Estimating the Indirect Economic Benefits from Science

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I. The Issue

Governments are major supporters of scientific research. Since 2003, the United States Federal government spent roughly $60 billion annually (in 2009 dollars) on basic and applied research. State and local governments support science directly through their support of universities and indirectly through tax breaks (Clemins [2009]). Spending on science is increasingly justified based on its economic benefits, like job creation, but there are mixed views of the benefits of scientific research. On the one hand, scientific research is seen to generate substantial benefits for the communities where it is produced. The success of Silicon Valley, the Route 128 corridor in Boston, the Research Triangle Park, and Austin are often attributed to the scientific research produced in these communities (see, for instance, Dorfman [1983]; Saxenian [1996]; and Feldman and Desrochers [2003]). On the other hand, 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 of research are disputed (Macilwain [2010]).

We distinguish two broad ways in which scientific research can benefit the economy. First, science can directly lead to valuable technological innovations like biotechnology or nanotechnology. The literature estimating the direct economic benefits of science uses a range of approaches to assign dollar values to the innovations that derive directly from scientific research. For instance, Mansfield's [1991] well-known study surveys R&D executives to determine the extent to which their new products and processes relied on scientific research. This work also measures the value of the new products and processes. Other studies track innovations through patents (Higgins, Thusby, and Thursby [2010]). Still others estimate the value of innovations arising from scientific research (e.g. Murphy and Topel [2006] estimate the total value of improvements in health with back-of-the-envelope estimates of the benefits attributable to biomedical science). Regardless of method, the reported estimates are quite large, typically well in excess of the real interest rate or even returns on risky assets (e.g. common stocks).

Second, science can have indirect benefits and policy discussions increasingly focus on these indirect benefits, such as the number of jobs "created" by research. Our focus is in this area, on the benefits that are generated by science beyond the technological

[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])."

innovations that arise from it directly. Existing work has emphasized a number of ways in which science can generate indirect benefits (Salter and Martin [2001] and Scott, Steyn, Geuna, Brusoni, and Steinmueller [2001] discuss mechanisms and survey the literature). For instance: (1) Researchers provide human capital for the economy. Often, cutting-edge science is best implemented by the scientists who conducted it. Consequently, researchers and their students often work for (or start) companies, increasing the absorption of science. Also, graduates from research institutions may be better equipped to perform in the knowledge economy. (2) Researchers may generate infrastructure, including equipment and facilities that support industrial innovation, or provide a hub for innovation (e.g. the research institutions in San Francisco may have attracted venture capital that then generated more innovation).

Although job creation receives a lot of policy attention, we contend that job creation metrics may not be the best way to measure the indirect benefits from science for a wide range of conceptual and practical reasons. Rather, economic logic says that the indirect benefits from science should be measured in terms of the additional surplus to firms and workers accruing from increases in productivity.

Many of the indirect benefits of science are believed to accrue locally, which makes them particularly important from the perspective of local policy makers. But, by summing the benefits received across locales, one can estimate national benefits. The localization of indirect benefits also means that their impact can be estimated by relating outcomes, such as wages, to measures of scientific activity across cities or states. Much of the existing literature takes this approach. As discussed below, three challenges must be address when using this approach: (1) unobserved differences across cities; (2) unobserved differences across workers; and (3) adjustment of factor inputs.

The skepticism about the economic benefits of science can be addressed by more rigorous research, which addresses the empirical challenges directly and convincingly. Our survey of the literature discuss the extent to which different works address these concerns and points toward ways in which these challenges can be addressed.

II. Job Creation as a Measure of Indirect Economic Benefits

Policy makers frequently frame discussions of the economic benefits from science in terms of job creation. This section discusses problems with job creation metrics. We divide the problems into two broad categories: (1) underlying conceptual problems, the objections that rigorous contemporary economics would raise to job creation measures, and (2) practical problems that remain even if one is willing to look past the conceptual challenges.

