3-6-2016

The Impact of Research and Development on Economic Growth and Productivity in the U.S. States

Luisa Blanco

Ji Gu

James E. Prieger

The Impact of Research and Development on Economic Growth and Productivity in the U.S. States*

Luisa Blanco (corresponding author), is an Associate Professor of Public Policy at Pepperdine University, 24255 Pacific Coast Hwy. Malibu, CA 90263, USA. lblanco@pepperdine.edu

Ji Gu is a PhD student at the University of Oklahoma, 308 Cate Center Drive, Norman, OK 73019, USA. jgu@ou.edu

James E. Prieger, is an Associate Professor of Public Policy at Pepperdine University, 24255 Pacific Coast Hwy. Malibu, CA 90263, USA. james.prieger@pepperdine.edu

March 6, 2016

JEL codes: O32, O41, O51, O38

How to cite this article:

Blanco, L. R., Gu, J., & Prieger, J. E. (2016). The impact of research and development on economic growth and productivity in the U.S. states. *Southern Economic Journal*, *82*(3), 914-934. https://doi.org/10.1002/soej.12107

* We thank the Charles G. Koch Charitable Foundation for the funding provided for this research project. Neither this nor any other funding source played any role in the study design; in the collection, analysis and interpretation of data; in the writing of the report; or in the decision to submit the article for publication. We also thank Robert Tamura for sharing some data and Tonghui Zhu for work on an earlier version of the paper. The opinions and any errors herein are solely those of the authors.

Abstract: Research and development (R&D) has a large effect on both state output and total factor productivity (TFP) in the long run. Our estimates for the private sector of the U.S. states from 1963 to 2007 show that the R&D elasticity averages 0.056 to 0.143. The implied returns to state Gross Domestic Output (GDP) from R&D spending are 82% to 211%. There are also positive R&D spillovers, with 70% to 80% of the total returns accruing to other states. We also find that states with more human capital have higher own- and other-R&D elasticities, and those in lowest tier of economic development have the least own-state R&D elasticity but the highest other-R&D elasticity. In addition, we find that the positive effect of R&D spillovers across states is larger when we consider R&D spillovers across states based on economic similarity of R&D across sectors.

1. Introduction

Research and development (R&D) is an important contributor to economic growth. R&D spending leads to growth through its positive effect on innovation and total factor productivity (TFP) (Romer, 1990). Improvements in technology through industrial innovation have been the driving force behind the inexorably rising standards of living in the developed world over the long run (Grossman and Helpman, 1994). When a firm invests in R&D, new ideas, intermediate goods, methods to reduce costs, and final consumer products can be developed, allowing the firm to become more efficient and profitable. In addition to the private benefits of R&D, there are positive spillovers within and among firms, industries, and geographic regions. Knowledge developed through R&D is non-rival, so that firms can benefit from the R&D investment of other firms, even when they are in different industries or regions (Arrow, 1962; Aghion and Howitt, 1992). This study attempts to quantify the effects that R&D spending has on economic growth and productivity.

Measuring the contribution of R&D to economic growth takes care, however, for there is great dispersion in both R&D activity and economic growth across nations. For example, R&D spending as a share of Gross Domestic Product (GDP) in 2009 was 4.7% in Israel, 3.6% in Sweden and South Korea, 3.4% in Japan, and 2.9% in the United States.[1] While some of these countries had robust growth during the 2000s, Japan did not, and the United States had modest economic growth at best. Brazil, Russia, China, Italy, and Spain, had R&D shares that were less than half as much as the United States, and some (but not all) of these countries grew at a much quicker pace than the United States. There is also little apparent correlation between R&D intensity and U.S. state GDP growth. Bivariate pooled OLS regression of the log change in real

GDP by state, which we refer to as State GDP (SGDP), on the R&D share of GDP yields no significant relationship over the years 1966 to 2007.[2] The relationship between contemporaneous R&D spending and economic growth appears to be highly variable.

We study the impact of R&D performed by industry on private sector output and TFP in the United States during the period 1963-2007. There are four key features of our study. First, ours is the first study to our knowledge to examine the impact of total private R&D on the aggregate economies of the U.S. states. For our analysis, we build a state-level panel dataset for the period 1963-2007. R&D spending is an investment in a durable good: knowledge. Thus, we construct state-level stocks of knowledge (depreciated R&D) for the estimations, which Romer (1986, 1990) argues is the appropriate input to the production function.

Second, our analysis also quantifies the spillover effect of R&D across states. Knowledge generally cannot be contained within borders, and firms in one state or country benefit from industrial knowledge produced by R&D performed elsewhere (Coe and Helpman, 1995). Our methodology allows for and measures such R&D externalities.

Third, we choose empirical methodology to assess the long run effects of R&D in the economy. The R&D stock is a determinant of the long-run trend component of TFP, but may have little to do with the short-run deviations from trend, as demonstrated by the pooled regression mentioned above. Much of the short-run variation in output and TFP is caused by fluctuations in the utilization of capacity in industry (Griliches and Lichtenberg, 1984). As Coe and Helpman (1995) and Hall and Jones (1999) argue, estimating the long-run relationships between R&D, output, and TFP requires methodology that exploits the information conveyed by shared trends in these variables. We therefore estimate cointegrating relationships among the data.

Fourth, we examine data from a large collection of related but distinct economic areas all sharing a common set of institutions and general level of economic development: the U.S. states. The general level of economic development, the strength of institutions, and attitudes toward risk-taking and entrepreneurship can greatly affect the relationships among R&D, innovation, and growth. By examining U.S. states instead of different countries, the number of complicating factors in the causal relationship between investment in knowledge and growth is reduced greatly. Nevertheless, we also look for heterogeneity in the impact of R&D among states with differing levels of human capital and economic output.

Our analysis shows that the R&D stock has a positive, sizeable, and significant long-run effect on output and TFP. Our baseline estimate of the elasticity of output to the stock of R&D in the state are 0.056, and ranges up to 0.143 in other specifications. These bounding elasticities are associated with own-returns to GDP in a state to R&D spending of 83% and 213%, respectively. It also appears that the own-elasticity for R&D increased slightly after 1993. We also find that there are positive R&D spillovers across states in the long run: on average, about 77% of total GDP created from R&D investment spills over to other states in the baseline estimation. Unlike the own-elasticity, the spillover elasticity for out-of-state R&D appears to be stable during our period of study. We also find that the direct and spillover effects of R&D vary with the levels of human capital and economic output in the state. In addition, we find that the positive effect of R&D spillovers across states is larger when we consider R&D spillovers across states based on economic similarity and relevance of R&D across sectors.

The paper is organized as follows. In Section II, we provide a literature review where we outline the theory and empirical work related to the links between R&D, output, and productivity. In Sections III and IV we discuss the data and methodology, respectively. Section V presents the results, and Section VI touches on policy implications and concludes.

2. Literature Review

What is the link between R&D and productivity growth? Private R&D expenditure contributes to the public stock of knowledge, leading to spillovers resulting in greater aggregate output (Romer, 1986). Sustained economic growth requires technological change, which results from investment in R&D and the attendant spillovers (Griliches, 1992; Grossman and Helpman, 1994). Empirical studies on the impact of R&D have been performed at several levels of analysis: the firm, industry, region, or country. Firm level analyses typically find rates of return to R&D that are generally in the range of 20% to 30%, but may be as high as 75%.[3] R&D own-elasticity estimates from industry studies tend to be close to those from firm-level data. Estimated rates of return based on aggregate production functions for entire countries (or regions) tend to be higher, since they internalize all intra-country (or region) spillovers among firms and industries. The studies using panel data on countries cited in Hall et al. (2010) have R&D own-elasticity estimates ranging from 0.01 to 0.22, resulting in rates of return from 6% to 123%.

