulating yields,

$$\frac{d\ln A_{ct}P_{ct}}{d\ln S_{ct}} = \begin{pmatrix} Labor's \\ Share \end{pmatrix} \frac{d\ln w_{ct}}{d\ln S_{ct}} + \begin{pmatrix} Real \\ Estate's \\ Share \end{pmatrix} \frac{d\ln r_{ct}^{R}}{d\ln S_{ct}} + \begin{pmatrix} Capital's \\ Share \end{pmatrix} \frac{d\ln r_{ct}^{K}}{d\ln S_{ct}}. \qquad (*)$$

The percentage change in productivity from an increase in science production can be estimated from the percentage change in total cost.[4] Intuitively, firm location decisions imply that the cost of producing a unit of a traded good is equated across all metros. Any increase in productivity in a metro will increase factor use in that metro, driving up costs to the point that they offset the productivity advantage. So long as costs in a metro remain lower, firms have an incentive to relocate to that metro, increasing the demand for real estate and labor, which will bid up costs until they compensate for the increased productivity. Conversely, if costs ever exceed the productivity gains in a metro, firms have an incentive to relocate out of that metro, driving costs down to the point where they no longer exceed the increase in productivity.[5] From a policy perspective, it is important to know whether the benefits of science exceed the costs. The total value of local productive spillovers from science can be estimated simply by multiplying output by this estimate of the increase in multifactor productivity from an increase in scientific activity.

Our result is quite general, depending on constant returns to scale, that enough firms are able to arbitrage productivity differences, and that the good is traded. In particular, this result does not

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[4] Our estimates If science raises productivity, reducing the price level of the goods produced in a city (worsens terms of trade), that

[5] While it might seem that an increase in, for instance, real estate prices because of science investments should be viewed as a cost rather than contributing to the productivity benefits of science, it is important to bear in mind that scientific activity raises real estate costs because firms and workers drive up real estate costs in their efforts to take advantage of a more productive environment.

depend on the specific functional form chosen for the cost/production function (beyond constant returns to scale). Nor does it depend on how science production affects the utilization of factor inputs, making it unnecessary to have information about the supply of labor or real estate to a metro. Lastly, although we have focused on the effects of science, this approach is quite general and can be applied to any production or consumption amenity and to amenities that affect both production and consumer utility.

Estimating the Effects of Science on Input Prices

To use this condition, one needs the cost shares of each input and how the prices of each input in a metro are affected by changes in scientific activity. We obtain cost shares for the inputs from national data. Subject to the challenges discussed above, one can estimate how nominal wages respond to changes in scientific activity from cross-sectional wage data such as that in the Census and/or American Community Survey. Capital rental rates for individual metros are difficult to obtain, but given that capital is typically taken to be highly mobile, it is natural to assume that the rental rate on capital is fixed across metros, that $\frac{d \ln r_{ct}^{K}}{dS_{ct}} = 0$.[6] Lastly, one can estimate how real estate prices are related to scientific activity using cross-sectional or panel data on real estate prices. Thus, it is possible to estimate the effect of science on productivity under reasonable assumptions using data that are readily available.

In the case of real estate prices, we have annual, metro-level measures and estimate equations like $\ln r_{ct}^{R} = \beta^{R} Science_{ct} + \gamma^{R} X_{ct} + \varepsilon_{ct}^{R}$, where $\ln r_{ct}^{R}$ denotes log real estate prices in metro *c* at time *t*; $Science_{ct}$ denotes scientific activity in metro *c* at time *t*; and X_{ct} denotes observable characteristics

[6] One violation of this assumption might arise if metros with more scientific activity have better access to, for instance venture capital. We include metro fixed effects in our estimates, which should minimize this concern. Our IV estimates should also minimize this concern, insofar as it is not clear that the changes in scientific activity induced by our instruments will increase access to venture capital.

of metro c at time t (e.g. population). In the case of wages, we have individual-level data and estimate models like $\ln w_{cti} = \beta^W Science_{ct} + \gamma^W X_{ct} + \theta^W x_{cti} + \varepsilon^W_{cti}$, where $\ln w_{cti}$ gives the log (nominal) wage of person i in metro c at time t, x_{cti} gives his or her characteristics, and X_{ct} again denotes observable metro characteristics (we cluster our standard errors for the presence of metro-level regressors in the model.) We distinguish the effects of science from that of education by including the share of college graduates in the metro in X_{ct}. We focus on models that use contemporaneous science spending, but the results are similar using moderate lags.

As indicated, researchers have estimated how variables such as scientific activity or the education distribution of the workforce affect nominal wages. However, nominal wages do not reflect workers' utility (because of differences in the cost of living). In our setup, it is straightforward to estimate how science affects real wages, from the effects of science on nominal wages and real estate costs. Doing so requires data on the share of real estate in consumption, which we denote α. Formally, the real wage equals the nominal wage adjusted for real estate costs, $w^R_{ct} = w^N_{ct} - \alpha r^R_{ct}$. The effect of science on real wages are given by $\hat{\beta}^{\mathrm{Re}\,al\,Wage} = \hat{\beta}^W - \alpha\hat{\beta}^{r^N}$. Moreover, as can be seen from (*) above, changes in multifactor productivity, A_{ct} can either be larger or smaller than changes in nominal wages because of changes in the utilization of labor and other inputs.

Unobserved Differences in Metros

Metros with important research-producing organizations may be different from those without important research-producing organizations. Such differences pose a challenge to estimating the effect of research on local economies (although it is not clear that they bias estimates upward). We employ two basic strategies to address these differences.

First, many of the factors that generate differences in equilibrium wages and real estate prices across metropolitan through workers' and firms' location decisions like climate, topology, and access to natural resources are stable. To address these differences, we include metropolitan area fixed effects in our wage and real estate equations.