Underlying Conceptual Challenges

Economists do not view the effects of policies on employment as fundamental, but rather view the effects on employment as being determined by the interplay of many factors. Specifically, economists think of science policy as affecting productivity. When productivity increases, firms look to hire workers. The economy is frequently, but obviously not always, at or near "full employment," only experiencing what is referred to as the "natural rate of unemployment."[2] If labor markets are near full employment and science policy increases productivity, potentially only a few jobs will be created because most people interested in working are already employed. Rather wages will be driven up as firms compete for workers. Thus, if the economy is at or near full employment, focusing on job creation will miss most or all of the impacts of science spending. Even if the economy is not at full employment (stimulus spending, for instance, occurs during periods when the economy is not at full employment), the effect of scientific activity on employment is likely to understate the full benefits of science.[3]

Another limitation of job creation measures is that they ignore workers' opportunity costs of time.[4] Consider a science program that creates 1 job with $60K in annual compensation (roughly the average annual compensation in the United States in 2007). Even if the person who takes that job was unemployed, he or she does not derive $60K in net benefits from the job. This is because a worker's net benefits from a job are the wage less the "opportunity costs" of his or her time - the value of that time in the next best activity. At full employment, compensation is likely to be close to opportunity costs, so the net benefits of increasing employment are small. Even when the economy is away from full employment, opportunity costs are not zero so that the worker's compensation of $60K is likely to greatly overstate the net benefits of the job to the worker.

Jobs also differ dramatically in terms of their compensation. It is natural to view the benefits of job creation as being greater if the jobs created have a high compensation level. Here too, standard economic theory takes a cautionary tone. Most high-paying "good jobs" go to "good workers." A job paying $30K could have either larger or smaller net benefits than a job paying $120K because the person receiving the $30K job could have an opportunity cost of $25K while the person getting the $120K job could have an opportunity cost of $119K. And if science policy means that a $40K job is created in place of a $30K job, it is far from certain that the same person will be hired to fill it.

Practical Challenges

Even if one is willing to look past all of these conceptual challenges, there are a number of significant practical challenges to estimating job creation. The most obvious way of measuring job creation is to count up the number of new jobs at the organizations receiving funding or tally the specific jobs that were funded and attribute them to the funding. This calculation poses three difficulties. First, it assumes that the new jobs are due to the funding. By way of analogy to medical experiments, this procedure is

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[2] Some unemployment is viewed as unavoidable due to frictions in the labor market as people entering the labor market after leaving school or childbearing search for jobs. There is also constant reallocation of jobs across sectors and regions, which generates unemployment.
[3] The effect of a policy on job creation depends on the extent to which new workers choose to work as wages increase; the ways in which firms search for employees and workers search for jobs; and the extent to which firms hire workers versus invest in additional equipment.
[4] On the other hand, income taxes mean that the social benefits to having additional people working are greater than the private benefits.

equivalent to counting up the number of patients who received a treatment and subsequently recovered. Surely some of the people who recovered would have done so even without the treatment. In the case of job creation, some of the new jobs might have been created even in the absence of funding. As in clinical medical trials, accurately estimating the number of jobs created requires a control group – a group of comparable organizations that did not receive the funding against which the funded treatment group's outcomes can be benchmarked.[5]

A second practical challenge arises because as new jobs are created, wages increase and some jobs that would otherwise have been created at other organizations are not created. In economic terminology, job creation from scientific activity can "crowd out" job creation elsewhere.

The third practical challenge is that it is difficult to know which jobs should be traced back to the funding because jobs are frequently outsourced from one organization to another. It is likely that any effort to trace jobs created back to the initial funding will miss many jobs that were created by it and any effort to cast a wide enough net to catch most or all jobs created by the funding is likely to be so broad as to capture many jobs that were not created by the funding. It is worth bearing in mind, that these challenges apply to the evaluation of many programs, not just investments in science.

III. Alternative Ways of Estimating Indirect Economic Benefits

These challenges, both conceptual and practical, lead us to caution against job creation metrics. What then is the alternative? We argue that economic theory provides a simple metric for measuring the indirect benefits from science. Specifically, it argues that one should measure the effects of science on productivity. Gross Domestic Product in the United States is $14.6 trillion. If scientific activity were to increase productivity by 1% then its value would be $146 billion. Some of these benefits may take the form of newly created jobs. Others may take the form of higher compensation to workers. Others still may take the form of higher profits to the owners of the firm, which are also important (and are frequently overlooked in policy discussions).