The present study follows most closely previous empirical analyses at the regional (Bronzini and Piselli, 2009) or country (Nadiri 1980) level. These studies measure the impact that R&D expenditure has on productivity and growth on the specific region or country where R&D expenditure originates, and some studies also look for spillovers to other areas. Coe and Helpman (1995) found that both domestic and foreign R&D stocks are critical for explaining greater productivity and economic growth in Organisation for Economic Co-operation and

Development (OECD) countries during1971-90. They posit that R&D from abroad could have a direct positive effect on domestic productivity through the development of new technologies and processes and an indirect positive effect through the importation of higher quality intermediate goods. Bayoumi et al. (1999) and Coe et al. (1997) also emphasize the role of trade in international R&D spillovers. Given the large amount of interstate trade within the United States, as well as the prevalence of multistate R&D performing firms, we therefore expect to find that significant cross-state R&D spillovers. R&D spillovers are often found to be stronger from nearby areas; e.g. in the regional work of Bronzini and Piselli (2009), Frantzen's (2000) study of OECD countries, and other work (Jaffe et al., 1993; Aiello and Cardamone, 2008). In our study we thus allow spillovers to enter the econometric model through various forms of spatial lags.

Coe and Helpman (1995) were the first to investigate R&D and growth using a framework of cointegrated panel data. Kao et al. (1999) and Coe et al. (2009) corroborate the findings of Coe and Helpman (1995) that R&D has a positive direct and cross-border spillover effects on TFP. Like Kao et al. (1999), we differentiate the short and long run effects of R&D on output and productivity. Coe et al. (2009) in addition highlight that differences among nations in institutions that affect the environment for doing business can be important determinants of R&D spillovers across countries. We largely sidestep this issue by using data from within a single, relatively institutionally homogeneous and integrated country, the United States. Coe et al. (2009) show that countries with high levels of human capital and a better environment for doing business benefit the most from domestic and international R&D. We also find that states with more human capital benefit the most from in-state and out-of-state R&D.

The latest strand of the literature on R&D and productivity examines regional data and examines spatial aspects of the relationship closely (Bronzini and Piselli, 2009; Wu, 2010).

Subnational studies are important because much recent work shows that geographical proximity is important for transmitting knowledge, given that much learning is localized (see Audretsch and Feldman, 2004). Bronzini and Piselli (2009) find that R&D has a positive effect on productivity in Italy and that the R&D stock in one region affects productivity levels in nearby regions. Our paper follows the spirit of Bronzini and Piselli's (2009) approach, although our choice of econometric method differs. While interstate research spillovers have been examined in the agricultural sector (e.g., Deininger, 1995; McGunn and Huffman, 2000; Alston et al., 2010), to our knowledge there is no empirical work that estimates the impact of R&D on aggregate output or productivity at the state level in the United States. This is no doubt due in part to a lack of enough R&D data at the state level in the past. We discuss in the next section our methods used to create a set of panel data for R&D expenditure and the stock of knowledge in the U.S. states, as well as other data used in our analysis.

3. Data

To estimate the parameters of the aggregate production function for states, we require data on output, R&D, labor, and physical and human capital. For the TFP equation, we require the labor and capital shares in addition. Our sample includes data from 50 states and the District of Colombia between 1963 and 2007. Much of our data come from standard sources for U.S. macroeconomic data, and the details and sources are in the Appendix, which is available online.[4] Data for SGDP are for private industry only (millions of 2005 dollars). The same is true for the capital stock and labor. For the human capital stock, we use the average years of schooling in the labor force, the most commonly used measure of human capital in the literature (Frantzen, 2000;

Bronzini and Piselli, 2009; int. al.). Unlike our other variables, which are only for private industry, of necessity our measure of human capital includes the education of government workers.

We use state level total R&D expenditure performed by private industry (converted to 2005 dollars). We log-linearly impute some missing values. To construct the R&D capital stock variable, we follow the perpetual inventory method used throughout the literature. Following Coe and Helpman (1995) and Bronzini and Piselli (2009), we use a 5% depreciation rate for R&D.[5] The final R&D capital stock variable is available for 83.1% of the possible 2,295 state-years in the sample. To estimate the spillover effect of R&D across states we create three measures of R&D performed in other states. In our main specification *RD_OTHER* is spatially lagged average domestic R&D performed outside the states. In particular, R&D from other states is weighted inversely to the distance from state i, resulting in a stock denoted RD_OTHER^D. Thus R&D from all other states contributes to spillovers, but the contributions from closer states are given more weight to reflect the common finding in much of the literature that knowledge spillovers are often localized (e.g., Audretsch and Feldman, 2004). In the second formulation, RD_OTHER^S, the R&D stock of each outside state is weighted by the economic similarity with state i, where heavier weight in the similarity index is put on R&D intensive industries. RD_OTHER^S captures the idea that R&D spillovers are expected to be higher among states with more similar, R&D intensive economies. For example, if state j has a relatively large drugs and medicines sector, and that sector is also large in state i, then the contribution to $RD\_OTHER^S{}_{it}$ of a dollar of R&D from state j will count more than that of a dollar of R&D from another state with a relatively non-technological economy.[6] For another robustness check we create a third version of the out-of-state average R&D stock, RD_OTHER^{C}, using spatial weights defined by contiguity of state borders.

Figure 1 depicts summary statistics for R&D intensity, which is the GDP share of current R&D expenditure, between 1963 and 2007 across states. The figure shows that there is more variation in the cross-section than the time series: while the median R&D intensity stays in a narrow band between 0.85% and 1.6% over time, the interquartile range across states ranges from 1.1 to 2.3 percentage points and some states have an R&D intensity in the range of 4 to 6% or higher.[7]

In general, rural states spent the least on R&D.[8] Alaska, South Dakota, Wyoming, and Mississippi all spent less than 0.5 percent of their GDP on R&D. Other states that contain important centers of advanced manufacturing and high technology spend more of their GDP on R&D. For instance, California (the home of Silicon Valley and much aerospace R&D during the period) and Washington (the home of Boeing, Microsoft, and many other high-technology firms) spent over twice as much as the average of 1.6% of GDP on R&D. Table 1 presents the summary statistics for all the variables discussed above.

4. Methodology

We derive our model and econometric approach following much of the recent empirical growth literature (e.g., Coe and Helpman, 1995; Bronzini and Piselli, 2009). A full description of the derivation of our theoretical and econometric models is available in the online Appendix. TFP is assumed to be determined by technical change and the stocks of human capital and R&D. Assuming a production function with Hicks-neutral TFP, our models for estimation are the following:

$$y_{it} = (\lambda_i + \tau_t) + \gamma hc_{it} + \delta RD_{it} + \pi RD\_OTHER_{it} + \alpha l_{it} + \beta k_{it} + \varepsilon_{it} \qquad (4.1)$$

$$tfp_{it} = (\lambda_i + \tau_t) + \gamma hc_{it} + \delta RD_{it} + \pi RD\_OTHER_{it} + \eta_{it} \qquad (4.2)$$

where the lower-case letters stand for natural logarithm, and ε_{it} and η_{it} are error terms. Our dependent variables in Equations (4.1) and (4.2) are SGDP (*y*) and TFP (*tfp*), respectively. The independent variables are: human capital (*hc*), R&D (*RD*), R&D spillover (*RD_OTHER*), labor force (*l*) and physical capital stock (*k*). We follow Bronzini and Piselli (2009) and first estimate the spillover effect of R&D across states using RD_OTHER^{D}, the weighted R&D stock from other states, constructed as described in section III. To account for the year effects τ_t, we time-demean all variables (without explicitly changing our notation) from here on.[9]

We estimate the models in Equations (4.1) and (4.2) using our unbalanced panel with all available data between 1963 and 2007. The equations are in log levels instead of log changes in order to assess the long-run relationships in the data. The levels of output, TFP, and the R&D stock also have the advantage of being much less sensitive to measurement error than their growth rates, which can bias estimation (Griliches and Hausman, 1986). However, such trending time series are likely to be integrated, and so we use estimation techniques appropriate for cointegrated data. We estimate the parameters of the long-run relationships in Equations (4.1) and (4.2) using the Pooled Mean Group (PMG) estimator. Since our main results are based on the estimation of our model using the PMG, below we provide an econometric model incorporating short-run dynamics, long-run relationships, and heterogeneity across panels.

