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The Impact of Research and Development on Economic Growth and Productivity in the US States

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Abstract We estimate the impact of R&D on TFP and output in the private sector at the state level in the US from 1963 to 2007. R&D has a large effect on both output and TFP at the state level in the long run. The R&D elasticity in a state averages 0.056 to 0.143, implying returns to state GDP from R&D spending of 83% to 213%. There are also positive R&D spillovers, with 77% of the total returns accruing to other states. The R&D elasticities are either stable or increase slightly after 1993. The effects of R&D are dependent on the levels of human capital and development. States with more human capital have higher own- and other-R&D elasticities. States in the lowest tier of economic development have the least own-state R&D elasticity but the highest other-R&D elasticity. We discuss implications for policy in the US and in developing countries.

Keywords: R&D spillovers; positive externalities; total factor productivity; cointegration; dynamic OLS estimator; pooled mean group estimator

JEL codes: O32, O41, O51, O38

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I. Introduction

Much empirical and theoretical work emphasizes that research and development (R&D) is an important contributor to economic growth. R&D spending is likely to lead to growth through its positive effect on innovation and total factor productivity (TFP) (Romer, 1990; Lucas, 1988). As Grossman and Helpman (1994) note, 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. When a firm invests in R&D, it is expected that new ideas, intermediate goods, methods to reduce costs, and final consumer products will 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).

There is great dispersion in both R&D activity and economic growth across nations. Table 1 presents average R&D spending as a share of Gross Domestic Product (GDP) during the periods 2000-2004, 2005-2009, and 2009 for a selected group of countries obtained from the World Development Indicators (WDI, World Bank, 2013).[1] There is no single trend in R&D spending worldwide; while 17 countries performed more R&D in 2005-2009 than in 2000-2004, 23 performed less. The 5 countries with the highest level of R&D spending as a share of GDP in 2009 are: Israel (4.46 %), Finland (3.93 %), Sweden (3.60 %), South Korea (3.56 %), and Japan (3.36 %). While all these countries are highly developed and some had robust growth during this

[1] Countries included in this table were selected based on data availability and their importance in the world economy.

period, Japan did not. The United States, which is in the eighth place, had R&D spending in 2009 that composed 2.90% of GDP, but had modest economic growth at best—and two recessionary years—during the 2000's. Table 1 also shows that countries like Brazil, Russia, China, Italy, and Spain, spent less than half as much as the United States on R&D. Countries with relatively low R&D intensity in the table are generally less developed than those that spend the most, although some of the lower R&D spenders had high growth rates during the previous decade. Thus the relationship between contemporaneous R&D spending and economic growth appears to be highly variable.

The great apparent heterogeneity among nations is due to at least four factors. Most importantly, the relationship between R&D and economic growth is a long-run relationship. As Griliches and Lichtenberg (1984) note, much of the short-run variation in output and TFP is caused by fluctuations in the level of capacity utilization in industry. 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. Second, R&D spending is an investment in a durable good, knowledge. Thus, the stock of knowledge is the appropriate input to the production function, not merely current-year investment (Romer 1986, 1990). Third, knowledge generally cannot be contained within national borders, and firms in one country benefit from industrial knowledge produced by R&D performed abroad (Coe and Helpman, 1995). Finally, the general level of economic development in the country, as well as its institutions and even attitudes toward risk-taking and entrepreneurship can greatly affect the relationships between R&D, innovation, and growth.

Given the great importance of R&D for development in the long run, this study attempts to quantify the effects that R&D spending has on economic growth and productivity. Understanding the role that R&D plays as a determinant of productivity, and consequently economic growth, is important for policymakers. As noted by Cincera (2005), studying the impact of R&D spillovers is necessary to identify effective science and technology policies that could lead to higher productivity and competitiveness across firms and industrial sectors. To reduce the number of complicating factors in the causal relationship between investment in knowledge and growth, 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 US states. We are thus able to sidestep the fourth set of causes of heterogeneity in the R&D-growth connection noted above. Thus, we study the impact of R&D on output and TFP in the United States during the period 1963-2007. Studying the impact of R&D in the United States is also relevant since this country performs the largest absolute amount of R&D[2] and (as noted above) is one of the highest investing countries in terms of R&D intensity.