If science affect local economies indirectly, one would expect stronger economic outcomes in cities that have a high level of scientific activity compared to those that have

[5] An obvious approach is what economists refer to as a regression discontinuity design. Consider a policy where organizations apply for funding and the best applications are funded. One could compare the outcomes at the organizations that were only slightly above the funding threshold to those that were only slightly below it. (Jacob and Lefgren [Forthcoming] take this approach to estimating the impact of grant funding on research output.) There are at least two problems with this approach. First, it requires information on organizations that did not receive funding. These organizations may either be unwilling to provide information or not take the time to provide accurate, comprehensive information. Second, if the process by which the applications are vetted is good and society is investing optimally in science, the applications that were just barely funded should be only slightly better than the applications that were not funded, so the estimated benefits of funding should be small even though the benefits of many projects are much larger.

less scientific activity. We argue that the indirect local economic benefits from science can be estimated by relating economic outcomes, including wages and real estate prices (and even employment), to measures of scientific activity. The existing literature takes this approach relating a wide range of outcomes to scientific activity, innovation, and education levels. Outcomes include: income and employment (Beeson and Montgomery [1993]; Goldstein and Renault [2004]; and Saha [2008]); employment growth and hi-tech industry employment (Beeson and Montgomery [1993] and Saha [2008]); human capital formation (Abel and Deitz [2009]); the occupation mix (Abel and Deitz [2009]); and patenting (Carlino and Hunt [2009]).

This approach has its own set of challenges. In what follows, we describe these challenges, describe the most commonly used data, and survey the existing literature, discussing the extent to which existing work addresses these challenges. We conclude by sketching an approach to address these challenges.

Challenges

The primary challenges to estimating the indirect local economic benefits from science using differences in economic outcomes across cities are:

> **(1)** ***Unobserved Differences across Cities (Causality)*** Economists think of cities differing in terms of amenities that make some of them more desirable places to live (e.g. good weather or access to mountains) or more productive for businesses (e.g. easy access to fertile land or shipping) than others. Many cities, like Boston and San Francisco, that have strong scientific institutions also have consumption amenities that appeal to workers. (Universities themselves may appeal to workers and/or foster attractive cultural amenities.) If so, workers will be attracted to these cities, which would tend to drive down wages in these cities, biasing down the estimated benefits of science. Alternatively, science producing organizations may flourish in cities that are more productive (e.g. because wealthier cities invest more in science), biasing estimates of the indirect benefits from science upward. Estimating the effects of science requires a strategy that addresses both potential biases.

> **(2)** ***Unobserved Differences across Workers (Selection)*** Cities with high levels of scientific activity may have highly-productive workers for two reasons. First, universities are major producers of science and also produce highly skilled workers (and the universities that produce the most research may produce the best workers). Second, cities with high levels of scientific activity may have amenities that are particularly appealing to highly skilled workers. If this sorting on ability is not addressed, estimates of the effects of science on wages will be biased upward.

> **(3)** ***Adjustment of Factor Inputs*** If research raises productivity in a city, it would be natural to expect workers to move to the area and for the city to expand. As workers move to the city, wages will be drive down, potentially biasing down the estimated wage benefits of science.

Survey of Literature

Measurement Issues

Because a large portion of science is performed by academic institutions and because most academic R&D is in the sciences and engineering, researchers have often relied on academic R&D to measure science (Beeson and Montgomery [1993]; Goldsetin and Renault [2006]; Saha [2008]; Carlino and Hunt [2009]; and Abel and Deitz [2009]). Kantor and Whalley [2009] consider all university expenditure as an explanatory variable, which includes expenditure on scientific research. In some studies the share of bachelors degrees in science and engineering is used as a measure of science (Beeson and Montgomery [1993] and Saha [2008]). Goldstein and Renault [2004] consider the presence of non-academic research institutions and Carlino and Hunt [2009] include scientific activity from private and government laboratories in their analysis. They also use academic R&D by field and source in their study. Bauer, Schweitzer and Shane [2009] include patents to measure innovative activity. Data for scientific activity like academic R&D are frequently drawn from the National Science Foundation's WebCASPAR https://webcaspar.nsf.gov/.

Because cities differ considerably in population, most studies express science in per capita terms (and use outcomes that do not depend on population). When science is measured in per capita terms, "college towns" like College Station, TX and State College, PA, have the highest level of science (Saha [2008]). Note that smaller cities receive less weight in individual level or population-weighted metro level analyses.

Addressing Unobserved Differences across Cities (Causality)

One approach to addressing differences across cities is to include a wide range of controls for the observable characteristics of cities. Population is used most frequently, followed by crime rates, employment in different industries, the presence of an airport hub, taxes, utility expenses, and student-teacher ratios. It is important to bear in mind that controlling for city characteristics that are affected by science, misattributes the benefits of science to these characteristics (although it can be useful for unpacking the ways in which science generates indirect economic benefits). For example, some studies relate patenting to scientific activity and patenting tends to be related to better outcomes. If we believe that science increases patenting, then simply controlling for patenting misattributes some of the benefits of science to patenting. Although, controlling for patenting indicates how much of the effect of science operates through patenting. Researchers typically draw data on income and city characteristics from the decennial Census, the *City and County Data Book*, the *State and Metro Area Data Book*, *County Business Patterns,* or the *Places Rated Almanac*.