The autoregressive distributed lag (ARDL) model we employ, expressed in error correction form, is:

$$\Delta y_{it} = \phi_i\left(y_{i,t-1} - \theta' x_{it}\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*} \Delta x_{i,t-j} + \alpha_i + \varepsilon_{it} \qquad (4.3)$$

where θ is the long run relationship of interest. The short run dynamics of the dependent variable are governed by the deviation from the long-run relationship. Parameter ϕ_i, which governs the speed of adjustment to the long run relationship, varies across states and must be between zero and -2 for the existence of a long run relationship between the dependent variable and the control variables. Under the assumptions of Pesaran et al. (1999), we have $y_{it} = \theta' x_{it} + \eta_{it}$, where for each i, η_{it} is stationary.[10]

Given that our data fall into the "large N, large T" case, the Pooled Mean Group (PMG) estimator developed by Pesaran et al. (1999) is appropriate. With the PMG estimator, the long run effect of R&D on output or TFP is estimated with $\hat{\theta}$, the estimates for ϕ_i will recover the long-run dynamics, and the estimates for λ^* and δ^* will capture the short-run effects and dynamics.[11] The PMG estimator allows us to obtain estimates that are consistent and asymptotically normal for stationary and non-stationary variables. The long run coefficients are assumed to be equal across states, but the intercept, short run coefficients and error variances differ across states. The lag order of the ARDL was selected using the Schwarz Bayesian Information criterion (SBIC).[12]

The PMG estimator is a good choice for analysis of these data for two reasons. The PMG estimator offers a convenient middle ground between traditional fixed effects estimators for panel data, in which all coefficients are common across panels (pooling), and the Mean Group (MG) estimator, in which no coefficients are restricted to be in common. The MG estimator (Pesaran and Smith, 1995) allows all coefficients to vary by group and then averages the coefficients. Note that with the MG estimator there is essentially no advantage in having a panel, since estimation devolves into state-by-state estimations. PMG is an intermediate estimator because it produces pooled estimates for the long run relationship between variables while allowing heterogeneity across groups in the short run relationships (Pesaran et al., 1991). We expect that the long run relationship between R&D, output, and TFP is largely similar across states due to the commonalities in institutions, economic development, and available infrastructure and technology within the United States. Recent work on the impacts of R&D that uses country level data assumes a common long run relationship among variables (e.g., Coe and Helpman, 1995; Coe et al., 2009). A fortiori, if the assumption of commonality in the long run relationships among R&D, growth, and TFP is justified across countries, then it is more justifiable for panels within a single country.[13]

In addition, the results of Hausman tests indicate that PMG estimator is a suitable choice for our application. We conduct Hausman tests of the PMG and MG estimates to test the assumption of common long-run relationships. The Hausman test looks for evidence that null hypothesis H_0: $\theta_i = \theta$ for all i is invalidated by heterogeneity in the long run estimates from the MG estimation. PMG estimation is not rejected in favor of MG estimation for any of the specifications tested.

The remaining question is why we do not use simple panel data estimators. There are several reasons. Most of the recent empirical work on the R&D-growth relationship uses cointegrating regressions (for example, Kao, Chiang, and Chen, 1999; Bronzini and Piselli, 2009; Coe et al., 2009; Ang and Madsen, 2013). Furthermore, we demonstrate that our variables are non-stationary. Using a traditional fixed effects panel estimator with differenced variables to solve the spurious regression problem would miss important information about the long run relationships in the data.[14] Indeed, estimates from a fixed effects growth model using the difference of all variables reveal no impact of R&D on SGDP growth at all, a nonsensical result flying in the face of decades of literature on the importance of R&D for economic growth.[15]

We also explore—and decide against—estimating our model using the Dynamic Ordinary Least Squares (DOLS) estimator. We choose the PMG estimator for our main analysis because the assumptions necessary for consistency of the DOLS estimator are more restrictive than those for the PMG estimator. The explication of the DOLS estimator, results, and discussion are in the online Appendix.

5. Results

In this section, we present the empirical results from the estimates from the baseline estimations, as well as the results of additional regressions designed to check the validity and robustness of our conclusions. As a preliminary matter, PMG estimation requires that the variables be integrated of no more than order 1, and thaot a cointegrating relationship exist among the regressors and the dependent variable. The results of tests for nonstationarity, order of integration, and cointegration are in the online Appendix.[16] When using the time demeaned variables, the various tests show that the assumptions necessary for PMG estimation cannot be rejected, except that there is mixed evidence for the nonstationarity of TFP. Hence, we focus here more on the results using SGDP than TFP as the dependent variable.

Baseline Estimations

The baseline PMG estimates are shown in Table 2, where results in Columns 1 and 2 (long-run coefficients only) are from the model that includes the R&D stock in other states weighted by distance. Estimates in Table 2, Column 3 are based on the model that considers other states' R&D stock weighted by economic similarity and R&D relevance, and estimates in Column 4 include an interaction of this variable with the other states' R&D stock weighted by distance. We observe that in all estimations we meet the condition for the existence of a long run relationship between the dependent and control variables: the average error correction term and its confidence interval are between zero and -2. Furthermore, the Hausman tests comparing the PMG and MG estimates for all specifications shown in Table 2 fail to reject the assumption of a common long-run relationship for all the states.[17]

Column 1, in Table 2, shows the estimates for the baseline model that uses SGDP as dependent variable and R&D stock in other states weighted by distance. Looking at the long run coefficients, we find that all of the inputs contribute in a positive and statistically significant way to SGDP. The long run coefficients of labor and physical capital stock are 0.729 and 0.334, respectively. The sum of these two coefficients is 1.06, indicating that there are slightly increasing returns to scale to physical inputs.[18] These estimates are also close to the conventional wisdom regarding labor and capital shares in the U.S. economy (2/3 and 1/3, respectively). Human capital is measured to have a large impact in the long run, with a coefficient of 1.257.

The long run coefficient of the log R&D stock is 0.056 in the SGDP model. This elasticity falls within the range of results for R&D own-elasticity estimates from country-level panel data studies cited in Hall et al. (2010). Our result for the own-elasticity of R&D in the U.S. states is not far from Coe and Helpman's (1995) elasticity for OECD countries of 0.097 and Bronzini and Piselli's (2009) estimates in the range of 0.014 to 0.076 for Italian regions. To convert our elasticity to an estimate of the marginal returns to R&D performed within a state, we can multiply the elasticity by Y/RD. Using the SGDP-weighted average R&D to output ratio for each state and then calculating a SGDP-weighted average across states returns an estimated marginal return to R&D of 82%.[19] For comparison, Coe and Helpman (1995) found that the returns to within-country R&D averaged 123% for G7 OECD countries and about 103% for the United States in particular.[20] Given that their estimate of the returns to R&D includes interstate spillovers and ours does not, it is natural that we find lower returns. Note that the marginal returns reported here are for the one-year impact based on the long run relationship in equation (4.4), in keeping with the practice in the literature.[21]

Similarly, the impact of the R&D stock in other states, RD_OTHER^D, is sizeable and statistically significant. The R&D spillover elasticity is 0.313. This figure is naturally much larger than the own-elasticity, since a 1% increase in the weighted average of other states' R&D stocks represents a huge amount of additional R&D performed out-of-state. The marginal return to a one-dollar increase in RD_OTHER^D (as would happen, for example, if each other state raised its R&D stock by one dollar) is 569%. Since the average weight of another state (including D.C.) in the calculation of RD_OTHER^D is 1/50, we can say (roughly speaking) that a dollar spent on R&D in another *single* state j has a marginal return of about 11.4% (=569%/50) for state i.

R&D spillovers among states can also be examined on a state by state basis. Table 3 shows the own-state marginal returns to R&D, the returns spilled over to other states, [22] the spillover ratio (defined as the latter divided by the former) and the percentage of total marginal returns that are spilled over to other states. The average spillover ratio is 4.9, indicating that every dollar added to own-state GDP from increased R&D is accompanied by almost $5 of SGDP created elsewhere. The average spillover fraction is 77%. There is wide variation in the amount of social returns that the states keep within their own borders. In the Appendix we provide similar statistics individually for each state.