Second, to address time-varying differences across metropolitan areas, we employ an instrumental variables strategy. We instrument for academic R&D spending with a "share-shift" index. Intuitively, this instrument exploits 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 – bio-medicine and other. Austin, TX and Portland-Vancouver, OR both have considerable academic R&D, but science in Portland-Vancouver is heavily focused on biomedicine (90.0% of academic R&D in 1973), while science in Austin is not (23.4% of academic R&D in 1973) an increase in the share of bio-medical R&D will likely raise R&D in Portland-Vancouver more than in the Austin. For each metro, the implied growth in academic R&D is a weighted average of the growth in academic R&D spending in each field where the weights for each metro correspond to the share of spending in that metro in that field.

Formally, our share shift index for per capita R&D in metro *c* at time *t* is $\hat{e}_{ct}^{PC}$, which is generated as

$$\hat{e}_{ct}^{PC} = \left(\sum_f s_{f|c0} \frac{e_{fnt}}{e_{fn0}} \right) e_{c0}^{PC} = \left(\sum_f \frac{e_{fc0}}{\sum_f e_{fc0}} \frac{e_{fnt}}{e_{fn0}} \right) e_{c0}^{PC},$$

where e_{fct} are expenditures in field *f* in metro *c* in time *t*; $s_{f|c0} = \frac{e_{fc0}}{\sum_f e_{fc0}}$ is field *f*'s share of Federal R&D in metro *c* in the base year, *t=0*, which we take to be 1973; $\frac{e_{fnt}}{e_{fn0}}$ is the growth in Federal R&D in field *f* nationally between 1973 and year *t*; and e_{c0}^{PC} is Federal R&D per capita in city *c* in 1973.

Figure 1 illustrates that has indeed been considerable shifts in the relative sizes of different fields and, in particular, growth in medical research relative to other fields, especially relative to the physical, social, and geo sciences. For our approach, it is important that research foci be persistent, which they are – in the case of biomedicine, the correlation between the share of academic R&D in biomedicine in 1973 has a correlation of .61 with the share in 2010.

IV Estimation

IV estimation of our real estate price equation is straightforward. In a first stage, we estimate

$$Science_{ct} = \pi_1^R \hat{e}_{ct}^{PC} + \pi_2^R X_{ct} + \nu_{cit}^W .$$

In our second stage, we estimate,

$$\ln r_{ct}^R = \beta^R Science_{ct} + \gamma^R X_{ct} + \varepsilon_{ct}^R .$$

IV estimation of the wage equation is somewhat more involved. In particular, our second stage equation contains individual characteristics, x_{cti} and, insofar as there is selection into metros based on observable characteristics, the means of these characteristics across metros will be endogenous. To address this concern, we estimate the mean of the individual characteristics in metro *c* in year *t*, $\bar{x}_{ct}$, and use the deviation of the characteristics from the metro-time mean, $\Delta x_{cti} = x_{cti} - \bar{x}_{ct}$ as instruments for x_{cti}. Formally, the first stage equation for scientific activity used when estimating our wage equation is

$$Science_{ct} = \pi_1^W \hat{e}_{ct}^{PC} + \pi_2^W X_{ct} + \pi_3^W \Delta x_{cti} + \nu_{cit}^W .$$

The first stage equation for the individual characteristics in our wage equation are,

$$x_{cti} = \pi_1^x IV_{ct} + \pi_2^x X_{ct} + \pi_3^x \Delta x_{cti} + \nu_{cti}^x .$$

The second stage wage equation is $\ln w_{cti} = \beta^W Science_{ct} + \gamma X_{ct} + \theta x_{cti} + \varepsilon_{cti}$.

In addition to eliminating bias from selective migration on *x*, instrumenting for x_{cti} with Δx_{cti} eliminates noise in the predicted values of $Science_{ct}$ generated by the inclusion of individual level variables in the first stage equation for $Science_{ct}$ (because $\hat{\pi}_3^W = 0$ by construction). (The first stage equations for the x_{cti} are strong and have the expected coefficients, i.e. load heavily on the demeaned version of the dependent variable.)

Differences in Worker Productivity

To address selection of high skilled workers into metros with more scientific activity, we use information on the states where people were born. We report results using scientific activity in a person's state of birth as instruments for scientific activity in their current metro. Some information is lost as data are aggregated to the state-level, but this strategy will eliminate the effects of selective migration.

Data

We employ data from a wide range of sources. The main outcome variables are the log of real weekly wages and real estate prices. The main independent variable is real per capita R&D expenditure in science and engineering (S&E) for individual colleges and universities, which are aggregated to the level of metropolitan areas by year. Control variables are drawn from a wide range of sources.

Census and American Community Survey Micro Data

We construct our first outcome variable— the log of real weekly wages—and obtain individual-level control variables using Census and American Community Survey (ACS) data from the Integrated Public Use Microdata Series (IPUMS; see Ruggles; Alexander; Genadek; Goeken; Schroeder; and Sobek [2010]). Because we want to measure the effect of science expenditure in metropolitan areas, we use the 1% weighted metro samples of the 1980, 1990 and

2000 Censuses. Because the long-form of the Census was discontinued after 2000, we use ACS for 2009, 2010, and 2011. These data contain large samples, permitting us to estimate labor market outcomes even for small metros with population above 100,000. We include Census/ACS control for individual characteristics including education, gender, race, ethnicity, and marital status.

Cities are aggregated into Consolidated Metropolitan Areas and Metropolitan Statistical Areas using definitions in the *State and Metropolitan Area Data Book 1997-1998* (U.S. Bureau of Census [1998]). CMSAs represent aggregations of cities that are economically connected to each other.