Colleges and universities have both educational and scientific components, making it important to control for education in a region when estimating the indirect economic benefits from science. Measures of local educational levels include the share of the population with bachelors degrees (Saha [2009]; Bauer, Schweitzer and Shane [2009]; Carlino and Hunt [2009]; and Kantor and Whalley [2009]) or the flow of degrees awarded per capita (Beeson and Montgomery [1993]; Saha [2008]; Abel and Deitz [2009]). The Higher Education General Information System (HEGIS) and its successor, the Integrated Postsecondary Education Data System (IPEDS) contain data on degrees and enrollments. These data are available through WebCASPAR. Educational attainment can be estimated from micro data such as the Census.

Given the myriad factors that make one city more attractive than another, it is unlikely that all relevant factors can be controlled explicitly by researchers. A common strategy is to rely on panel data and use fixed effects estimates. This strategy looks at changes in scientific activity over time within cities. It sees whether the cities with the greatest increases in scientific activity also experience the largest improvements in outcomes.[6] For instance, if Washington, D.C. has good outcomes because it is the capitol and also has a high level of scientific activity, the fixed effects estimates eliminate the permanent effects of its being the capitol. Unfortunately, the fixed effects estimator is invalid if changes in scientific activity in a city over time are related to changes in either consumption or production amenities in that city. There is also a possibility of reverse causality, whereby changes in incomes or other outcomes affect scientific activity (e.g. through investments in science).

In these cases, fixed effects estimates will not identify the effect of scientific research on local outcomes. Instrumental variables estimation is the most common solution. Formally, an instrument should be correlated with scientific activity but not directly related to the outcome variables. The most frequently used instruments in the literature are historical levels of scientific activity in the city (Saha [2008]; Bauer, Schweitzer and Shane [2009]; and Carlino and Hunt [2009]). Kantor and Whalley [2009] have a novel instrument. They use the market value of university endowments interacted with asset market returns. The idea is that the market value of the endowment affects the spending of a university but it does not directly affect local labor market outcomes. Carlino and Hunt [2009] uses a range of instruments, arguing that the presence of hills and highways in a city affects job densities and innovation but that they do not directly affect outcomes.

Results

Table 1 summarizes results from existing studies. Using cross-sectional data, Beeson and Montgomery [1993] find that university activities have no significant effect on income, employment rates, net migration rates, or the share of employment in high tech industries. The effects of universities on income are of a modest, but economically meaningful magnitude – a one standard deviation increase in the university variables increases predicted income by about 2%. In contrast, the economic effect on labor force composition is not trivial – a one standard deviation increase in R&D increases the employment of scientists by 25% and a one standard deviation increase in the share of

[6] It is important to note that the fixed effects estimates give the effects of changes in scientific activity on changes in outcomes. Such transitory variations in science may have larger or smaller effects on outcomes, so that fixed effects estimates should not be seen as giving the same effect as cross sectional estimates. Most studies also include time fixed effects to control for aggregate trends in scientific activity.

science and engineering degrees among all bachelors increases the predicted employment of scientists by 14%.

Saha [2008] considers many of Beeson and Montgomery's [1993] variables, but uses panel data for 1980, 1990, and 2000, allowing him to estimate fixed effects models in addition to cross-sectional models. He finds positive and significant effects of academic R&D and the share of science and engineering degrees among all bachelors in a city on income controlling for individual education, work experience, and the metro level stock of bachelors degrees. A one standard deviation increase in R&D increases income by 4% and a one standard deviation increase in all the university variables increased wages by 12%. He finds more modest effects on employment status.

In a study that covers a substantial amount of non-science university activity, Kantor and Whalley [2009] find small but statistically significant agglomeration spillovers caused by university spending. The estimates indicate that a 10% increase in higher education spending increases local non-education sector labor income by about 0.5%. This study is noteworthy because its instrumental variables strategy is unique (if not beyond question), expanding the foundation of our understanding of these issues.

There is some evidence that the benefits of science are increasing over time. Goldstein and Renault [2004] find that the indirect economic benefits of universities became positive and significant after 1986. Consistent with this finding, Saha [2008] hypothesizes that wage effects in his work are larger than Beeson and Montgomery's [1993] in part because the effects of science may be increasing over time.