The 255 short run state-specific coefficients are not reported in the table, but in the Appendix (Table A.6) we report the mean short-run coefficients. The mean short run coefficient for the R&D stock is insignificant. Thus, on average across states, own-R&D has no impact on SGDP in the short run after controlling for the long-run relationship. This is in accord with results of the simple panel regression mentioned above (see note 15), where R&D was found to be unimportant after differencing the long run relationships out of the data. The result emphasizes that the mechanisms in the economy transforming R&D activity into economic growth are primarily long-run in nature, and perhaps exclusively so. We also find that the average short-run coefficient for other states' R&D is insignificant at the 5% significance level. Since we observe no significant short-run impact of R&D after accounting the long-run relationships in the data, in the following discussion of results we focus solely on the long run coefficients (see Appendix, Table A.5, for short run coefficients).

We also estimate the impact of R&D directly on TFP using the PMG estimator and equation (4.2). The coefficients are shown in Column 2 of Table 2. All the long run coefficients in the model for TFP are statistically significant and the long-run elasticities are higher than those estimated in the baseline model for SGDP. The elasticity coefficient for the R&D stock of 0.143 implies that the own-state marginal returns to R&D are 211% on average, which is high compared to most other estimates in the literature.[23] The regressions for TFP require the assumption of constant returns to scale in labor and capital (see the Appendix). Since the baseline estimation for SGDP formally rejects this assumption, it may be that the elasticities from the TFP regression are biased.[24] Recall further that the evidence for cointegration in this regression, discussed in the previous section, was weaker than for the other regressions. For all these reasons, and to err on the side of understating the returns to R&D, we therefore use SGDP instead of TFP as the dependent variable in the remainder of the paper. The spillovers calculated from the TFP regression are larger in amount but smaller relative to within-state returns. The elasticity for other-state R&D is 0.531, leading to a spillover ratio of 3.2 and a spillover fraction of 70% (using the same methodology as for the figures in row 1 of Table 3).

In Column 3 of Table 2, RD_OTHER^S replaces RD_OTHER^D in equation (4.1). When weighting R&D from other states by economic similarity and R&D relevance, the elasticity for the other-state R&D stock is more than twice the magnitude of the estimate in Column 1. This reflects the greater impact of foreign R&D in the home state when accounting for whether R&D done elsewhere is performed in technologically proximate industries.[25] The elasticity for own-state R&D also rises, leading to an estimated 154% own-return on R&D and a spillover to other states of $4.47 for every dollar created for the home state (see the last row of Table 3). The log likelihood of the estimated model, however, is slightly lower than the main model in Column 1.

In Column 4 of Table 2, both RD_OTHER^D and RD_OTHER^S are included and interacted in the regression specification. All the R&D-related coefficients are positive and highly significant. The positive coefficient on the interaction term $RD\_OTHER^D \times RD\_OTHER^S$ indicates that when R&D performed in other states is technologically and economically proximate to the home state, distance-weighted R&D performed elsewhere matters even more for the home states' growth. Conversely, the interaction term also shows that when R&D performed in other states is geographically closer to the home state, R&D weighted by economic similarity and R&D relevance that is performed elsewhere increases the home states' growth even more.

If the contiguity-based definition of the other-state R&D stock, RD_OTHER^C, is used, the results are qualitatively similar to the results in column 1 (results are in the Appendix, Table A.4)[26] Own- and other-state R&D still have positive, highly statistically significant effects on SGDP. The largest quantitative difference is that the impact of own-R&D ($\hat{\delta} = 0.087$) gains importance at the expense of other-state R&D ($\hat{\pi} = 0.044$).[27]

Robustness Checking and Extensions

In this section, we explore whether the long run effect of R&D on SGDP is robust to alternative specifications and extensions. For all these additional regressions, the dependent variable is SGDP and other-state R&D stock is distance weighted. We begin with estimating the model without including the spillover effect of R&D, to demonstrate that our finding of a large own-R&D elasticity does not depend on the spatial assumptions employed in our construction of the other-R&D stock. The results of the PMG estimation when *RD_OTHER* is omitted are in column 1 of Table 4. The estimated own-elasticity for R&D is larger (0.076 versus the estimate of 0.056 from the baseline estimation) when we do not include other states' R&D stock. This finding is in accord with the literature, where it is emphasized that it is important to include the spillover effect when looking at the impact of R&D. Otherwise, given the generally positive correlation between domestic and foreign R&D stocks, the direct effect of R&D is overestimated.

We also test for evidence of change in the R&D elasticities between the periods 1963-1992 and 1993-2007. The R&D coefficients may differ in the later period for two reasons. There may have been structural shifts in the economy that changed the returns to R&D or the magnitude of R&D spillovers. For example, information and communications technology (ICT), which greatly affected the nature of R&D as well as production (Howells, 1995), had a rising contribution to U.S. economic growth during the period of our study (Jorgenson, 2001). Furthermore, our R&D data are available more consistently in the later period, and there may therefore be a composition effect. For the latter reason, testing whether the R&D coefficients changed also serves as a test for bias in the estimates due to missing data in the earlier period.

To test for change in the R&D elasticities, we interact the R&D variables with an indicator variable for the period 1993-2007. These estimates are shown in column 2 of Table 4. The results indicate that the own-R&D elasticity increased in the later period, but only by a small amount. The elasticity from the long run coefficient is 0.050 in the early period and increases by a statistically significant 0.008 in the later period. The own-R&D elasticity during 1993-2007 is thus very close to the estimate from the entire sample in column 4 of Table 2. There is no evidence that the elasticity from out-of-state R&D changed over time. Taken altogether, these results indicate that any bias due to missing R&D data in earlier years is small at most.

We also estimate a specification in which the lagged R&D stocks, RD_{it-1} and $RD\_OTHER^{D}_{it-1}$, replace the current-period R&D stocks in equation (4.1). By using contemporaneous R&D in the previous estimations, we have followed the bulk of the recent literature. However, given that it takes time for R&D to result in innovations (Mansfield et al., 1971; Ravenscraft and Scherer, 1982), we may expect the impact of lagged R&D to be higher than that of contemporaneous R&D. The results are in column 3 of Table 4. The own-R&D elasticity of 0.074 is indeed higher than in the baseline estimation, but the other-R&D elasticity of 0.217 is lower. [28] However, given the wide confidence intervals for the other-R&D elasticities, we cannot conclude that other-R&D elasticity is actually lower when lagging RD_OTHER^{D}.[29]

The final estimation in Table 4 addresses a technical issue regarding autocorrelation. The assumptions for the PMG estimator require that the error term in equation (4.3) be white noise. Testing of the residuals from the estimation in Column 1 of Table 2 indicate that there may be autocorrelation in two states.[30] Re-estimating with the lag lengths in the ARDL for those two states increased by one yields residuals for which we accept the null hypothesis of white noise. The estimates are substantially similar to the main results from Column 1 of Table 2, although the other-state R&D elasticity is somewhat smaller at 0.225 (leading to an average spillover ratio of 3.2; see final row of Table 3).

The PMG estimations above restrict the long run coefficients to be the same across states. We now explore whether the direct and spillover effect of R&D in the long run varies across states with different levels of human capital and output per worker. Having better educated workers leads to greater assimilation of the new knowledge created through R&D. Given that the literature has found evidence of such complementarity between R&D and the skill level of workers (Hall et al., 2010), it is expected that the benefits of R&D are likely to be greater for those states with higher levels of human capital. In relation to the level of output per worker, we expect that states with higher levels of economic output will have a more advanced infrastructure and an environment that would allow R&D to have a greater impact on growth and productivity.