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 or above 4000 are excluded from the sample. Lastly, following earlier work and 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 (Beeson and Montgomery [1998]). The estimation sample includes 3,143,726 individuals in 253 metros.

The education level in a city may generate spillovers. 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. We construct the share of college graduates for each city year pair as a control variable.

Real Estate Price Data

We construct our second outcome variable— the log of real estate prices— using Freddie Mac's Constant Mortgage Home Price Index (CMHPI), which is calculated quarterly going back to 1975 for many metropolitan areas. 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, 2000 and 2010 obtained from the MSA-series available on Freddie Mac’s website[7].

These data have strengths and weaknesses for our purposes. First, the ideal measure of real estate costs would cover 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 estate prices are not available for the number of cities and years that we study. We have obtained data on residential and commercial real estate prices for 14 metros for 2000 and 2010. The correlation in the changes in each are .751, indicating that changes in residential real estate prices are a reasonable proxy for commercial real estate prices. There are also variations in the quality of real estate. An advantage of our data is that they credibly adjust for quality using repeat sales.

Main Independent Variables: Academic R&D Expenditure

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 for 27 fields, spanning the physical sciences, life sciences, math, engineering, geology, and social science, which includes economics, psychology and political science, and by source (e.g. federal, state, local, and

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[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/

industrial) for 1980, 1990, 2000 and 2010[9]. 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[10].

R&D is measured in thousands of dollars. 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.

Instrumental Variables

Our instrument for academic R&D is the share shift index described above. It uses historic R&D data by field. We use 1973 as the baseline for our share shift index.

Other Data

Metropolitan Area Characteristics: A range of control variables for metropolitan areas such as population, violent and property crime rates and public school attendance were obtained from the *State and Metropolitan Data Set* 1980, 1990, 2000 and 2010. To proxy for the cost of living in each metropolitan area, data on average utilities costs were collected from the *Places Rated Almanac* of 1972, 1980, 1990, 2000, and 2007. Measures for 2010 were linearly extrapolated from the 2000 to 2007 trends. Because of potential endogenity bias introduced by these variables, we report estimates both with and without these controls.

Scientific Output*:* Our main results use academic R&D, an input into science, as the

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[9] 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.
[10] 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.

primary independent variable. We probe the robustness of our estimates to a measure of scientific output using the NBER-Rensselaer Scientific Papers Database of scientific papers and their citations (Adams and Clemmons [2008]). This dataset uses two million papers written by authors at top US universities and R&D performing firms between 1981 and 1999.[11] The coverage differs from that of our R&D measure. First, R&D comes from nearly 600 universities that receive grants. The Adams Clemmons data considers only 110 top universities. Second, R&D data is available for 1980, 1990, 2000, and 2010. The Adams Clemmons data starts in 1981 and ends in 1999. When using these data, we linearly extrapolate to 1979 (to match the 1980 Census) and stop in 1999 (matched to the 2000 Census).

Descriptive Statistics

Table 1 reports descriptive statistics for our wage sample. Academic R&D spending (in 1982-1984 dollars) rises from $43 per person in 1979 to $100 per person in 2009-2011, averaging $83 per person across all years, with a standard deviation of $22.7. Roughly 28% of the workers in the cities in our sample have a college degree, with a standard deviation of 9%.

Results

Wage Estimates

Table 2 presents our main OLS and fixed effects wage estimates. The OLS estimates show a strong positive relationship between academic R&D and wages. Given this estimate, a 1 standard deviation change in academic R&D would be associated with 3.4% higher wages. As indicated, there are fixed differences across metropolitan areas that likely affect equilibrium wages through workers' and firms' location decisions, including climate, topology, and access to natural resources. To control for these differences, Column 2 reports estimates with metro fixed effects. These estimates are

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[11] The Adams Clemmons data also include citations received by these papers. Unfortunately, the truncation of the

slightly higher than the OLS estimates.

As indicated, it is important to distinguish the effects of scientific activity from that of an educated population. Columns (3) and (4) report analogous results including the share of the population with a college degree. The OLS and estimates of academic R&D are substantially reduced, but the fixed effects estimates are unchanged.

The remaining columns of Table 2 repeat the previous specifications including the following controls for time-varying metro characteristics: property crimes per 10,000, violent crimes per 10,000, total public school enrollment, and average utility costs. The estimates are virtually unchanged.

To control for unobserved, time-varying differences across metros, Table 3 reports IV estimates with and without fixed effects. The first stage equation in Panel B columns (1)-(4) uses the share shift index described above. A $1 increase in funding predicted by changes in funding based on the initial field mix of metros is associated with a $.46 increase in actual per capita spending. The strong relationship is expected. The fact that the coefficient is less than 1 suggests some crowding out in metros experiencing positive shocks and/or that institutions that are experiencing adverse shocks invest heavily to maintain their research spending. The first stage F-statistic is 11.363. The second stage estimates in Panel A is slightly higher than the OLS estimates. The Column 2 reports fixed effects IV estimates. Unfortunately, the first stage equation for these estimates is quite weak, so the second stage estimate are imprecise. Columns (3) and (4) repeat the estimates including time-varying controls. These estimates are slightly smaller than the corresponding estimates in columns (1) and (2).

To provide a sense of magnitudes we consider the effect of a $1 per capita increase in academic R&D (on a base of $83 per capita). This would raise academic R&D by roughly $316

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sample makes it difficult for us to use citations.

Million. Assuming a middle-range coefficient of .18 (between the OLS estimates with fixed effects and the IV estimate without fixed effects), wages would increase by .018%. The wage bill in 2013 was roughly $8.9 trillion. Thus a $1 per capita increase in academic R&D would raise total earnings by roughly $1.6 billion.