There are four key features of our study. First, to our knowledge, ours is the first study that examines the impact of total private R&D on the aggregate economies of the US states. Our approach is similar to the one taken by Bronzini and Piselli (2006), who study the impact of R&D on productivity in Italy by regions. For our analysis, we build a panel dataset covering all states and the District of Columbia for the period 1963-2007. Second, our analysis looks not only at the direct effect that private R&D spending has on output and productivity at the state level, but also quantifies the spillover effect of R&D across states. As Jaffe (1989) and Jaffe et al. (1993) note, a proper foundation for public policy requires knowledge of the social rates of return to R&D at different levels of geographic aggregation. Work such as that of Jaffe (1989) examining returns to research expenditure within a state understates the social returns (as the author acknowledges) since some of the returns flow to other states. In fact, we find the spillover effect across states to be sizeable.

[2] In 2007, 33 cents out of every worldwide R&D dollar spent came from the US (NSB, 2010)

The third key feature of our study is that we focus on R&D performed by industry, in contrast to many studies that include publicly performed R&D. Private sector R&D is expected to play a more direct role in promoting productivity and economic growth than research performed by universities or governmental institutions. We also focus the analysis on the impacts on private sector output and productivity. Fourth, we choose empirical methodology to assess the long run effects of R&D in the economy. 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. This leads us toward methods for estimating cointegrating relationships among the levels of the R&D stock and output or TFP, and away from some methods popular in the macroeconomic growth literature that discard the information contained in the levels by looking only at rates of change. Our methods include the dynamic OLS (DOLS) and pooled mean group (PMG) estimators, both of which are suited to cointegrated data. Despite our main interest in long-run relationships, the latter estimator also allows flexible modeling of the short-run dynamics as well.

Our analysis shows that the R&D stock has a positive, sizeable, and significant long-run effect on output and TFP. Our baseline estimates of the elasticity of output to the stock of R&D in the state are 0.056 (when the dependent variable is output) and 0.143 (when the dependent variable is TFP). These 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. 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.

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 for the US and developing countries and concludes.

II. Literature Review

A. Theory on the impact of R&D

Solow's (1956) neoclassical growth model, which treats productivity, capital accumulation, and population growth as the main sources of economic growth, has been modified by later authors to add R&D as a central determinant of growth. Griliches (1979) introduced the idea that productivity growth is the consequence of expenditures on R&D. In the endogenous growth model developed by Romer (1986), firms' expenditure on R&D results in greater aggregate output because private R&D leads to spillovers through its contribution to the public stock of knowledge.[3] R&D expenditures are central to economic growth because technological change is the result of conscious economic investment, and sustained growth would not be possible without the R&D spillovers (Griliches, 1992).

Grossman and Helpman (1994, p.24), in their review of growth theory and endogenous innovation, argue forcefully that technological progress has been the main driver of growth in the world, where "most technological progress requires, at least at some stage, an intentional investment of profit-seeking firms or entrepreneurs." Thus, under this view, industrial innovation

[3] See Romer (1994) for a good review of endogenous growth models.

resulting from R&D investment is the chief engine of economic growth. According to Grossman and Helpman (1994), a large investment of resources is required in order to reap benefits from the development of scientific ideas. Firms have an incentive to invest in R&D if there is an opportunity for them to increase profits. Therefore, if the profitability of R&D is raised (for example, through policy that promotes investment) and more investment goes into private-sector R&D, the innovation process accelerates, resulting in higher productivity.

B. Empirical evidence on the impact of R&D

Empirical studies on the impact of R&D can be classified based on the unit or level of analysis: the firm, industry, region, or country. Firm level analyses, beginning with the early work of Mansfield (1965) and Griliches (1980a) focus on the impact that a firm's R&D expenditure has on its own productivity.[4] Some of these analyses also measure spillovers from one firm's R&D expenditure to other firms and industries. Analyses at the industry level (Griliches, 1973, 1980b) also look at how R&D in a specific industry leads to higher productivity in that industry and other industries as well. Empirical analyses at the regional (Bronzini and Piselli, 2006) or country (Griliches, 1964; Nadiri 1980a, 1980b) level study 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 or countries. The present study follows the more recent vein of regional studies.

