Estimating the Payoff to R&D

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If the President of the US/head of your agency/the CEO of your firm asked you to assess the contribution of research and development (R&D) to the long term economic growth of the country/ firm and to estimate the economic return of investing in R&D, what would you do?

One natural way to address the question would be to examine past R&D investments to see if they paid off in the marketplace. You might randomly sample research and development projects undertaken by firms (whose spending constitutes over 2/3rds of national R&D) and by universities and government labs (who do most basic R&D) and examine the economic results. Did the returns exceed the costs by enough to justify the investments? Given readily available administrative or survey data on R&D expenditures, your task would be to estimate the value side of the equation: the new knowledge created and the economic payoff of the products or processes associated with that knowledge. Since industry R&D is close to direct production while academic and other basic R&D is far upstream from goods and services, the place to start would be with firm-based R&D projects.

You would quickly discover that random sample data on firm-funded research projects are non-existent. Patent data provide the closest parallel to a survey of economically relevant projects related to R&D. But patents are an imperfect sample of the output from R&D. Inventors patent only some economically valuable ideas. They do not patent the output from projects that produce nothing of likely economic value. While some patents result from sizable R&D expenditures, other patents arise from tinkering with minimal research and development spending. Still, estimates of the returns to patents provide insight into what one might find in a random sample of R&D projects. The chief finding from analysis of the economic value of patents is that the value is highly skewed as in a winner-take-all tournament or option portfolio (Scherer and Hartoff, Hartoff et al). Thus, we might expect that most R&D investments do not pay off much if at all while a few pay off massively.

Another natural way to address the question would be to examine a set of major economic advances or innovations and to examine the role of R&D in those advances. You might randomly sample a set of successful economic innovations – new drugs, scanning equipment, measuring devices; computer search algorithms; longer-lasting light bulbs, healthier foods; and so on – and try to determine the role of R&D in those advances. You would quickly discover that while case studies provide valuable insight into some innovations there is no regular survey of innovations, much less of their research content.

The NSF's new Business R&D and Innovation Survey (BRDIS) provides a fruitful framework for considering the economic payoff question. The survey identifies firms that do R&D and firms that innovate. It shows that firms that do R&D are far more likely to innovate than other firms. Sixty-six percent of R&D performing firms report creating new or significantly improved products. Fifty-one percent of R&D performing firms report creating new or significantly improved processes. By contrast, just 7% of firms that do not do R&D report product innovations and just 8% of the firms that do not do R&D report process innovations (Boroush 2010, table 2). But because only 3% of all the firms in the BRDIS do R&D, over 3/4ths of all reported innovations are produced by firms who report no-R&D activity.

Absent a sample of R&D projects, economists try to answer the payoff question by including R&D in aggregate production function/growth accounting equations. This approach relates sales (S) or value added to employment (E), physical capital (K), and possibly materials, and to an estimate of R&D knowledge capital (RK). Most studies use a Cobb-Douglas production function:

(1) Ln S = a lnE + blnK + c Ln RK + error term. The derivative of ln S with respect to RK gives the elasticity of output to R&D capital, which we can readily transform into the marginal product of changes in knowledge on output: dS/dRK = c S/RK. Estimates of c are almost always positive, which is necessary but not sufficient for *investments* in R&D to pay off for society.[1]

Because knowledge is an intangible unmeasured form of capital, economists and national income statisticians use the perpetual inventory method to estimate it from R&D expenditures (RD):

(2) $RK = \int e^{-(vt)} RDt\, dt$ or in discrete terms, RK= (1-v) RK(t-1) + RD(t), where v is a depreciation or obsolescence rate that analysts presume to be positive.

A related way to estimate the impact of R&D on production is through sources of growth accounting (Denison, 1962). Differentiating the production function with respect to its inputs yields a relation between the growth of output and sum of the growth of inputs, including growth of knowledge:

(3) S' = aL'+bK' + c RK' + d M' + u , where ' refers to percentage or ln changes in the inputs and where the growth of the stock of knowledge RK' is (R-v RK)/RK.