In estimating the benefits of science, it is important to control for education levels. Thus, Saha [2008] and Abel and Deitz [2009] both find that after controlling for the share of college graduates in the population, the estimated effect of academic R&D falls.

Academic R&D does appear to affect the sectoral composition of local economies. Abel and Deitz [2009] show that academic R&D had a positive and significant effect on both the share of the population with bachelors degrees as well as on the occupation mix – mostly in the physical and life sciences occupations. Kantor and Whalley [2009] find that the spillovers are larger for firms that cite university patents more in their patents. These results are consistent with Beeson and Montgomery's [1993] estimates for scientists (but not high technology employment).

In the literature, patenting is used both as a determinant of outcomes and as an outcome in its own right. Treating patenting as an independent variable, Bauer, Schweitzer, and Shane [2009] find that patenting and human capital levels are important determinants of per capita income. Treating patenting as an outcome, Carlino and Hunt [2009] find academic R&D has positive and significant effects on innovative activity as measured by patents. Zucker, Darby, and Brewer [1998] find that the presence of star scientists is associated with more biotechnology startups. These results complement each other – science generates patents, which in turn raise income – providing a first step toward understanding the ways in which science affects outcomes.

Science may take time to affect economic outcomes. To account for this possible delayed effect, researchers have included lags of scientific activity in their analyses (Beeson and Montgomery [1993]; Saha [2008]; Carlino and Hunt [2009]; and Kantor and Whalley [2009]). Beeson and Montgomery [1993] and Saha [2008] find that the direction and statistical significance of the estimates remain unchanged when lags of science variables are introduced. Kantor and Whalley [2009] find little change in their main results when lagged science variables are introduced. The statistical significance of university expenditures was reduced when lags were used, but the direction and the significance of all other variables remained. Carlino and Hunt [2009] lagged all independent variables to minimize endogeneity. They also show that when lagged values of innovative activity are included as an independent variable, academic R&D continues to be positive and significant.

If cities where incomes are higher produce more science (e.g. because they invest more in scientific institutions) including city fixed effects and using instrumental variables should reduce the magnitude of the estimates. Interestingly, most work (Saha [2008]; Bauer, Schweitzer, and Shane [2009]; and Kantor and Whalley [2009]) finds that fixed effects and/or instrumental variable estimators are larger than the OLS estimates. This finding suggests that scientific activity is highest in areas that are appealing places to live or where productivity would otherwise be lower (e.g. because universities are sited in out-of-the-way places). It is also worth noting that none of the studies controls for unobserved differences in worker ability or controls for factor input adjustments satisfactorily.

IV. Conclusions and Directions for Future Work

Policy makers are increasingly interested in the indirect economic benefits from science. There are a number of papers that shed light on this issue. While the results from these studies are far from uniform, there is at least some evidence that scientific (and other innovative) activity in a city is associated with higher earnings and shifts in the industrial and occupation distribution toward technology and science.

We have argued that strategies to estimate the indirect economic benefits from science by relating wages and other outcomes in a city to scientific activity rest on firmer scientific ground than efforts to measure job creation. At the same time, there are three significant challenges that must be address when taking this approach: (1) unobserved differences across cities (causality); (2) unobserved differences across workers (selection); and (3) adjustment of factor inputs.

The first of these issues has begun to be addressed in the literature. The second two have received considerably less attention, making them important directions for future research.

It is possible to employ longitudinal data on individuals to address unobserved differences in worker ability (challenge 2). Specifically, one might estimate how increases in scientific activity in a city affect the people born or living in the city at a point in time. If all the estimated benefits of science are due to selection of workers into cities, one would expect that fluctuations in scientific activity in a city would not affect the people born in a city. By contrast, if fluctuations in scientific activity are strongly correlated with outcomes for the people born in a city, it would suggest that the estimated benefits are not driven by selection. (Moretti [2004a] takes a similar approach to estimating human capital spillovers in cities.)

To address factor input adjustments (challenge 3), our work in progress develops a model of the determination of wages and rents in cities. We show that if wages in a city increase and rental rates on real estate do not decrease or rental rates on real estate in a city increase and wages do not decrease, then productivity must have increased in the city. Thus, it is possible to estimate the local productivity benefits.