At the firm level, Audretsch and Feldmann (2004), Cincera (2005), Fritsch and Franke (2003), Griliches (1979, 1985), Kaiser (2002), and Khan (2006), among many others, have provided evidence of the positive effects of R&D on productivity. Wieser (2005) and Hall et al. (2010) provide excellent reviews of the different studies on the impact of R&D at the firm level.

[4] See Hall et al. (2010) for a guided tour through the extensive empirical literature on the returns to R&D. We mention only a few seminal examples in this paragraph.

While many of these studies have been performed on data from US firms (e.g., Griliches, 1988), others look at firms from Canada (Hanel, 2000), Taiwan (Tsai and Wang, 2004), Italy (Aiello and Cardamone, 2005), and elsewhere. Hall et al. (2010) characterize the literature as finding "plausible" estimates overall, with the own-elasticities of output with respect to R&D spending at the firm level ranging from 0.01 to 0.25 but centered on 0.08 or so. These elasticities lead to rates of return to R&D that are generally in the range of 20% to 30%, but may be as high as 75%.

Hall et al. (2010) conclude that R&D own-elasticity estimates from industry studies tend to be "quite close" to those from firm-level data. Own-elasticity estimates and 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%.

Regarding spillovers across firms and industries, there is a significant amount of work showing that geography plays an important role for the positive spillovers that derive from R&D. Jaffe et al.'s (1993) analysis—the first to look for evidence of geographic knowledge spillovers—concluded that proximity was highly relevant by examining patent citation data in the US. Aiello and Cardamone (2008) studied the spillovers of R&D across firms and industries in Italy and came to a similar conclusion for knowledge spillovers. Orlando (2004) found that geographic proximity is still important for R&D spillovers across firms after controlling for technological proximity, but mainly for cross-industry spillovers.

In relation to R&D spillovers across regions and countries, Coe and Helpman (1995) found that while domestic R&D is associated with greater productivity and economic growth, foreign "knowledge stocks" are also critical for explaining TFP. 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 goods or services. Using data from 21 OECD countries during the period 1971-90, they provide empirical support to these claims. Similarly, Frantzen (2000) carried out a cross-section analysis of OECD countries. He found that economic growth in those countries was closely related to innovation, which was influenced by domestic and foreign R&D, and that the importance of R&D is higher in G7 countries than in economically smaller countries. Spatial spillovers are also found to be important in the regional work of Bronzini and Piselli (2006).

According to Bayoumi et al. (1999), besides the impact that domestic R&D has on a country's productivity in the long run, R&D spillovers can result from international trade. Under this view, a country could achieve higher productivity by trading with other countries that have a large stock of knowledge. Bayoumi et al. (1999) show empirically that the degree to which a country benefits from R&D spillovers would be determined by the size of trade between the country and its trading partners. Furthermore, Coe et al. (1997) argue that developing countries could benefit more from the R&D spillovers derived from trading with developed countries than from investing in R&D themselves. Given the large amount of interstate trade within the US, as well as the prevalence of multistate R&D performing firms, we therefore expect to find that the benefits of R&D in the US spill across state borders.

Kao et al. (1999) assess the econometric validity of Coe and Helpman's (1995) modeling in light of advances in estimation methods for cointegrated panel data. They argue that Coe and Helpman's (1995) use of OLS leads to estimation bias, and propose the use of dynamic OLS (DOLS) instead. We begin (but do not conclude) our empirical exploration by adopting their methodology. Regardless of the bias issue, Kao et al. (1999) and Coe et al. (2009) corroborate the findings of Coe and Helpman (1993) that R&D has a positive direct and cross-border spillover effects on TFP. Coe et al. (2009) in addition highlight that institutional differences among nations 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 US. 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. More recently, Eberhardt et al.'s (2013) analysis also provides support for the importance of R&D spillovers across countries, as well as a review of the latest empirical work on R&D spillovers.