The growth of knowledge part of (3) can be rewritten as a function of the ratio of research spending to sales: c_g (R/S-vRK/S), where c_g = cS/RK = dS/dRK. Thus, the regression of changes in ln sales on the lagged ratio of research spending to sales corrected for the depreciation of R&D capital/sales estimates the marginal product of R&D spending.

Hall, Mairesse, and Mohnen (2009) summarize econometric studies of the impact of R&D from production function and growth accounting equations. The two approaches find that R&D has a significant sizable impact on the level or growth of production but different studies estimate a wide range of impact parameters (see their tables 2, 3, and 4). Save for Siegel and Lichtenberg (1989) and Griliches' early work (1980, 1986) most studies use R&D and sales data from Compustat to estimate production or growth equations. With few exceptions most studies estimate rates of return at a point in time rather than over time. And while analysts recognize that firms choose R&D in response to economic incentives, most studies treat the input variables, including R&D, as exogenous. Hall (2007) notes that the implications for investment depend critically on the unobserved rate of depreciation/obsolescence about which we have little direct information.

This paper reviews the problems in estimating the payoff to R&D with production function/ growth accounting and offers some solutions to the problems based on our on-going work with the NSF's Survey of Industrial Research and Development (SIRD) and establishment level production data in the Boston Census Research Center. The main theme of the paper is that production function/ growth accounting is necessary but not sufficient for answering the payoff question. We need additional analytic techniques and data to increase our understanding and illuminate policy choices.

The additional analytic techniques are:

1) Application of *natural experiments/instrumental variable methodologies* to assess returns to R&D from credibly exogenous changes in R&D spending;
2) *Back-casting* the contribution of R&D in successful and where possible unsuccessful

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[1] The return to *investment in R&D* depends on the impact of R&D expenditures on the stock of knowledge as well as on the effect of the stock on production. By the chain rule: dS/dRD = dS/dRK dRK/dRD.

innovations, in order to illuminate the economic payoff of basic R&D and possible substitution between R&D expended innovations and non-R&D innovations.

The additional bodies of data are:

3) Information on the *application of firm-based R&D to the establishment units* that produce goods and services, in order to eliminate econometric problems in estimating returns due to measurement error/attenuation bias in the R&D "treatment";
4) *A random sample of R&D projects* that follows the life of the project, to pin down the obsolescence/ depreciation rate of R&D and the distribution of returns among projects;
5) *A random sample of innovations* that may/may not have relied on R&D funded knowledge, to determine the contribution of R&D to the innovations.

We describe the problems with the current production function/growth accounting methodology and the way these additional analytic and data tools can help resolve them in two stages. Section I addresses issues in estimating the stock of R&D knowledge. Section II addresses issues in determining the impact of changes in the R&D stock of knowledge on output.

I. Estimating the stock of R&D knowledge

The National Science Foundation/Census Bureau's SIRD provides potentially the best available data on firm level R&D. The records cover several thousand firms that have done R&D at one time or another from 1972 to 2007. As with many surveys over long periods of time, changes in survey design, aberrant observations, and so on create problems that one must deal with to obtain valid statistics (Foster and Grim, 2010). The tabulations in this paper are for 282 large firms that report all the relevant data each year and that account for a large proportion of the US's industrial R&D.

As a first step in examining these data, we conducted an ANOVA of measures of RD spending and of our estimated stock of RD in total and relative to sales. The results show that 85 or so percent of the variation in RD or RD/Sales is among firms, just 1-2% occurs over time, and 13%-14% is the firm-time interaction. Variation in RDK is more evenly divided across firm and in firm-time interactions.