Selection into Metros

Selection into metros is a second concern with our estimates. To address it, we instrument for academic R&D at time *t* in the metro in which they are living at time *t*, $Science_{ct}$, with academic R&D at time *t* in the metros in the state in which they were born, $Science_{s^B t}$ using the state of birth variable in the Census and ACS. In this approach, we drop people born in states that did not have any institutions with (reported) academic R&D in a given year. We also drop people who were born outside of the United States or who do not have a reported state of birth. The estimates are reported in columns (5) and (6) of Table 3. The first stage for the IV estimates without fixed effects (in column 3) is quite strong and the estimated effect is statistically significant, and larger than the corresponding OLS and IV estimates. Unfortunately, when we include fixed effects, the first stage becomes less precise and the point estimates become noisy.

Alternative Measure of Scientific Activity

These estimates measure scientific activity using money spent on science, which is effectively an input, not an output. Spending is appealing for four reasons. First, it is a lever that policy makers control; second, it allows us to generate an explicit rate of return to science; third it is available for many metros over a long time period; and fourth, insofar as people are a critical "transmission vector" for science, spending may proxy well for the number of people who are employed in scientific activities in a metro. At the same time, it is natural to ask whether our results are sensitive to the use of a measure of scientific inputs rather than scientific outputs.

To address this question, we rely on scientific publication data generated by James Adams and Roger Clemmons [2008]. We match the 110 universities covered in these data to 64 metros for the years 1981-1999.[12] The estimates are reported in Table 4. Panel A repeats the estimates using academic R&D for the sample of metros and years for which we have publication data. These estimates are quite similar to those above, with stronger IV results. Panel B reports estimates using publications as the measure of scientific activity. These estimates are quite strong. To compare magnitudes between the 2 sets of estimates, we report the effect of a 1 standard deviation change in each variable. The implied effect of a 1 standard deviation change using the two measures are remarkably similar and vary across specifications in a similar way. All told, using a measure of scientific inputs rather than outputs seems to have little effect on our estimates.

City Size and Shape of Relationships

It is natural to consider whether our estimates are being driven by "college towns," with relatively small populations and large (frequently public) universities. To address this question, Table 5A includes interactions between metro population and academic R&D. The estimates show that the relationship between scientific activity and wages is more positive in metros with large populations. Thus, there is no indication that college towns dominate our estimates.

Are the marginal benefits of science increasing or decreasing in spending? To address this question, Table 5B contains higher order terms in academic R&D. The estimates consistently show positive linear terms and negative squared terms, so that the marginal benefits of academic R&D are declining. The implied maxima range between $817 and $1302 per capita with the fixed effects estimates tending to be at the higher end and the estimates with time-

[12] We linearly extrapolate the data back to 1979 to match to our census data and exclude the 2009, 2010, and 2011 ACS data.

varying metro controls somewhat lower. These estimates should be interpreted with considerable caution both because they do not control for causality, because the spending is far beyond the support of the data, and because of the restrictiveness of the simple quadratic functional form.

Changes Over Time

Academic R&D is increasing over time and the economy is increasingly emphasizing knowledge industries. To assess whether science is also becoming a more important determinant of wages, Table 5C reports estimates that include interactions with calendar year. The estimates show an increase in the strength of the relationship between academic R&D and wages, between 1980 and 1990, conceivably due to the Bayh Dole Act. The coefficients remain high in most specifications, although they typically do not continue to increase.

Estimates by Education

Table 5D explores how scientific activity 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 academic R&D is associated with a large increase in the supply of highly educated workers. To address these issues, we estimate interactions between scientific activity and education. The estimates indicate that the relationship between academic R&D and wages is weak or perhaps negative among people who have no college, increasing monotonically in education. The estimates are robust to controlling for the share of the population with college degrees.

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 workers may be close to the margin to retire. Table 5D 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 the youngest or oldest. Thus, the estimates peak for workers in their late 20s through 40s trailing off after that gradually. Although these estimates do not allow us to identify specific mechanisms, they are consistent with prime-age workers having more human capital and being less mobile than young workers and further from the margin to retire than older workers and having more (relevant) human capital than older workers.

Summary of Wage Results

Taken together, these estimates indicate that scientific activity, measured in a variety of ways, raises wages. These results are robust to a variety of controls for unobserved differences across metros and selection into metros. If anything the strength of this relationship is concave and has increased over time. The benefits of scientific activity are not limited to college towns, and largest for people with a college education and in their prime working years.

Real Estate Estimates

Our model implies that the effect of scientific activity (or another variable) on local productivity can be measured using the effect on wages and real estate prices. Table 6 reports estimates for real estate prices. The OLS estimates are quite weak, but including fixed effects increases the estimates. Because research universities produce students as well as research, we again include the share of college graduates as a control, which reduces the estimates somewhat. Columns (5)-(8) include time-varying metro controls. These have a very small effect on the estimates, although they reduce statistical significance.

Table 7 reports instrumental variables estimates. The first stage equations in Panel B are quite strong, especially the model without fixed effects. The second stage IV estimates in Panel A parallel the non-IV estimates. Specifically, the IV estimates without fixed effects, like the corresponding OLS estimates, are quite weak, but the IV estimates with fixed effects are strong. The fixed effects IV estimates are larger than the IV estimates without fixed effects, but the difference is not statistically significant. Including time-varying metro-level controls in columns (3) and (4) has little effect on the estimates.

Effect on Productivity and Real Wages

We use our estimates to impute the local productivity spillovers from science. In addition to the estimates above, we require estimates of the shares of labor, land, and capital in aggregate production. From the National Income and Product Accounts, we estimate that labor's share of national income is 60.7%. We further estimate that real estate's share of the capital stock is 36.8% while the share of non-real capital is 63.2%.[13] Using these shares, the midpoint estimate for wages of .18, and the fixed effect estimate for real estate of .1708, we estimate that a $1 per capita increase in science spending (costing $316 Million) would increase productivity by .0134%. With GDP in 2013 of $16.0 trillion, the increase in productivity would be $2.27 billion. Given the wide range of estimates for the real estate equation (especially), this estimate should

[13] We use BEA Table 2600, and treat non-residential buildings as real capital and all other tangible and intangible fixed assets as non-real capital.

be taken as only broadly indicative of magnitudes.