The latest strand of the literature on R&D and productivity takes its data from the regional level and examines spatial aspects of the relationship closely. 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). Focusing on the case of China, Wu (2010) studies provincial data to find that R&D has a positive effect on the regional innovation rate, and that innovation has a positive effect on productivity and consequently economic growth in China. Bronzini and Piselli (2006) study the long-run relationship between regional TFP, R&D, human capital, and public infrastructure in Italy during the period 1980-2001. They find that R&D has a positive effect on productivity and that the R&D stock in one region affects productivity levels in nearby regions, showing that geography is relevant for R&D spillovers. Using data from the United States, our paper follows the spirit of Bronzini and Piselli's (2006) approach, although our choice of econometric method differs. Our method of estimation is also related to the work of Kao et al. (1999) since we are interested on determining the short and long run effects of R&D on output and productivity. While interstate research spillovers have been examined in the agricultural sector (e.g., Deininger, 1995; Evenson, 1996; 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 US states, as well as other data used in our analysis.

III. 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. We obtained real Gross Domestic Product (GDP) for private industry by state,[5] which we refer to as State Gross Domestic Product (SGDP), from the Bureau of Economic Analysis (BEA, 2013a).[6] The units are millions of 2005 dollars.

We use Garofalo's and Yamarik (2002) state-level panel dataset for the private capital stocks.[7] Our measurement of the labor force is employment in the private sector, which is the sum of farm employment and private nonfarm employment. We obtained these data for the

[5] The real GDP by state series from BEA are not available before 1987, and the chained indexes by state series are not available before 1977. Therefore we used the US GDP implicit price deflator (from NIPA table 1.1.9, with change of basis from 2009 to 2005) for the US and applied it to the nominal state GDP series.

[6] The BEA changed its methodology in the state product accounts in 1997, switching from the SIC to the NAICS for classification of industry. Given that we do not break GDP down by industry, we ignore this change.

[7] We use their Net Private Capital Stock created for 1-digit SIC and NAICS industries. We also converted the basis of the series from 2000 to millions of chained 2005 dollars.

period 1969 to 2007 from the BEA (2013b).[8] For the six missing years of data before 1969, we constructed analogous figures for private industry employment based on the BEA's methodology.[9]

For the human capital stock, we use the average years of schooling in the labor force. Average educational attainment is the most commonly used measure of human capital in the literature (Benhabib and Spiegel, 1994; Frantzen, 2000; Bronzini and Piselli, 2006; int. al.). We use data constructed by Turner et al. (2006), which covers the years 1963 to 2000. We supplemented this series with data from the US Census Bureau's Current Population Survey (CPS) to extend coverage to 2007,[10] resulting in a blended measure of human capital by state, 1963-2007. Unlike our other variables, which are for private industry, of necessity our measure of human capital includes the education of government workers.

We use total R&D expenditure performed by private industry, which was obtained by state from the National Science Foundation's Industrial R&D Information System (IRIS) (NSF,

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[8] Our labor force data comes from BEA Tables SA25 and SA25N, Total Full-Time and Part-Time Employment by Industry.

[9] We calculate employment in private industry from 1963 to 1968 from various available but inconsistent sources in the following way. First, we collected government employment (GE) from the Statistical Abstracts of the US for each year (GE_SA_t). These data do not match the figures available from BEA from 1969 on, but we assume that the implied growth rate in GE is correct. Therefore, using 1969 as the reference year, we use the data from the Statistical Abstracts to calculate a government employment (GE) index series ($GEI_t = GE\_SA_t/GE\_SA_{1969}$) for t = 1963,…,1969. Applying the index to the GE figure from BEA (GE_BEA) for 1969 creates a synthetic series for GE during 1963-1968 ($GE_t = GE\_BEA_{1969}/GEI_t$) that blends smoothly into the BEA series in 1969. We then calculate a similar index series for total employment (TE) for the period 1963-1969 ($TEI_t = TE\_B_t/TE\_B_{1969}$), where TE_B is total employment from Turner et al. (2006) (we thank Robert Tamura for sharing these data). Applying the index to the BEA figure for total employment (TE_BEA) for 1969 creates a synthetic series for TE: $TE_t = TE\_BEA_{1969}/TEI_t$). Then we estimate private employment PE as the difference between total employment and government employment: $PE_t = TE_t - GE_t$.