1 Depreciation Rate/Obsolescence Rate

A major problem in turning measured R&D flows into a stock is finding a credible depreciation/ obsolescence rate to apply in equation (2). (Hall 2007). Analysts who use the perpetual inventory method to calculate physical stocks in national accounting or growth analysis rely on used-asset prices and the life spans of equipment or plants to estimate plausible rates of depreciation (OECD, Baldwin, John, Guy Gellatly, Marc Tanguay, and Andre Patry). But we have no such data available to assess the depreciation/obsolescence rate of knowledge capital (Mead, 2007). Some analysts estimate depreciation on the basis of a structural model of the production process (Nadiri and Prucha (1996), Huang, Ning, and Erwin Diewert, 2007). Hall (2007) backed out estimates of the depreciation rate from a production functions for sales and for the stock market value of the firm and obtained widely different estimates of depreciation, from -10% in the share price data to 30% in the sales data (table 2). One problem in inferring depreciation rates from production function data is that depreciation rates essentially scale the estimated stock with the result that there is little difference in the relation between future output and RDK at different rates of depreciation/obsolescence. Another problem is that, as the ANOVA calculations showed, most of the variation in R&D is across firms rather than over time.

But inability to reliably estimate the depreciation/obsolescence rate does not gainsay the value of the production function/growth accounting approach toward answering the payoff question. The general consensus of analysts who apply the technique is that private R&D has a reasonably high payoff. The reason that the estimated parameter on R&D knowledge in the production function is sufficiently high for R&D to pay off regardless of the depreciation rate used to create the stock of useful knowledge. We demonstrate this by calculating the value of the coefficient on the stock of R&D in the production function that would make R&D profitable for a range of depreciation/ obsolescence rates from 100% to 0%; and then comparing estimated coefficients to the critical value of the parameter.

Consider, for example, the case in which depreciation/obsolescence was so rapid that the stock of R&D consists primarily of current R&D. Under this assumption an investment in January would have to raise output and profits enough to pay for itself within 12 months. Applying a discount rate of 1/(1+r) to future sales, the coefficient c on R&D in the production function must exceed (1+r)(R/S) for the R&D to be profitable.[2] If R/S was about .02 and the future sales were discounted with a discount rate of 1.20, c >.024 would suffice for the investment to pay off.

At the other extreme, if the rate of depreciation/obsolescence was small, say zero, the stock of RD is effectively the sum of RD over the period of accumulation. This effectively makes each year's R&D a fixed interest bond in perpetuity subject to diminishing returns because of the ln functional form[3] and the discounting of future returns to current dollars. Assuming a constant c coefficient, dRD would earn $\sum$ (cS/RK)/1.20^t over its infinite future life span. In this case a coefficient c> 0.034 would be necessary for additional R&D spending to be profitable.

Our estimates of c in the NSF/Census data set from regressions of ln Sales on ln Employment, year dummies, and measures of RD capital with different depreciation rates and different lags are all above these values.

2 Patents as stock of knowledge

Beginning with Schmookler (1966) economists have estimated the relation between the stock of knowledge and output using patent statistics. Patents have some virtues compared to R&D. They relate to specific projects that are presumptively economically valuable and that thus can give direct evidence on the elusive depreciation or obsolescence rate. Pakes and Shankerman (1984), for instance, used patent renewal rates to estimate an annual rate of depreciation in the knowledge in patents of 25%. Data on the licensing of patents could also help assess the depreciation/obsolescence of knowledge: the greater the decline in the number or value of licenses over time, the more rapid would be depreciation. Data on the citations of patents could also help assess the rate of depreciation: declining citations to a patent would imply that its value was depreciating over time.

The number of patents held by a firm offers an alternative or complementary indicator of the firm's stock of knowledge. Accordingly, analysts have estimated production functions in which they include measures of the stock of patents as well as estimates of the stock of R&D capital. They have found that the number of patents is much more weakly correlated with output than the estimated stock of R&D knowledge. Recognizing that patents differ greatly in their contribution to economically

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[2] The value of the increment of future sales is dS/(1+r). The impact of R&D on sales is dS = cS/R dR. R&D would payoff as long as dS/(1+r)- dR >0 or [cS/R dR]/(1+r) -dR>0 which simplifies to c> (1+r) R/S

[3] With the ln form dR&D has a bigger impact on log RK when RK is small than when it is large.

useful knowledge, Hall, Jaffe, and Trajtenberg (2005) took the number of citations to a firm's patent as an indicator of the firm's patent related stock of knowledge. The correlation between the output of the firm and citation-weighted patents is greater than the correlation between output and a simple count of patents, but it still short of the correlation between the stock of R&D and productivity.