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 the midrange 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 academic R&D represent an increases in real wages.

Conclusion

Policy makers and researchers have long sought to estimate the local economic spillovers from scientists. While much of the policy discussion focuses on job creation, economic logic implies that these spillovers should be measured using productivity. We develop and implement a general framework for imputing the effects of science on productivity using a cost function approach. Our estimates show a strong positive effect of science on wages and a generally positive, but mixed effect on real estate prices. Together these estimates imply that science raises local productivity.

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Figure 1. Trends in Federal Academic R&D Spending, by Field.

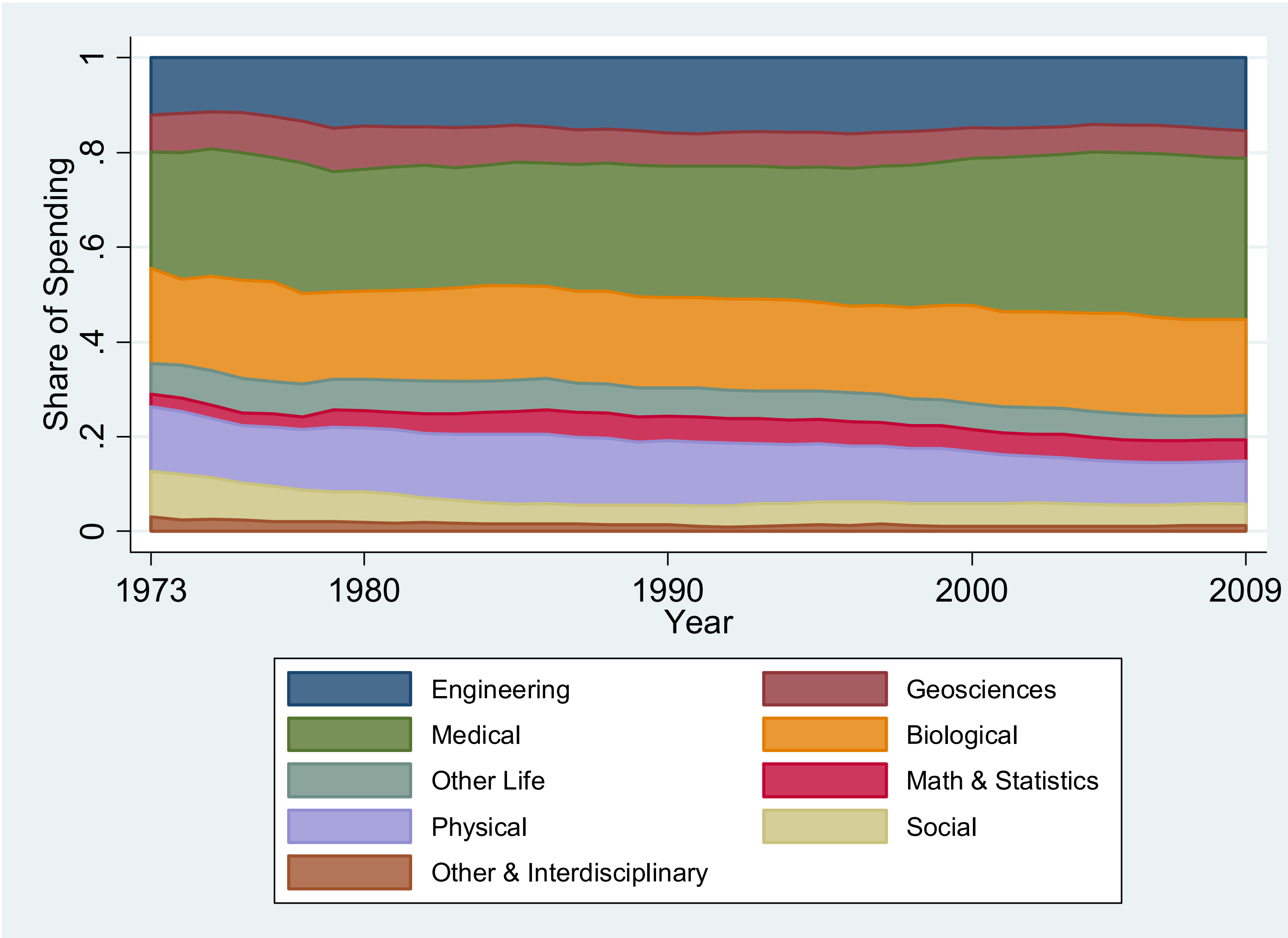

Table 1. Summary Statistics

	1980		1990		2000		2009-2011		All Years	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Individual Variables										
Weekly Wage	783.97	526.35	866.53	599.54	962.54	669.88	921.53	683.1	898.44	650.73
Log Weekly Wage	6.43	0.72	6.52	0.74	6.63	0.74	6.54	0.8	6.54	0.78
Age	37.57	12.66	38.41	11.55	40	11.25	41.89	11.95	40.49	12.03
Female	0.44	0.5	0.47	0.5	0.48	0.5	0.48	0.5	0.47	0.5
Married	0.67	0.47	0.64	0.48	0.61	0.49	0.58	0.49	0.61	0.49
Non-Citizen	0.38	0.19	0.58	0.23	0.09	0.29	0.1	0.3	0.08	0.28
Black	0.09	0.29	0.1	0.3	0.11	0.31	0.11	0.31	0.1	0.31
Other Race (Non-White)	0.03	0.16	0.07	0.26	0.14	0.34	0.14	0.34	0.11	0.31
Hispanic	0.06	0.23	0.08	0.28	0.12	0.33	0.16	0.37	0.13	0.34
Years of Schooling	12.72	2.91	13.19	2.64	13.52	2.81	13.65	2.89	13.43	2.86
Experience	18.84	13.28	19.23	11.87	20.48	11.43	22.24	12.17	21.06	12.28
Observations	481,406		532,615		376,153		1,884,767		3,274,878	
Metro Variables										
Academic R&D	0.043	0.110	0.072	0.205	0.072	0.132	0.100	0.250	0.083	0.227
College Grad Share	0.18	0.05	0.22	0.06	0.3	0.07	0.32	0.08	0.28	0.09
Share Shift Index	0.02	0.05	0.03	0.09	0.05	0.09	0.08	0.24	0.06	0.19
Number of Metros	227		234		88		195		744	

Notes—The means of the individual-level variables in Panel A are weighted by the Census Bureau population weights. All dollar values in 1982-1984=100 dollars.

Table 2: The impact of academic R&D on log wages: OLS and FE Estimates								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Academic R&D	0.1500***	0.1772***	0.0409	0.1515***	0.1512***	0.1902**	0.0406	0.1544**
	(0.0398)	(0.0616)	(0.0431)	(0.0524)	(0.0409)	(0.0768)	(0.0440)	(0.0628)
College Grad Share			0.5429***	0.5806***			0.5556***	0.5784***
			(0.0943)	(0.0756)			(0.0876)	(0.0687)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes		Yes		Yes
Includes Metro Controls					Yes	Yes	Yes	Yes
R-squared	0.3074	0.3123	0.3093	0.3132	0.3075	0.3122	0.3093	0.3131
Observations	3,232,247	3,232,247	3,232,247	3,232,247	3,200,629	3,200,629	3,200,629	3,200,629
Number of Metros	260	260	260	260	252	252	252	252

Notes At the individual-level, all specifications include years of schooling, a quadratic in experience, and indicator variables for race, ethnicity, citizenship, gender, and marital status. At the metro-level, all specifications include a quadratic in log population. Columns 5-8 also include controls for the violent crime rate, property crime rate, public school enrollment, and average utility costs. All estimates are weighted by the Census Bureau population weights. Standard errors, which are clustered at the metro-level, are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3: The impact of academic R&D on log wages: 2SLS Estimates						