[10] From each year's March supplement to the CPS, we constructed weighted estimates for each state of the number of years of education of individuals in the civilian labor force. Schooling in the CPS (variable A_HGA) is interval censored, so our calculation assumed that "grades 1 to 4" = 3 years, "grades 5-6" = 5.5 years, "grade 12 but no HS diploma" = 11.5 years, "some college but no degree" = 13 years, associate college degrees = 14 years; bachelor's degrees = 16 years; master's degrees = 18 years, professional school degrees and PhDs = 20 years. We created an index series for each state, using methodology similar to that described in footnote 9 for the employment statistics. The indices are used to create synthetic state-specific series that blend into the data from Turner et al. (2006) in 2000. This procedure tacitly assumes that the growth in human capital after 2000 can be accurately estimated from the CPS. Differences between the series before blending were generally small: in 2000, the overlapping year, the average difference was 1.1% with an interquartile range of 0 to 3.5%.

2013).[11] These data are from a stratified random sample survey, the Survey of Industrial Research and Development, and thus are subject to sampling as well as measurement error, but the survey is designed to include large performers of R&D with certainty.[12] There were missing observations for some states and years for two reasons. In 18 out of the 45 years of our sample, the NSF collected no data.[13] In other cases, the data are not reported if one firm did most of the R&D in the state that year. We log-linearly impute missing values, but only if they are missing for no more than three consecutive years. The R&D expenditure is converted from nominal to real 2005 dollars with the BEA's aggregate output price index for R&D investment.[14]

To construct the R&D capital stock variable, we follow the perpetual inventory method used throughout the literature. Specifically, we estimate initial R&D capital stock with the formula $I_0/(g + \delta)$, where I_0 is the average investment of the first 3 years available, g is the average geometric growth rate of the level of investment in each series, and δ is the depreciation rate.[15] Following Coe and Helpman (1995) and Bronzini and Piselli (2006), we use a 5% depreciation rate for R&D.[16] The final R&D capital stock variable is available for 83.1% of the

[11] The measure includes all expenditure on R&D performed by industry, regardless of the source of funds. Late data are from Table 60, "Funds for and companies performing industrial R&D in the United States, by state and source of funds: 1999–2007." Table H-21, "Total (company, Federal, and other) funds for industrial R&D performance, by State for selected years: 1963–98" supplies earlier years.

[12] For example, by the end of the period all companies among those known to conduct R&D in any of the previous five survey years and that spent $3 million or more on R&D were included with certainty. Details on the complex sampling scheme are in Appendix A to NSF (2011).

[13] Data are missing for even years from 1964-1996 and for 2000.

[14] The BEA R&D Satellite Account for 2010, available at http://www.bea.gov/rd/xls/1959_2007_rd_data_2010RDSA.xls, contains alternatives for indexing R&D investment. Copeland et al. (2007) describers the aggregate output price index that we use as "a second-best solution that reflects implementation challenges and data limitations" (p.4).

[15] In states with a break in the time series after imputation, the calculation of the stock variable begins anew after the break (i.e., data from before the break are not used).

[16] 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 knowledge stock.

possible 2,295 state-years in the sample. States with many missing values are typically those with the smallest population.[17]

In our analysis we also consider the spillover effect of R&D across states. To estimate the spillover effect we create a distance-weighted measure of R&D performed in other states. We thus assume that an R&D dollar spent in more distant states has less of a spillover than does R&D performed in adjacent states. We use $RD\_other_{it} = \sum_{j \neq \mathrm{i}} w_{ij} RD_{jt}$, which is the weighted sum of other states' R&D stock. Weights w_{ij} are the inverse distances between state population centroids from US Census Bureau (2000), normalized to sum to unity for each i. Thus, RD_OTHER_{it} is average domestic R&D performed outside the state, where the average is computed with spatial lags. As stated above, R&D data has many missing values. To overcome this difficulty, we rescale the weights for each year and states as necessary. Rescaling the weights restores the correct magnitude to the weighted average, but does not fully get around the measurement error in out-of-state R&D created by the missing data.