Investigating references in patent data, we have found that citations to patents and papers on the front page of the patent, which give legal support to the patent claims, understate the number of citations to earlier patents and scientific papers in the text of the patent. The text is where the inventors reference the work on which the patent discovery relied, independently of its impact on the legal status of the patent claim. To access the in-text information we developed a program for extracting in-text citations from the patents. In a sample of 97 patents we found that the citations to patents in the text of the patent raised the number of citations by nearly 50% from those given in the front part of the patent. This more inclusive accounting of citations should give a better measure of the quality of patents and insight into the depreciation of knowledge
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To link the stock of patent knowledge to R&D expenditures requires an additional “patent production function” equation that estimates the contribution of R&D to the firms' number and quality of patents. Pakes and Griliches (1984) produced the first econometric estimations of a patent production function. Hausman, Hall, and Griliches (1984) and Hall and Ziedonis (2001) and others have estimated the patent production function. Hausman, Hall and Griliches obtained an elasticity of patenting with respect to R&D between .75 and .87; Hall and Ziedonis find an elasticity of about .99.

3- Back-casting basic research and innovation

The production function/growth accounting methodology does not offer a credible way to assess the economic return of basic research far upstream from production. The government supports most basic research through grants to university investigators or to research institutes. There is better data on the specifics of these projects than on industry-based R&D projects. We know the scientific papers associated with grants and the impact of those papers in terms of citations, and can also track whether the grant produced patents and whether patents cited the scientific papers (using in-text as well as front page citations, just described). Basic research is, however, likely to affect the economy in more indirect ways. Potential innovators presumably learn the latest scientific advances in university study or in seminars and conferences, which leads them to think about problems in ways that produce new solutions to economic problems. How might we track the impact of basic research far upstream from economic value?

Our approach is to apply a three step back-casting methodology. First, we identify innovations. Second, we assess the extent to which the innovations relied directly or indirectly on basic research. Third, we consider a counter-factual situation in which the government/other funder had not supported the relevant basic research and assess the likelihood that the firm/society could have resolved problem the innovation addressed without that funding. To see if this technique could help assess the impact of basic research on outcomes, we first applied it to the contribution of NIH spending on the breakthrough scientific knowledge. We took the list of papers that contributed to *Science* magazine’s “Top Ten Breakthroughs of the Year” and calculated the proportion of the breakthrough papers that relied on NIH directly. NIH funded more than its share of breakthrough papers.

We are applying the same technique to clinical innovations, using the Cleveland Clinic's “Top Ten Medical Innovations of the Year” as our measure of successful innovations. Since 2007 the

Cleveland Clinic has used a rigorous expert nomination, evaluation, and selection process to identify the top ten innovations that are "changing the practice of medicine"[4]. We will examine the scientific papers and patents underlying these innovations, which include medical devices and practices, on the basis of expert interviews, and semantic analysis of the scientific literature that uses the same terminology as the innovation. We are also applying the technique to medical drugs. We identified the patents of best-selling drugs[5], and the prior patents and scientific papers underlying these patents, including the in text citations.

The back-casting methodology identifies the historical link between outcomes and research support. If a particular advance has no backward link to R&D funded basic science, we would conclude that it occurred independently of R&D expenditures. But finding that an outcome used some basic scientific advance does not mean that the R&D was *necessary* for producing the economic outcome. Perhaps the firm/agency would have found the key information or solved the underlying problem in a different way. To assess these issues requires a more speculative counter-factual investigation of what might have happened absent the R&D expenditure that funded the underlying basic research. We envisage discussions with experts to try to develop plausible counterfactuals.