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2nd Stage Estimates						
Academic R&D	0.1933***	0.5380	0.1753***	0.4584	0.5912**	-0.9686
	(0.0527)	(0.5196)	(0.0491)	(0.4408)	(0.1340)	(1.4051)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes		Yes
Includes Metro Controls			Yes	Yes		
Panel B: First Stage Estimates						
Share Shift	0.4626***	0.1681	0.4721***	0.2097		
	(0.1372)	(0.1025)	(0.1256)	(0.1286)		
State of Birth					0.5097**	0.0363
					(0.1012)	(0.0225)
F-statistic	11.363	2.689	14.123	2.657	25.35	2.598
Metros	260	260	252	252	253	253
Observations	3,232,247	3,232,247	3,200,629	3,200,629	1,681,628	1,681,62 8

Notes—At the individual-level, all specifications include years of schooling, a quadratic in experience, and indicator variables for race, ethnicity, citizenship, gender, and marital status. At the metro-level, all specifications include a quadratic in log population. Columns 3 and 4 also include controls for the violent crime rate, property crime rate, public school enrollment, and average utility costs. All estimates are weighted by the Census Bureau population weights. Standard errors, which are clustered at the metro-level, are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4: Alternative Measure of Scientific Activity

	Panel A: Academic R&D				*Panel B: Papers Per Capita*			
	(1) OLS	(2) FE	(3) IV	(4) IV-FE	(5) OLS	(6) FE	(7) IV	(8) IV-FE
Estimated Coefficient	0.1795**	0.0812+	0.2069**	0.2047**	13.6302**	5.9337+	15.0419**	15.3639*
	(0.0412)	(.0445)	(0.0445)	(0.0792)	(2.4847)	(3.278)	(2.9254)	(6.4299)
Impact of a 1 SD Increase	0.02945	.01333	.03395	.03358	.03251	.01415	.03588	.03665
R-squared	0.3474	0.3512	0.3473	0.3424	0.3475	0.3512	0.3474	0.3423
1st Stage Coefficient			1.34905	1.46825			0.01855	0.01956
			(0.0861)	(0.2195)			(0.00205)	(.00376)
1st Stage F-statistic			246	42			84	30

Notes—64 Metros

Table 5A. Interactions with Population.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Academic R&D								
* 150,000 or Less	-0.0195	0.1314*	-0.0793***	0.1315*	-0.0140	0.1423*	-0.0803***	0.1317*
	(0.0300)	(0.0757)	(0.0269)	(0.0723)	(0.0350)	(0.0838)	(0.0294)	(0.0761)
* 150,001 - 500,000	0.0838**	0.1521***	0.0311	0.1374***	0.0882**	0.1674***	0.0308	0.1444**
	(0.0355)	(0.0508)	(0.0390)	(0.0489)	(0.0358)	(0.0635)	(0.0380)	(0.0573)
* 500,001 - 1,000,000	0.1416***	0.3060***	0.0165	0.2429***	0.1333**	0.2888***	0.0090	0.2280***
	(0.0531)	(0.0789)	(0.0557)	(0.0720)	(0.0540)	(0.0798)	(0.0587)	(0.0723)
* 1,000,001 - 2,000,000	0.0792**	0.2285***	-0.0656	0.1365*	0.0711*	0.2115***	-0.0687	0.1264*
	(0.0368)	(0.0804)	(0.0413)	(0.0704)	(0.0369)	(0.0762)	(0.0438)	(0.0725)
* 2,000,001 or More	0.8943***	0.5941	0.4947***	0.3479	0.8854***	0.6081*	0.4997***	0.3689
	(0.2207)	(0.3678)	(0.1752)	(0.3275)	(0.2055)	(0.3473)	(0.1681)	(0.3145)
College Grad Share			0.4625***	0.5729***			0.4755***	0.5688***
			(0.0697)	(0.0660)			(0.0684)	(0.0609)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes		Yes		Yes
Metro-Level Controls					Yes	Yes	Yes	Yes
Observations	3,232,247	3,232,247	3,232,247	3,232,247	3,200,629	3,200,629	3,200,629	3,200,629
Number of Metros	260	260	260	260	252	252	252	252
R-squared	0.2101	0.2150	0.2137	0.2176	0.2099	0.2147	0.2134	0.2173