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.[18]

[17] The states with missing observations for R&D stock (with the number missing, out of 45 years possible, in parentheses) are: Montana (32), North Dakota (32), Idaho (30), Alaska (24), Vermont (23), Delaware (22), South Dakota (22), New Hampshire (21), West Virginia (21), Hawaii (20), Maine (17), New Mexico (16), Oregon (16), Washington (16), Nevada (12), DC (11), Nebraska (9), Wyoming (9), Georgia (8), Virginia (8), California (7), Mississippi (7), and Kentucky (5).
[18] The notable outlier on the high side is Michigan in 1993, which had an R&D to GDP ratio of 0.095.

Table 2 shows that during this period, Massachusetts and Missouri show the largest average spending on R&D as a share of GDP, over 4 percent. In general, states that are less populous and have large rural areas spent the least on R&D. 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. Also notable is Washington, DC with an average R&D intensity of 2.9%, a large figure no doubt due in part to proximity to the seat of federal R&D spending decisions. Table 3 presents the summary statistics for all the variables discussed above.

Finally, the labor and capital shares of GDP in the private sector are needed to calculate TFP. Following Gomme and Rupert (2004), labor's share of GDP in a state is found as the ratio of unambiguous labor income (UL) to the sum of UL and unambiguous capital income (UK) (both restricted to the private sector). UL is compensation of employees and UK accounts for corporate profits, rental income, net interest income, and depreciation in the state. To smooth the resulting UL series, a three-year moving average is taken.[19]

IV. Methodology

For the derivation of the empirical model we use to estimate the impact of R&D on output and productivity, we follow much of the empirical growth literature (e.g., Coe and

[19] UL is taken directly from BEA NIPA data for the private sector. UK is calculated using the national income accounting identity UK = (private sector GDP) – (private sector UL + private sector ambiguous labor income), where ambiguous labor income = taxes less subsidies + proprietor income (Gomme and Rupert, 2004). All data are from the state accounts. The three-year moving average is applied to each state's UL series before computing UK.

Helpman, 1995; Bronzini and Piselli, 2006) and assume a production function with Hicks-neutral TFP:

$$Y_{it} = TFP_{it} {L_{it}}^{\alpha} {K_{it}}^{\beta} \tag{1}$$

where *i* is a state index, and *t* is a year index. *Y* represents private sector output, *L* is private sector labor, *K* is the private sector physical capital stock; and *TFP* is Total Factor Productivity. TFP is driven by technological change, which in turn is driven by R&D investment, human capital accumulation, and other factors. Therefore we have that

$$TFP_{it} = A_{it} {HC_{it}}^{\gamma} {RD_{it}}^{\delta} \tag{2}$$

where A_{it} is the "unexplained" technical change, HC_{it} is the human capital stock, and RD_{it} is the stock of R&D capital, all for state *i* in year *t*. We parameterize unexplained technological change as the product of state- and year-specific fixed effects: $A_{it} = \exp(\lambda_i + \tau_t)$. Substituting this expression for A_{it} into Equation (2) and TFP_{it} into Equation (1), we get:

$$TFP_{it} = e^{\lambda_i + \tau_t} {HC_{it}}^{\gamma} {RD_{it}}^{\delta} \tag{3}$$

$$Y_{it} = e^{\lambda_i + \tau_t} {HC_{it}}^{\gamma} {RD_{it}}^{\delta} {L_{it}}^{\alpha} {K_{it}}^{\beta} \tag{4}$$

From Equations (3) and (4) we derive the following econometric equations:

$$y_{it} = (\lambda_i + \tau_t) + \gamma hc_{it} + \delta rd_{it} + \alpha l_{it} + \beta k_{it} + \varepsilon_{it} \tag{5}$$

$$tfp_{it} = (\lambda_i + \tau_t) + \gamma hc_{it} + \delta rd_{it} + \eta_{it} \tag{6}$$

where the lower-case letters stand for natural logarithm, and ε_{it} and η_{it} are error terms for state *i* in year *t*.

We adopt alternate assumptions about α and β for purposes of comparison. In our first econometric approach, in which *SGDP* is the dependent variable (Equation (5)), we make no assumptions about returns to scale and place no restrictions on α and β. The second approach is based on Equation (6). TFP is calculated for the dependent variable as $TFP_{it} = Y_{it}/({L_{it}}^{\alpha} {K_{it}}^{\beta})$, where α and β are calculated directly from input shares in the SGDP accounts. This second method thus tacitly imposes constant returns to private inputs labor and capital, so that β = 1-α.