We categorize states based on their time-averaged levels of human capital and SGDP per worker into three groups: low, medium, and high. A full set of dummy variables for the groups are interacted with regressors *RD* and RD_OTHER^{D} in these estimations. The long-run estimates from these models are shown in Table 5, with the estimates for states differentiated by levels of human capital in column 1. The results show that R&D has positive effects on SGDP for all groups of states, and the impacts are higher when there is more human capital in the state. Both the own-R&D and other-R&D elasticities rise with the level of human capital, and a joint Wald test confirms that there are statistically significant differences among the coefficients. However, the other-R&D coefficient is insignificant for the lowest human-capital group of states, perhaps indicating that some threshold level of human capital is required in order to reap the benefits of R&D spending from other states. The idea of the necessity of improving domestic human capital through technical education in order to appropriate the benefits of foreign technology is at least as old Friedrich List's writings on national systems of innovation in the mid nineteenth century (Freeman and Soete, Ch. 12, 1997).

When investigating whether the effect of R&D differs across levels of GDP per worker (Column 2 of Table 5), we find a similar story for own-R&D elasticity but the opposite for the other-R&D coefficients. Again, a joint Wald test confirms that there are statistically significant differences in the R&D elasticities among the groups. The elasticities for the own-R&D stock increase with GDP per worker, but are only significant for those states with medium and high levels of output. Three interpretations of these results are possible. It may be that a state needs to have a certain level of development to benefit from the state spending on R&D. The states in the lowest output group, which evinces no significant effect of own-R&D, are rural, mostly small states. Such states may not have the human capital or R&D intensive industries that benefit from performing R&D. It may also be the case that states in the lowest output group do not perform enough R&D to affect SGDP measurably. The real R&D stock for the low- output group averages less than a third as much as for the middle group, and less than one-tenth as much as for the highest output group.[31] Finally, it may be the case that the states in the lowest output group do not have many multistate R&D performing firms, and that such firms are a significant transmission mechanism for R&D spillovers across state lines. We return to the implications of this latter point in the concluding section.

On the other hand, the results in Column 2 of Table 5 show that states in all groups benefit from spillovers. Here the elasticities are largest for those states with the lowest SGDP per worker and vice versa. The sensitivity of SGDP to out-of-state R&D in states with low levels of output per worker may be high because these states both do the least *in*-state R&D and have the least impact to show for it. Such states rely heavily on the knowledge created by other states.

6. Conclusion

Our investigation of the relationship between investment in R&D capital and productivity allows us to draw the following conclusions. First, all specifications estimated show that R&D performed within a state has a positive, significant effect on SGDP through TFP in the long run. The finding is robust to the inclusion or exclusion of other-state R&D, to the latter variable's definition, to allowing the elasticity to change over time, and to the lag lengths chosen for R&D and for the ARDL. The estimated contemporaneous marginal return within the state to R&D investment is 82% in our baseline estimation and even higher in alternative specifications. The accumulated returns over ensuing years are many times larger in present value. Thus, our study demonstrates—apparently for the first time—that the positive linkages from R&D to productivity growth found in the literature at the firm, industry, and national levels also apply to the U.S. state level.

The magnitude of the effect of R&D on growth we find for the United States is in within the range of estimates found from cross-country samples, smaller than Coe and Helpman (1995) found for OECD countries, but larger than what Bronzini and Piselli (2009) found for Italy. Differences in the estimated effect of R&D are likely due to differences between countries in the way in which R&D translates into economic activity. These differences may derive from differences in institutions or firm characteristics; firm-level exploration of the R&D drivers of national growth is a promising area of future study.

Second, we find that R&D does not seem to have significant short-run impacts on productivity, whether the R&D is performed within the state or in other states. This highlights the long run nature of the link between R&D investment and growth in a state's economy.

Third, we find strong evidence of positive R&D spillovers among U.S. states. Our baseline results indicate that for every dollar R&D investment adds to own-state GDP, an average of nearly $5 of GDP is created in other states. This estimate varies between $3.25 and $6.06 in alternative specifications. Considering the R&D spillovers another way, we also find that a dollar spent on R&D in one state has a marginal return of about 11% in another state on average.

Fourth, we find some variation in the R&D elasticities across the sample. The evidence indicates that the own-elasticity of R&D increased, albeit only slightly, between the periods 1963-1992 and 1993-2007. Furthermore, the levels of human capital and development are relevant when looking at the impact of R&D. The more human capital a state has, the higher are the own- and other-R&D elasticities. At the lowest levels of human capital in a state, there is no measurable impact from R&D performed in other states at all. Similarly, when output per worker is low there is no impact of in-state R&D activity on productivity. Economic output in such states is also the most sensitive to the R&D stocks of other states.

Our findings have implications for public policy. Many authors have long argued that the difficulties in appropriating the fruits of knowledge production gives the government a role in promoting R&D to improve social welfare (Nelson, 1959; Arrow, 1962). We have shown that the lion's share of the benefits of R&D activities for output and productivity leak across state lines. Therefore, basic considerations of political economy imply that state governments have deficient incentives to promote investment in R&D. To the extent that intervention is desired and that effective policy can be found to promote private R&D (Hall and Van Reenen, 2000), it thus appears that multistate cooperative or federal efforts are warranted.[32] Cooperative efforts are also desirable since Wilson (2009) finds that state R&D tax credits mainly draw R&D activity from surrounding states, so that states play a nearly zero-sum game. Furthermore, our analysis provides evidence for synergy between human capital and the impacts of own-R&D and R&D "spill-ins" from other states. This highlights the continuing need for states to seek to improve opportunities and attainment in education, particularly in the science, technology, engineering, and mathematics (STEM) areas that are necessary for R&D.

For further research, as more statistics become available on R&D funding by sub-national public sources, it would be interesting to explore whether privately funded R&D has different productivity effects than publicly funded R&D. Determining whether there is a difference in the returns to R&D in the private sector with respect to R&D spending in the public sector would provide important implications for Science and Technology policy. Another fruitful avenue of inquiry may be to complement the aggregate data we examine with a study of firm-level data, to identify how much of the interstate spillovers are privately captured within firms. Such knowledge would help assess the strength of the rationale for state and regional R&D policy intervention based on deficient private incentives.

References

Adams, James D., and Adam B. Jaffe. 1996. Bounding the Effects of R&D: An Investigation Using Matched Establishment-Firm Data. *The RAND Journal of Economics* 27 (4): 700-21.

Aghion, Philippe, and Peter Howitt. 1992. A Model of Growth through Creative Destruction. *Econometrica* 60 (2): 323-51.

Aiello, Francesco, and Cardamone Paola. 2008. R&D Spillovers and Firms' Performance in Italy. *Empirical Economics* 34 (1): 143-66.

Alston, Julian M., Matthew A. Andersen, Jennifer S. James and Philip G. Pardey. 2010. *Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending*. New York City, NY: Springer.

Ang, James B., and Jakob B. Madsen. 2013. International R&D Spillovers and Productivity Trends in the Asian Miracle Economies. *Economic Inquiry* 51 (2): 1523-41.

Arrow, Kenneth J. 1962. Economic Welfare and the Allocation of Resources for Invention. In *The Rate and Direction of Inventive Activity: Economic and Social Factors*. Princeton, NJ: Princeton University Press, pp. 609-26.

Audretsch, David B., and Maryann P. Feldman. 2004. Knowledge Spillovers and the Geography of Innovation. In *Handbook of Regional and Urban Economics, Vol. 4*, edited by J. Vernon Henderson and Jacques-François Thisse. Amsterdam, Netherlands: Elsevier, pp 2713-39.

Bayoumi, Tamim, David T. Coe, and Elhanan Helpman. 1999. R&D Spillovers and Global Growth. *Journal of International Economics* 47: 399–428.

Blackburne, Edward and Mark Frank. 2007. Estimation of Nonstationary Heterogeneous Panels. *Stata Journal* 7(2): 197-208.

Blanco, Luisa, Ji Gu, and James Prieger. 2015. The Impact of Research and Development on Economic Growth and Productivity in the U.S. States: Online Appendix. Accessed May 19, 2015. Available at http://digitalcommons.pepperdine.edu/sppworkingpapers/56/ and http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2607818.