Given the BRDIS evidence that despite low rates of innovation, non-R&D performing firms still account for the majority of innovations, a full accounting of the economic contribution of R&D requires an assessment of the extent to which to those innovations rely, if at all, on R&D created advances. The back-casting technique provides one way to assess that but to do so researchers would need a sizable data base on innovations. In 1982 the Small Business Administration funded a study that compiled a data base of some 8,000 innovations, from new technology announcements in the relevant technology, engineering and trade journals (Audretsch and Feldman, 1996). To our knowledge, there has been no comparable study since. Today's web-scraping technology should allow for a more cost-effective way to construct a data set of innovations from public announcements and trade journals. Alternatively, it might be possible to ask a sample of firms in the BRDIS about a sample of their R&D projects and innovations and follow those projects and innovations over time

II. Problems in estimating the impact of R&D output

4- Establishment vs Firm Output

The major sources of industrial R&D data, the NSF's SIRD and Standard & Poor's Compustat files, provide information on R&D, sales and employment for firms. This creates a problem in estimating production functions because firms do not produce output. The establishments within a firm produce output. We need information on establishment-level R&D or use of R&D outcomes to fit the appropriate establishment level production function. Save in the unlikely situation in which each establishment in the firm uses R&D created knowledge similarly, firm-based production functions give downward biased estimates of the actual effect of R&D on production. The reason is that relating firm-level output to firm-level R&D, firm-based analyzes do not distinguish between establishments which use the R&D knowledge and those which do not use it. This confounds establishments with the R&D "treatment" with those without it. To the extent that productivity varies or changes differentially among establishments within a firm and R&D does not spillover from treated establishments to others,

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[4] The criteria for nomination include: significant clinical impact and patient benefit in comparison to current practices (40%); high probability of commercial success (20%); be in or exiting clinical trials and available on the market in the year (20%); significant human interest in application or benefit (20%).

[5] For instance, www.drugs.com; MedAdNews 200 – World's Best-Selling Medicines*;* IMS Health.

the bias can be substantial.

A numerical example illustrates the point. Consider two firms with two establishments each. Firm A does no R&D and is the “control” for firm B that does R&D. Without R&D all four establishments produce 8 units of output. Firm B applies its R&D knowledge to one of its establishments and raises output by 2 units. Comparing output in the treated establishment with output in its untreated establishment or in firm A's establishments would reveal the true 2 unit. With a Cobb-Douglas production function the effect of R&D measured in ln points would be ln 10/8 or 0.22 impact. Aggregating the establishment outputs to the level of the firm, a linear production function would recover the 2 unit effect. Firm A would product 16 units and firm B would produce 18 units – a 2 unit difference. But the curvature of the Cobb-Douglas ln form would give estimate of ln (18/16) or .118 ln points. Aggregation of output applies the R&D treatment to the untreated establishment as well as to the treated one in a form where the marginal product of RD falls with additional non-R&D inputs.

Our estimates of the extent to which productivity and productivity growth varies across establishments *within* multiple establishment firms in Annual Survey of Manufactures data suggests that the bias could be large. We have found that about 90% of the variation in levels and growth of productivity among establishments in the ASM occurs *within firms* rather than across them. While firm-level dummy variables have a statistically significant effect on levels or growth rates of productivity, they soak up only a modest proportion of the variance among establishments. From the 1970s to the 2000s, moreover, dispersion in the level and growth of productivity *within firms* increased (Barth, Bryson, Davis, Freeman, 2010). Without information about the application of R&D knowledge to different establishments it is not possible to explain the bulk of the within-firm variation in productivity growth or productivity in terms of R&D (or any other measures of firm-level activity.

An alternative to aggregating establishment data to the firm level would be to allocate R&D spending among the establishments of firms performing R&D proportionate to the size of those establishments and then to estimate an establishment level production function. Our analysis suggests that this will give a better estimate of the true R&D effect than aggregating data to the firm-level, as is common in the production function literature. Dividing R&D among all establishments of a firm gives too little R&D to establishments that truly use the new knowledge and too much R&D to those that do not use it. But these can be offsetting biases in a comparison with R&D in firms that do little or no R&D. Consistent with this analysis, our estimates of the impact of R&D capital in production function models that aggregate Annual Survey of Manufacturers data to the firm level give smaller estimated coefficients on R&D than do estimates based on establishments in those firms.