Additional and better data will be valuable for quantifying the indirect benefits of science and unpacking the ways in which those benefits arise. Valuable data include: (1) data linking patents to the scientific publications that they build upon; (2) data linking researchers and students from their universities and laboratories to the companies they start or work for or with, including through consulting arrangements; and (3) data tracing technologies from Universities to industry through licensing agreements.

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Table 1. Summary of Studies.

Authors, Year, Outlet	**Data**	**Results**	**Controls for Unobserved Difference in Cities (Causality)**	**Controls for Unobserved Differences in Workers (Selection)**	**Controls for Factor Input Adjustments**
Patricia Beeson and Edward Montgomery 1993 Review of Economics and Statistics	Wages: Census Employment: National Planning Association Academic R&D: NSF Bachelors degrees, Science Degrees: HEGIS City characteristics: State and Metropolitan Area Data Book	Moderate but insignificant effects on wages. Effects on high tech employment and employment growth. Analysis at metro level.	Controls for observable city chars.	Controls for observable worker chars.	No
Subhra Saha 2008 Ph.D. Dissertation Ohio State University	Wages: Census Academic R&D: NSF Bachelors Degrees, Science Degrees: HEGIS/IPEDS City characteristics: State and Metropolitan Area Data Book IVs: Historic Data for R&D, Degrees	Large and significant effect of academic R&D on wages; smaller effects on employment. Science and engineering degrees increase income and employment rates. Analysis at metro level.	Yes (controls for observable city chars.; Fixed Effects; IV)	Controls for observable worker chars.	No
Shawn Kantor and Alexander Whalley 2009 NBER Working Paper #15299	Average Income: County Business Patterns University expenditures: HEGIS/IPEDS City characteristics: City and County Data Book IV: Endowments – HEGIS/IPEDS and S&P stock market index	Small but significant effect of university spending on average income. Largest effects in industries such as pharmaceuticals and electronics. Analysis at county level.	Yes (Fixed Effects, IV)	No	No

Table 1. Summary of Studies (continued).

Authors, Year, Outlet	Data	Results	Controls for Unobserved Difference in Cities (Causality)	Controls for Unobserved Differences in Workers (Selection)	Controls for Factor Input Adjustments
Gerald Carlino and Robert Hunt 2009 Federal Reserve Bank of Philadelphia	Patent intensity: OECD/EPO Patent Citations Data Job density: Country Business Patterns Academic R&D: NSF Private Sector R&D: *Directory of American Research and Technology* Congressional earmarks of agency funds for academic R&D: *Chronicle of Higher Education* Other Metro Controls: *County Business Patterns* IV: Lagged college graduate population share; employment densities; topography	Educated workforce has a significant and positive effect on innovative activity. R&D in private and government labs and academia have modest effects on patenting. Statistically insignificant effect for the applied portion of federal R&D. Analysis at metro level.	Yes (Fixed Effects, IV)	No	No
Jaison R. Abel and Richard Deitz 2009 NY Federal Reserve, Staff Report #401	College Graduate Employment Share: Census Academic R&D: NSF Bachelors Degree, HEGIS/IPEDS	Academic R&D has a large and significant effect on both the stock of human capital as well as on the occupation mix. The flow of degrees has a very small impact on the stock of degrees. Analysis at metro level.	Yes (Fixed Effects)	No	No

Table 1. Summary of Studies (continued).

Authors, Year, Outlet	**Data**	**Results**	**Controls for Unobserved Difference in Cities (Causality)**	**Controls for Unobserved Differences in Workers (Selection)**	**Controls for Factor Input Adjustments**
Harvey Goldstein and Katherine Renault 2004 Regional Studies	Academic R&D: NSF Metro Variables: 1990 Census	Small effect of university presence before 1986, then somewhat larger effects. Analysis at metro level.	Yes (Quasi Experimental Structure)	No	No
Paul Bauer, Mark Schweitzer, and Scott Shane 2009 Cleveland, Federal Reserve Working Paper	Personal income: Bureau of Economic Analysis Population: Census High school and college attainment rates: Current Population Survey for 1979-2004 and census tabulations before that Patent data: *Annual Report of the Commissioner of Patents and USPTO*	The authors find positive and significant results of the knowledge stock variables on per capita income of states. State level analysis.	Yes (Fixed Effects and IV)	No	No
Lynne Zucker, Michael Darby and Marilynn Brewer 1998 American Economic Review	Biotech startups: the North Carolina Biotechnology Center and Bioscan Star scientists: GenBank and other sources	Presence of star biotechnology scientists associated with more biotechnology startups. Analysis at metro level.	Includes controls and lags.	No	No