Bronzini, Rafaello, and Paolo Piselli. 2009. Determinants of Long-Run Regional Productivity with Geographical Spillovers: The Role of R&D, Human Capital and Public Infrastructure. *Regional Science and Urban Economics* 39 (2): 187-99.

Coe, David T., and Elhanan Helpman. 1995. International R & D Spillovers. *European Economic Review* 39: 859-87.

Coe, David T., Elhanan Helpman, and Alexander W. Hoffmaister. 1997. North-South R&D Spillovers. *Economic Journal* 107 (440): 134-49.

Coe, David T., Elhanan Helpman, and Alexander W. Hoffmaister. 2009. International R&D Spillovers and Institutions. *European Economic Review* 53 (7): 723-41.

Deininger, Klaus W. 1995. *Technical Change, Human Capital, and Spillovers in United States Agriculture, 1949-1985*. New York City, NY: Garland Publishing, Inc.

Demsetz, Harold. 1969. Information and Efficiency: Another Viewpoint. *Journal of Law and Economics* 12(1): 1-22.

Engle, Robert F. and Granger, Clive W.J. 1991. *Long-Run Economic Relationships, Readings in Cointegration.* New York City, NY: Oxford University Press.

Frantzen, Dirk. 2000. R&D, Human Capital and International Technology Spillovers: A Cross-Country Analysis. *The Scandinavian Journal of Economics.* 102 (1): 57-75.

Freeman, Chris, and Luc Soete. 1997. *The Economics of Industrial Innovation, 3rd ed.* Cambridge, MA: MIT Press.

Griliches, Zvi, and Frank R. Lichtenberg. 1984. R&D and Productivity Growth at the Industry Level: Is There Still a Relationship? In *R&D, Patents, and Productivity*. Edited by Z. Griliches. Chicago, IL: University of Chicago Press, pp. 465-502.

Griliches, Zvi, and Jerry A. Hausman. 1986. Errors in Variables in Panel Data. *Journal of Econometrics* 31 (1): 93-118.

Griliches, Zvi. 1992. The Search for R&D Spillovers. *The Scandinavian Journal of Economics* 94.

Grossman, Gene, and Elhanan Helpman. 1994. Endogenous Innovation in the Theory of Growth. *The Journal of Economic Perspectives* 8 (1): 23-44.

Hall, Bronwyn H., Mairesse, Jacques and Mohnen, Pierre. 2010. Measuring the Returns to R&D. In *Handbook of the Economics of Innovation, Vol. 2* edited by B.H. Hall and N. Rosenberg. Amsterdam, Netherlands: Elsevier, pp. 1033-82.

Hall, Bronwyn, and John Van Reenen. 2000. How Effective Are Fiscal Incentives for R&D? A Review of the Evidence. *Research Policy* 29(4–5): 449-69.

Howells, Jeremy R. 1995. Going Global: The Use of ICT Networks in Research and Development. *Research Policy* 24 (2): 169-84.

Jaffe, Adam B., Rebecca Henderson, and Manuel Trajtenberg. 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics* 108 (3): 577-98.

Jorgenson, Dale W. 2001. Information Technology and the U.S. Economy. *American Economic Review* 91 (1):1-32.

Kao, Chihwa, Min-Hsien Chiang, and Bangtian Chen. 1999. International R&D Spillovers: An Application of Estimation and Inference in Panel Cointegration. *Oxford Bulletin of Economics and Statistics* 61 (1): 691-709.

Mansfield, E., J. Rapoport, J. Schnee, S. Wagner, and M. Hamburge. 1971. *Research and Development in the Modern Corporation*. New York City, NY: W. W. Norton.

McGunn, Alan, and Wallace E. Huffman. 2000. Convergence in U.S. Productivity Growth for Agriculture: Implications of Interstate Research Spillovers for Funding Agricultural Research. *American Journal of Agricultural Economics* 82 (2): 370-88.

Nadiri, M. Ishaq 1980. Sectoral Productivity Slowdown. *American Economic Review* 70 (2): 349-55.

Nelson, Richard R. 1959. The Simple Economics of Basic Scientific Research. *The Journal of Political Economy* 67: 297-306.

Pesaran, M. Hashem, and Ron Smith. 1995. Estimating Long-Run Relationships from Dynamic Heterogeneous Panels. *Journal of Econometrics* 68: 79-113.

Pesaran, M. Hashem, Yongcheol Shin, and Ron Smith. 1999. Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association* 94 (446): 621-34.

Ravenscraft, D. J., and F. M. Scherer. 1982. The Lag Structure of Returns to Research and Development. *Applied Economics* 14: 603-20.

Romer, Paul M. 1986. Increasing Returns and Long-Run Growth. *Journal of Political Economy* 94 (5): 1002-37.

Romer, Paul M. 1990. Endogenous Technological Change. *Journal of Political Economy* 98: 71-102.

Scott, John and Pascoe, George. 1987. Purposive Diversification of R & D in Manufacturing. *Journal of Industrial Economics* 36(2): 193-205.

Wieser, Robert. 2005. Research and Development Productivity and Spillovers: Empirical Evidence at the Firm Level. *Journal of Economic Surveys* 19 (4): 587-621.

Wilson, Daniel J. 2009. Beggar Thy Neighbor? The In-State, Out-of-State, and Aggregate Effects of R&D Tax Credits. *The Review of Economics and Statistics* 91(2): 431-36.

Wu, Yanrui. 2010. *Innovation and Economic Growth in China*. Nedlands, WA: University of Western Australia, Business School, Economics working paper No.10-10.

Endnotes

---

[1] Data source: World Bank's WDI, http://data.worldbank.org/data-catalog/world-development-indicators.

[2] The coefficient on R&D intensity is -0.113 (0.073). The data for the regression are described below.

[3] Instead of citing the dozens of studies on the impact of R&D at the firm and industry levels, we refer the reader to the excellent reviews of Wieser (2005) and Hall et al. (2010).

[4] See Blanco et al. (2015) for an online appendix available online at: http://digitalcommons.pepperdine.edu/sppworkingpapers/56/ and http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2607818. Refer to online Appendix for references to data sources.

[5] Hall et al. (2010) report that the empirical literature typically finds that estimates of the effects of R&D are insensitive to different depreciation rates in constructing the R&D stock.

[6] At the heart of the construction of RD_OTHER^S is the index S_{ij}^{GDP} for the similarity of the economies of states i and j: $S_{ij}^{GDP} = \sum_k S_k^{RD} \min\{s_k^i, s_k^j\}$, where S_k^{RD} is the share of industrial sector k in national R&D, s_k^i is the share of state i's economy in sector k, and year subscripts are suppressed in the notation. S_{ij}^{GDP} is larger the closer are the shares in the two states' economies of the different sectors, where similarity in R&D intensive sectors is upweighted. This measure is similar in spirit (but not detail) to the measure of similarity in R&D diversification of Scott and Pascoe (1987). See the online Appendix for complete details.

[7] The notable outlier on the high side is Michigan in 1993, which had an R&D to GDP ratio of 0.095.

[8] See Table A.1 in the Appendix for R&D intensity by state.

[9] We do not include the stock of public infrastructure in the production function, as Bronzini and Piselli (2009) do. In the case of the United States, we expect public infrastructure to be relatively homogenous across states, and we do not find it necessary to include this variable in our estimation of the model.

[10] Recall that we time-demean all variables to account for trends not otherwise explained by the model, which further ensures the stationarity of η_{it}.

[11] For more detailed description of the structure of the PMG model, refer to Pesaran et al. (1999) and Blackburne and Frank (2007).

[12] We performed the lag test for each state in the sample and select the lag length that is appropriate in most states (we use the modal lag as selected according to the SBIC: $p = q = 1$). In our main estimations we thus impose a common lag length to all panels. If the lag length is too short for the actual stochastic process at work in some panels, there will be autocorrelation in the residuals for those panels. We test this in the robustness section below. Imposition of a common lag length is common in the empirical literature using the PMG technique.

[13] Furthermore, pooling when estimating the long run relationships among variables in our analysis allow us to reduce the problem of missing data in the R&D variables for some states in some years.