Table 5B. Shape of Relationship.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Academic R&D	0.3145***	0.3728***	0.1018	0.3026***	0.3137***	0.4079**	0.1025	0.3127**
	(0.0843)	(0.1337)	(0.0709)	(0.1112)	(0.0817)	(0.1714)	(0.0728)	(0.1448)
Academic R&D^2	-0.1792***	-0.1506*	-0.0621*	-0.1162*	-0.1761***	-0.1785	-0.0627*	-0.1297
	(0.0639)	(0.0836)	(0.0364)	(0.0700)	(0.0599)	(0.1123)	(0.0369)	(0.0965)
College Grad Share			0.5239***	0.5765***			0.5353***	0.5740***
			(0.0924)	(0.0749)			(0.0858)	(0.0682)
Implied Maximum ($ per capita)	878	1238	820	1302	891	1143	817	1205
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes		Yes		Yes
Metro-Level Controls					Yes	Yes	Yes	Yes
Observations	3,232,247	3,232,247	3,232,247	3,232,247	3,200,629	3,200,629	3,200,629	3,200,629
Number of Metros	260	260	260	260	252	252	252	252
R-squared	0.3077	0.3123	0.3094	0.3132	0.3078	0.3122	0.3093	0.3131

Table 5C. Interactions with Time.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Academic R&D								
* 1980	0.0953	0.0101	-0.0219	0.0833	0.1294	0.0586	-0.0111	0.0904
	(0.0793)	(0.1331)	(0.1097)	(0.1238)	(0.0842)	(0.1775)	(0.1130)	(0.1600)
* 1990	0.2029***	0.1802*	0.1004	0.2073**	0.2165***	0.2224	0.1016	0.2195*
	(0.0737)	(0.1088)	(0.0881)	(0.1004)	(0.0781)	(0.1398)	(0.0916)	(0.1215)
* 2000	0.1770***	0.0986*	0.1036***	0.1056**	0.1844***	0.1175	0.1032***	0.1070
	(0.0214)	(0.0560)	(0.0141)	(0.0516)	(0.0236)	(0.0789)	(0.0158)	(0.0668)
* 2009-2011	0.1292**	0.2164**	0.0011	0.2006**	0.1197**	0.2573**	-0.0010	0.2235**
	(0.0523)	(0.0963)	(0.0269)	(0.0871)	(0.0466)	(0.1157)	(0.0275)	(0.1030)
College Graduate Share			0.5504***	0.5746***			0.5612***	0.5723***
			(0.0925)	(0.0751)			(0.0859)	(0.0691)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes		Yes		Yes
Metro-Level Controls					Yes	Yes	Yes	Yes
Observations	3,232,247	3,232,247	3,232,247	3,232,247	3,200,629	3,200,629	3,200,629	3,200,629
Number of Metros	260	260	260	260	252	252	252	252
R-squared	0.3075	0.3124	0.3094	0.3132	0.3075	0.3123	0.3093	0.3131

Table 5D. Interactions with Education.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Academic R&D								
*No HS	-0.0292	-0.0418	-0.1625	-0.0570	-0.0293	-0.0344	-0.1633	-0.0605
	(0.1067)	(0.0941)	(0.1298)	(0.0926)	(0.1130)	(0.1013)	(0.1353)	(0.0973)
* Some HS	0.0485	0.0519	-0.0496	0.0364	0.0511	0.0579	-0.0494	0.0325
	(0.1010)	(0.0700)	(0.1230)	(0.0680)	(0.1076)	(0.0770)	(0.1271)	(0.0718)
* HS Grad	0.0956*	0.1251***	0.0090	0.1062**	0.0998	0.1342**	0.0120	0.1067**
	(0.0569)	(0.0464)	(0.0708)	(0.0417)	(0.0607)	(0.0599)	(0.0718)	(0.0504)
* Some College	0.1399***	0.1734***	0.0433	0.1535***	0.1395***	0.1810**	0.0445	0.1529**
	(0.0397)	(0.0590)	(0.0439)	(0.0526)	(0.0409)	(0.0726)	(0.0450)	(0.0622)
* College Grad	0.1742***	0.2083***	0.0773**	0.1853***	0.1715***	0.2156**	0.0775**	0.1848**
	(0.0479)	(0.0710)	(0.0371)	(0.0632)	(0.0460)	(0.0832)	(0.0378)	(0.0717)
* Grad/Prof	0.2497***	0.2754**	0.1491***	0.2508**	0.2489***	0.2835**	0.1513***	0.2513**
	(0.0816)	(0.1108)	(0.0504)	(0.1018)	(0.0772)	(0.1227)	(0.0499)	(0.1112)
College Grad Share			0.4734***	0.4880***			0.4736***	0.4885***
			(0.0913)	(0.0752)			(0.0857)	(0.0687)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes		Yes		Yes
Metro-Level Controls					Yes	Yes	Yes	Yes
Observations	3,232,247	3,232,247	3,232,247	3,232,247	3,200,629	3,200,629	3,200,629	3,200,629
Number of Metros	260	260	260	260	252	252	252	252
R-squared	0.3210	0.3255	0.3225	0.3261	0.3211	0.3254	0.3224	0.3260