It would of course be better to allocate R&D among establishments by some measure that would more accurately reflect their actual use of the stock of knowledge. To the extent that establishments with more scientists, engineers, and technicians make greater use of the firm’s R&D than firms with fewer scientists, engineers, and technicians, establishment level data on the employment of scientists, engineers, and technicians from the BLS's Occupational Employment Statistics (http://www.bls.gov/oes/) survey would provide the information to better link R&D to establishment outcomes . Patent data on the location of inventors at the firm might also indicate which establishments within a firm are more likely to use new R&D-created knowledge. Evidence from the SIRD on the states where a firm spent its R&D could also help identify the establishments where the spending was likely to have had its greatest impact. Finally, discussions with major R&D firms would illuminate how firms in fact rolled out the results of R&D projects to establishments.

5- Exogenous Variation in R&D

The production function/growth accounting methodology takes as given levels or changes in the input variables, including R&D knowledge capital. To the extent that the factors that influence a firm's investment in R&D or employment of inputs correlated with R&D also influence output, the regression of output on inputs will not estimate the true coefficients of the production function. The potential lag between R&D and its effects on output should partially reduce but not eliminate the problem. A firm in a market where sales are trending upward may choose, for instance, to do more R&D than a firm in a market where sales are trending downward, which would link R&D to future sales through a mechanism beyond the production function. An analysis that did not allow for this would not give good insight into what might happen if, say, government changed the R&D tax credit or if some change in the supply of scientists and engineers altered the cost of research.

What is missing from the extant production function econometrics is analysis of a truly exogenous change in R&D that would identify its causal impact on production in the same manner that an exogenous change in the demand for a product identifies the supply curve of the product or an exogenous change in the price of a good identifies the demand curve. There are several plausible candidate instruments for such an analysis. As intimated above, changes or differences in R&D tax credits are likely to change R&D in ways unrelated to technological or market conditions. Analysis of R&D tax credits in the US and elsewhere show that the tax credits produce genuine changes in R&D spending (Hall and Van Reenen, 2000), but have not gone beyond this first stage regression to examine how the part of the R&D spending due to the credit affects production.

State R&D tax credits in the US provide another source of exogenous variation for determining the causal effects of R&D on output. Thirty-four US states have adopted R&D tax credits (see Table 1), with differing rates of tax-savings for R&D expenditures. Each state allows firms to claim a credit against their state tax liability for qualified R&D spending above a base amount determined by the firm's past R&D expenditures. The credit rates range from 2.5% (Minnesota, post-1986) to 20% (Arizona, pre 2001), compared to the 20% federal tax credit.[6] Paff (2005) estimates that firms' in-house R&D investments responded more to the California tax credit than to the federal tax credit.

Other plausible exogenous shocks to industrial R&D would be changes in government funding, such as for energy efficiency or nanotechnology that would shift demand for research in those areas; government procurement policies tilted toward products that fulfill certain standards; changes in the supply of scientists and engineers that affect the cost of R&D; and innovations in the capital equipment that scientists use in their research.

For basic research, where federal government support is critical, changes in the budgets of agencies due to the vagaries of Congressional appropriations is the main source of exogenous shocks to the market. These changes include the 1998-2003 doubling of the NIH budget, the subsequent decline in real spending, and the recent ARRA burst of spending, as well as the earlier post-Sputnik burst of US R&D spending. We have examined how the NIH doubling affected scientific papers and patents by comparing papers on grants funded during the doubling period with funding before the doubling when NIH supported fewer projects, and found that scientists funded in the doubling period published fewer papers than did those during the earlier period, presumably because NIH gave grants to more marginal projects in the doubling period. Information on applicants for grants would allow for other ways of

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[6] See Wu (2008) for details of individual state R&D tax credit programs and evidence that they influence firm-level R&D investment.

assessing the impact of funding levels on scientific output.[7] In addition, exogenous changes in research support due to decisions to direct research to particular areas would also provide pseudo-experimental data for estimating the research production function. Bhattacharya and Packalen (2008) report that changes in obesity and diseases associated with aging as well as changes in research opportunities affect the direction of medical research publications.