[14] Engle and Granger (1991, p.54) argue that "by analyzing only the differences of econometric time series, all information about potential (long-run) relationships between the levels of economic variables is lost."

[15] Estimates from this alternative regression are not included in paper, but are available upon request.

[16] See Tables A.2 and A.3 in the online Appendix.

[17] The p-values for the test of the consistency of the PMG estimates versus the MG estimates (not shown) are 0.69, 0.89, 0.12, and 0.82 for the estimations shown in Columns 1, 2, 3, and 4 of Table 2, respectively.

[18] The confidence interval for the sum is [1.04,1.09], which rejects constant returns to scale in favor of increasing returns to scale. We return to this point in our discussion of the models with TFP as the dependent variable.

[19] The formula we use for the marginal impact of own R&D is $\delta \sum_i a_i r_i$, where δ is the own-elasticity for R&D, $a_i = \bar{Y}_i / \sum_j \bar{Y}_j$ is the cross-state GDP weight, $r_i = \sum_t b_{it} Y_{it} / RD_{it}$ is the average output to R&D ratio in the state, and $b_{it} = Y_{it} / \sum_s Y_{is}$ is the within-state GDP weight.

[20] Although Coe and Helpman (1995) do not report a figure specifically for the US, we find the latter figure by multiplying their reported GDP/RD ratio of 4.39 by their estimated elasticity for the US of 0.2339 (=1.027).

[21] Since increasing the stock of R&D in one year also increases available R&D capital in future years, the accumulated marginal impact of R&D expenditure is much greater. With R&D depreciation of 5% and discounting future GDP at 10% per annum, for example, the accumulated marginal returns in present value are greater than the single-year returns by a factor of 7.3. Increasing the R&D stock by \$1 in year t leads to stocks increased by \$(1-δ) in year t+1, \$$(1-\delta)^2$ in year t+2, and so on. Therefore if the estimated one-time marginal return to R&D expenditure is m and the discount rate is ρ, the present value of accumulated marginal returns is $M = m \sum_{s=t}^{\infty} [(1-\delta)/(1+\rho)]^{s-t} = m(1+\rho)/(\delta+\rho)$. With ρ=10% and δ=5%, M = 7.33. This scaling factor can be applied to all the reported marginal returns in the paper.

[22] The formula for the marginal impact of R&D in state i on output in other states is $\pi \sum_{j \neq i} w_{ji} s_j$, where π is the elasticity of output with respect to the out-of-state R&D stock, w_{ji} is the spatial weight from the definition of RD_OTHER^D, $s_j = \sum_t b_{jt} Y_{jt} / RD\_OTHER_{jt}^D$ is the average output to out-of-state R&D ratio in the state, and b_{jt} is as defined in note 19.

[23] See Table 5 in Hall et al. (2010).

[24] Apart from the assumption of constant returns, there is another difference between the SGDP and TFP regressions. The regressions of SGDP assume that the long-run coefficients on labor and capital are identical across states. The calculations involved in creating the TFP variable instead use state-specific labor and capital shares. Therefore while the TFP regression relies on a restrictive assumption of constant returns, it allows more flexibility than the SGDP regressions regarding the shares. Thus we would not necessarily expect the estimates from the SGDP and TFP regressions to be the same. Furthermore, neither assumed data generating process nests the other, preventing simple specification testing.

[25] When RD_OTHER^D rises by one unit, some of the R&D performed elsewhere may be largely irrelevant to the home state because it was performed in industries that make up a small part of the home state's economy or for which R&D is not very important. RD_OTHER^S as used here accounts for both of those factors, and thus the apparent importance of R&D performed elsewhere rises.

[26] These results are calculated at the request of a referee.

[27] This is not surprising, given that spatial weighting based on contiguity ignores the presence of most R&D done elsewhere in the nation.

[28] If the lag length is increased to two and three years, the own-R&D elasticity remains higher than in the baseline estimation using contemporaneous R&D (the elasticities are 0.062 and 0.070, respectively). The other-R&D elasticities show more sensitivity to lag length, with elasticities of 0.318 (two-year lag) and 0.247 (three-year lag). However, the log likelihood from these estimations is lower than that reported in column 3 of Table 4.

[29] The substantial overlap of the confidence intervals for the coefficients on other-R&D from the estimations using current R&D [0.23,0.39] and lagged R&D [0.14,0.28] suggests that the hypothesis test for equality of coefficients would not have a low *p*-value.

[30] A variety of tests for autocorrelation were employed; see the Appendix for details.

[31] The R&D stock averages $4,618 million for the low GDP-per-worker group, $15,497 million for the middle group, and $48,043 million for the highest group.

[32] Demsetz (1969), however, contends forcefully that the existence of positive externalities in R&D do not necessarily indicate that government should intervene in the market, because actual governmental intervention is also imperfect. A careful comparative institutions approach and analysis of specific policies is necessary before concluding that the market underperforms relative to realistic alternatives.

Tables

Table 1. Summary statistics for the estimation sample

	Mean	Std. Dev.	Min	Max
Value in Levels				
SGDP	142,577	177,706	4,512	1,570,402
TFP	0.15	0.04	0.07	0.53
Physical capital	172,815	216,764	6,370	1,730,723
Labor force, persons	2,397,588	2,486,807	119,608	18,200,000
Human capital, years	12.34	1.22	8.88	15.04
R&D Stock	21,586	42,089	6.56	538,478
Other States' R&D Stock, RD_OTHER^{D} (wgtd by distance)	21,478	11,554	5,598	85,625
Other States' R&D Stock, RD_OTHER^{S} (wgtd by economic similarity & R&D relevance)	23,740	11,543	7,225	58,044
Other States' R&D Stock, RD_OTHER^{C} (wgtd by contiguity)	20,743	22,330	1	163,385
Values in Logarithms				
ln(SGDP)	11.33	1.05	8.41	14.27
ln(TFP)	-1.93	0.24	-2.67	-0.64
ln(Physical capital)	11.53	1.02	8.76	14.36
ln(Labor force)	14.25	0.97	11.69	16.72
ln(Human capital)	2.51	0.10	2.18	2.71
ln(R&D Stock, δ = 5%)	8.68	1.92	1.88	13.20
ln(Other States' R&D Stock), RD_OTHER^{D}	9.84	0.53	8.63	11.36
ln(Other States' R&D Stock), RD_OTHER^{S}	9.96	0.49	8.89	10.97
ln(Other States' R&D Stock), RD_OTHER^{C}	9.24	1.77	0	12.00

Notes: All dollar values are millions 2005$. Summary statistics for annual observations for the period 1963-2007 for 50 states and the District of Columbia. Statistics are based on the sample of state-years for which R&D data are not missing after imputation (1,907 observations).

Table 2. Baseline PMG estimation results

Dependent Variable:	SGDP (1)	TFP (2)	SGDP (3)	SGDP (4)
Long run coefficients				
R&D Stock	0.056***	0.143***	0.105***	0.077***
	(0.005)	(0.012)	(0.007)	(0.006)
Other States' R&D Stock (RD_OTHER^D, weighted by distance)	0.313***	0.531***		0.271***
	(0.039)	(0.080)		(0.044)
Other States' R&D Stock (RD_OTHER^S, weighted by economic similarity and R&D relevance)			0.688***	0.453***
			(0.084)	(0.076)
Interaction term ($RD\_OTHER^D \times RD\_OTHER^S$)				1.723***
				(0.416)
Years of Schooling	1.257***	2.811***	0.515***	0.670***
	(0.124)	(0.121)	(0.128)	(0.130)
Physical Capital Stock	0.334***		0.338***	0.365***
	(0.039)		(0.029)	(0.035)
Labor Force	0.729***		0.676***	0.635***
	(0.039)		(0.029)	(0.036)
Error Correction (ϕ_i), averaged across states	-0.181***	-0.107***	-0.168***	-0.179***
	(0.025)	(0.017)	(0.031)	(0.033)
No. Obs.	1,842	1,842	1,842	1,842
Log Likelihood	5,021.1	4,169.3	5,020.2	5,143.2

Figures are the long-run coefficients and standard errors (in parentheses) from pooled mean-group (PGM) estimation. Figures shown for the error correction term are for the average of the state-specific estimates of ϕ_i. The short run coefficients are omitted in the table. Estimations include observations for 44 years during the period 1963-2007, from all 50 states and DC, with some missing observations. Estimations include a minimum of 12 observations per state and a maximum of 44, with an average number of observations per state of 36. All estimations include state-specific short-run dynamics, error variances, and fixed effects, and also account for year fixed effects through time-demeaning all variables.