Table 5E. Age Interactions.								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Academic R&D								
* 18-25	0.0312	0.0757	-0.0674	0.0547	0.0338	0.0915	-0.0678	0.0595
	(0.0914)	(0.0670)	(0.1074)	(0.0640)	(0.0964)	(0.0774)	(0.1100)	(0.0693)
* 26-30	0.1676***	0.1957***	0.0599	0.1723***	0.1690***	0.2103**	0.0592	0.1765***
	(0.0434)	(0.0658)	(0.0461)	(0.0565)	(0.0448)	(0.0819)	(0.0478)	(0.0677)
* 31-35	0.1934***	0.2119***	0.0835**	0.1877***	0.1952***	0.2267**	0.0833**	0.1924**
	(0.0469)	(0.0739)	(0.0392)	(0.0645)	(0.0462)	(0.0888)	(0.0398)	(0.0750)
* 36-40	0.1838***	0.2026***	0.0770**	0.1777***	0.1865***	0.2184***	0.0778**	0.1837***
	(0.0417)	(0.0677)	(0.0369)	(0.0586)	(0.0412)	(0.0835)	(0.0372)	(0.0698)
* 41-45	0.1552***	0.1733***	0.0487	0.1477**	0.1567***	0.1887**	0.0488	0.1536**
	(0.0392)	(0.0660)	(0.0355)	(0.0570)	(0.0387)	(0.0810)	(0.0358)	(0.0676)
* 46-50	0.1426***	0.1654**	0.0348	0.1392**	0.1426***	0.1798**	0.0340	0.1443**
	(0.0372)	(0.0655)	(0.0315)	(0.0565)	(0.0364)	(0.0812)	(0.0315)	(0.0679)
* 51-55	0.1465***	0.1727***	0.0392	0.1463***	0.1473***	0.1881**	0.0392	0.1524**
	(0.0381)	(0.0638)	(0.0353)	(0.0553)	(0.0379)	(0.0795)	(0.0355)	(0.0665)
* 56-60	0.1674***	0.1977***	0.0595*	0.1711***	0.1670***	0.2121**	0.0584*	0.1760**
	(0.0406)	(0.0695)	(0.0315)	(0.0605)	(0.0400)	(0.0852)	(0.0318)	(0.0720)
* 61-65	0.1269**	0.1567**	0.0210	0.1302**	0.1265**	0.1719*	0.0199	0.1359*
	(0.0501)	(0.0753)	(0.0355)	(0.0658)	(0.0493)	(0.0902)	(0.0359)	(0.0767)
College Grad Share			0.5303***	0.5668***			0.5432***	0.5627***
			(0.0938)	(0.0753)			(0.0871)	(0.0687)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes		Yes		Yes
Metro-Level Controls					Yes	Yes	Yes	Yes
Observations	3,232,247	3,232,247	3,232,247	3,232,247	3,200,629	3,200,629	3,200,629	3,200,629
Number of Metros	260	260	260	260	252	252	252	252
R-squared	0.2821	0.2875	0.2849	0.2888	0.2822	0.2874	0.2848	0.2886

Notes—At the individual-level, all specifications include years of schooling, a quadratic in experience, and indicator variables for race, ethnicity, citizenship, gender, and marital status. At the metro-level, all specifications include a quadratic in log population. The metro-level controls include the violent crime rate, property crime rate, public school enrollment, and average utility costs. All estimates are weighted by the Census Bureau population weights. Standard errors, which are clustered at the metro-level, are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 6: The impact of academic R&D on Real Estate Prices: OLS & FE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Academic R&D	-0.0072	0.1708***	-0.0197	0.1317**	-0.0034	0.1674**	-0.0149	0.1251
	(0.0236)	(0.0588)	(0.0248)	(0.0626)	(0.0247)	(0.0792)	(0.0256)	(0.0807)
College Grad Share			0.2938	0.6352*			0.2686	0.5863*
			(0.1822)	(0.3618)			(0.1841)	(0.3481)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes		Yes		Yes
Metro-Level Controls					Yes	Yes	Yes	Yes
Observations	887	887	887	887	856	856	856	856
R-squared	0.8588	0.9188	0.8592	0.9195	0.8594	0.9204	0.8597	0.9210

Notes—All specifications include a quadratic in log population. Columns 5-8 also include controls for the violent crime rate, property crime rate, public school enrollment, and average utility costs. Standard errors, which are clustered at the metro-level, are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 7: The impact of academic R&D on Real Estate Prices: IV

	(1)	(2)	(3)	(4)
Panel A: 2nd Stage Estimates				
Academic R&D	0.0266	0.3599*	0.0246	0.4022*
	(0.0301)	(0.1976)	(0.0319)	(0.2260)
Year Fixed Effects	Yes	Yes	Yes	Yes
Metro Fixed Effects		Yes		Yes
Metro-Level Controls			Yes	Yes
R-squared	0.8585	0.9079	0.8592	0.9077
Panel B: First Stage Estimates				
Share Shift	0.9726***	0.4442***	0.9729***	0.3744***
	(0.1666)	(0.1399)	(0.1638)	(0.0928)
F-statistic	34.07	10.08	35.27	16.28
Observations	887	881	856	849
Number of Metros	283	283	236	236

Notes—All specifications include a quadratic in log population. Columns 5-8 also include controls for the violent crime rate, property crime rate, public school enrollment, and average utility costs. Standard errors, which are clustered at the metro-level, are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.