While these analyzes have sought to identify exogenous changes in R&D funding on the production of knowledge, the same basic strategy could provide a better fix on the effects of research on economic outcomes as well.

6 Social Rates of Return

While much work focuses on the private return to investments in science and engineering, much policy concern is about the presumed spillover of benefits from the person or group making the investment to the rest of society. The spillovers of R&D suggest that the production function analyzes that relate the output of the firm to its R&D are a lower bound of the social benefits. The standard way to address social returns is to add a “spillover term” to the production function, where the spillover measures the proximity of the productive unit to producers of knowledge other than itself in geographic space or technology space, or in both together. For instance, one can examine whether bio-tech firms located in a state or city where universities or other firms invest heavily in biotech research have higher or lower output. Positive spillovers imply higher productivity. Research that use such methods generally find positive spillover effects, which imply that social returns do indeed exceed private returns (Hall, Mairesse, Mohnen, 2009, table 5). As an example of such an analysis, Naomi Hausman (2010) examined the effects of federal government support of university research, post the Bayh-Dole Act, on future growth of employment in the industries that were most closely linked to the research. She defined the geographic area subject to the possible university spillovers by the counties within specified distance of the universities receiving the grants. She found that long-run employment and payroll per worker increased in counties surrounding universities that received more pre-Bayh-Dole federal funding and that employment in industries closely related to local university innovative strengths increased rapidly after Bayh-Dole in industries.

Conclusion: Next steps

The analysis of returns to R&D using the production function/growth accounting framework has yielded the important result that the private return is positive and exceeds returns from investments in general even though it has not pinned down the rate of depreciation/obsolescence of R&D created knowledge. But the methodology does not by itself provide an answer to the questions about the R&D contribution to growth and economic return to investing with which this paper began. We have reviewed some of the problems with the methodology and offered ways to deal with those problems.

In terms of analytic techniques our analysis shows that the production function estimates can be improved by shifting from analyzing the relation of R&D on sales or productivity at the level of the firm to sales or productivity at the level of the establishment and by using natural experiments/instrumental variable methodologies. We have suggested that changes in R&D tax credits

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[7] For instance one could compare the output of persons with similar quality research proposals in years when funding is generous and when it is not. Jacob and Lefgren 2007 compare the future papers and patents of funded researchers whose priority scores were just above the funding line in a given year with those of researchers whose priority scores were just below the funding line and were not funded.

at the state as well as federal level can provide a valuable instrumental variable for identifying the effects of exogenous changes in R&D on output. In addition, to illuminate the way basic R&D affects the economy broadly, we need the back-casting methodology to determine its effect on the more applied research and development that produces goods and service innovations in the economy. We also need this technique to assess the contribution of R&D of any kind to the innovations undertaken by firms that do no R&D.

In terms of data, we have highlighted the need for information on the application of firm-based R&D to the establishment units that produce goods and services by linking existing BLS data on occupational employment at the enterprise level to Census and NSF data; the value of a new random sample of R&D projects that follows the life of the project; and the value of new random sample survey of innovations that may/may not have relied on R&D funded knowledge.

In sum, while no single technique or body of data can answer the questions about the contribution and returns of R&D, we can gather new data and combine existing bodies of information in ways that will increasingly box in the answers and thus help guide the science of science policy.

Table 1
Overview of State R&D Tax Credit Laws

Year	Number of States With R&D Credit At End of the Year	Number of States Added by Year	New States
1982	1	1	Minnesota
1983-1987	7	6	Arkansas, California, Indiana, Iowa, West Virginia, Wisconsin
1988-1992	13	6	Colorado, Illinois, Kansas, Massachusetts, North Dakota, Oregon
1993-1997	22	9	Arizona, Connecticut, Maine, Missouri, New Jersey, North Carolina, Pennsylvania, Rhode Island, Washington
1998-2002	32	10	Delaware, Georgia, Hawaii, Idaho, Maryland, Montana, New Mexico, South Carolina, Texas, Utah
2004	34	2	Louisiana, Ohio

Table adapted from Table 1 of Wu (2008).

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