*** denotes significance at the 1% level.

Table 3: Average marginal returns to R&D investment, within state and spillovers

Estimation used			Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction
Table	Column	Description	A	B	B/A	B/[A + B]
2	(1)	Distance weighted other-state R&D stock (*RD_OTHER*^{D}; *Y* = SGDP)	0.823	1.992	4.902	0.767
2	(2)	Distance weighted other-state R&D stock (*RD_OTHER*^{D}; *Y* = TFP)	2.106	3.376	3.245	0.696
2	(3)	Economic-similarity weighted other-state R&D stock (*RD_OTHER*^{S}; *Y* = SGDP)	1.539	4.367	6.058	0.795
4	(4)	Additional lags for two states in the ARDL specification (*RD_OTHER*^{D}; *Y* = SGDP)	0.882	1.429	3.278	0.698

Notes: Marginal returns in columns A and B are calculated as weighted averages: figures are calculated first at the state and year level and then are averaged across years (weighted by SGDP in the state across years) and states (weighted by time-averaged SGDP across states). Figures in columns A and B are expressed as the one-time marginal returns to a $1 increase in the own-state R&D stock. Estimates are based on the estimated elasticities from the PMG estimations from the given tables and columns. Figures in the last two columns are calculated at the state level using the formula in the column heading, and then are averaged across states (weighted by time-averaged SGDP across states).

Table 4. Additional PMG estimation results

Dependent Variable:	Without other-state R&D (1)	Period-specific R&D Elasticity (2)	Lagged R&D (3)	Additional Lags (4)
Long run coefficients				
R&D Stock	0.076***	0.050***		0.060***
	(0.006)	(0.005)		(0.005)
R&D Stock, later period		0.008***		
		(0.002)		
R&D Stock, lagged			0.074***	
			(0.006)	
Other States' R&D Stock (*RD_OTHER*^{D})		0.215***		0.225***
		(0.035)		(0.039)
Other States' R&D Stock, later period		0.010		
		(0.031)		
Other States' R&D Stock, lagged			0.217***	
			(0.036)	
Years of Schooling	1.407	1.338***	1.226***	1.470***
	(0.139)***	(0.112)	(0.129)	(0.132)
Physical Capital Stock	0.436	0.347***	0.508***	0.392***
	(0.029)***	(0.036)	(0.028)	(0.037)
Labor Force	0.657	0.755***	0.532***	0.666***
	(0.028)***	(0.037)	(0.030)	(0.038)
Error Correction (ϕ_i), averaged across	-0.182	-0.204***	-0.189***	-0.181***
states	(0.031)***	(0.026)	(0.037)	(0.027)
No. Obs.	1,842	1,842	1,791	1,840
Log Likelihood	4,958.9	5,087.4	4,935.6	5,032.6

*** denotes significance at 1% level.
See notes to Table 2. In Column 4, lag lengths in the ARDL are $p = q = 2$ for Arkansas and Utah and remain at $p = q = 1$ for other states (as in all other estimations).

Table 5. Additional PMG estimation results: Heterogeneous R&D elasticities

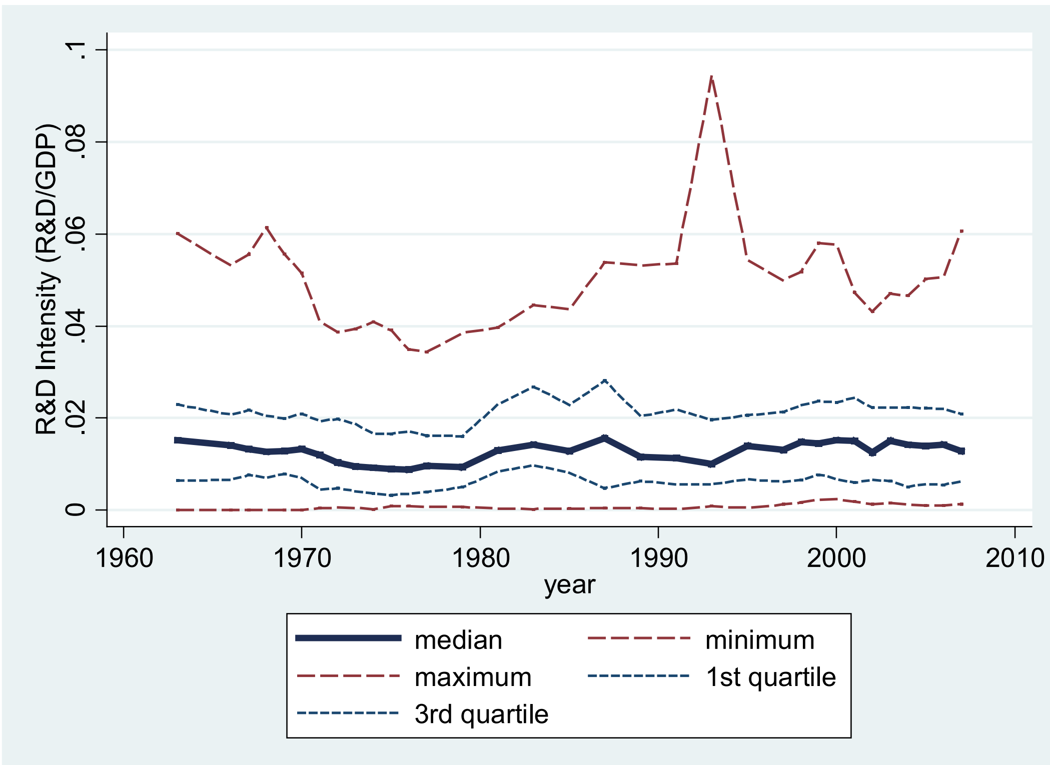
Groups based on: *Y = SGDP*	Levels of Human Capital (1)	Levels of GDP/worker (2)
R&D Stock, Low Group	0.058***	0.003
	(0.014)	(0.007)
R&D Stock, Medium Group	0.064***	0.084***
	(0.006)	(0.010)
R&D Stock, High Group	0.086***	0.088***
	(0.011)	(0.009)
Other States R&D Stock (RD_OTHER^D), Low Group	0.081	0.308***
	(0.081)	(0.098)
Other States R&D Stock (RD_OTHER^D), Medium Group	0.160***	0.297***
	(0.040)	(0.082)
Other States R&D Stock (RD_OTHER^D), High Group	0.596***	0.117**
	(0.088)	(0.055)
Years of Schooling	1.579***	1.208***
	(0.134)	(0.133)
Physical Capital Stock	0.425***	0.109*
	(0.032)	(0.048)
Labor Force	0.645***	0.992***
	(0.033)	(0.051)
Error Correction (ϕ)	-0.176***	-0.192***
	(0.028)	(0.028)
Short run coefficients omitted in table		
No. States	51	51
No. Obs.	1,842	1,842
Log Likelihood	5,030.1	5,035.5

***, **, and * denotes significance at 1%, 5%, and 10% level, respectively.

Figures are the long-run coefficients and standard errors (in parentheses) from pooled mean-group estimation. The high, medium, and low groups refer to group-specific coefficients for the three levels of human capital (column 1) and GDP/worker (column 2). See also notes to previous estimation tables.

Figures

Figure 1. Industrial R&D as a fraction of GDP in U.S. states, 1963-2007



Notes: figures include R&D performed by industry. Nominal data are used for R&D expenditure and state GDP. Authors' calculations; using NSF data as described in text.