To include the spillover effect of R&D across states in our model, we follow Bronzini and Piselli (2006) and introduce *RD_OTHER*, the distance-weighted R&D stock from other states, into Equation (3):

$$TFP_{it} = e^{\lambda_i+\tau_t} HC_{it}{}^{\gamma} RD_{it}{}^{\delta} RD\_OTHER_{it}{}^{\pi} \quad (7)$$

Therefore, Equations (5) and (6) including the spillover effects are:

$$y_{it} = (\lambda_i + \tau_t) + \gamma hc_{it} + \delta rd_{it} + \pi rd\_other_{it} + \alpha L_{it} + \beta K_{it} + \varepsilon_{it} \quad (8)$$

$$tfp_{it} = (\lambda_i + \tau_t) + \gamma hc_{it} + \delta rd_{it} + \pi rd\_other_{it} + \eta_{it} \quad (9)$$

To account for the year effects τ_t, we time-demean all variables (without explicitly changing our notation) from here on except where noted.

We estimate the models in Equations (8) and (9) using our unbalanced panel with all available data between 1963 and 2007. The equations are in levels, which we preserve in our choice of econometric methodology 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 integrated and cointegrated data. Based on the likely cointegration of the data, we estimate the parameters of the long-run relationships in Equations 8 and 9 using the Dynamic Ordinary Least Squares (DOLS) and the Pooled Mean Group (PMG) estimators. To enable unbiased estimation of the long-run relationships, in empirical application we also want to model flexibly the short-run dynamics. Below we provide an econometric model incorporating short-run dynamics, long-run relationships, and heterogeneity across panels that leads to the DOLS and PMG estimators.

Begin with the autoregressive distributive lag form of Pesaran et al. (1999), denoted ARDL(p,q,q,…,q):

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij} x_{i,t-j} + \alpha_i + \varepsilon_{it} \tag{10}$$

where x_{it} is a vector of the regressors from Equation (8) (or Equation (9), depending on which specification is being estimated), α_i is a fixed effect, and ε_{it} is white noise. Note that the specification allows state-specific coefficients on the lagged dependent variable and regressors, allowing for dynamics that differ across units of the panel.

Before estimating the unrestricted form of Equation (10), we first restrict $p = q = 0$ and furthermore assume y and x are each $I(1)$ and are cointegrated. Then $\theta = \delta_{i0}$ is the coefficient vector describing the long run (cointegrating) relationship between y and x. Kao and Chiang (2001) show that (under certain conditions) a consistent estimate of θ, $\hat{\theta}_{DOLS}$, can be obtained from the following panel Dynamic OLS (DOLS) regression

$$y_{it} = \theta' x_{it} + \sum_{j=-r}^{r} C_{ij} \Delta x_{i,t+j} + \alpha_i + \nu_{it} \tag{11}$$

where the lag/lead length $r \rightarrow \infty$ as $T \rightarrow \infty$. The DOLS model is restrictive because it requires all variables be $I(1)$, y and x to be cointegrated, and the variance structure and short run dynamics to be identical across states. Thus we use the DOLS model only for our initial estimations.

Now return to Equation (10) and relax the restrictions imposed by the DOLS model. Instead, allow vector x to be I(0) or I(1), and assume that the order of integration of y is no more than the order of x. However, we still assume the long run relationship between y and x

(captured by θ) is common across states. Then, we can re-write Equation (10) in error correction form:

$$\Delta y_{it} = \phi\left(y_{i,t-1} - \theta' x_{it}\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{*} \Delta x_{i,t-j} + \alpha_i + \varepsilon_{it} \qquad (12)$$

where θ and the starred coefficients are functions of the original parameters in Equation (10).[20] Note that θ is again the long run relationship of interest. The short run dynamics of the dependent variable is governed by the deviation from the equilibrium long-run relationship. Note that the parameter ϕ, which governs the speed of adjustment to the long run relationship, is assumed to be the same across states. 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.[21]

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, we will be able to estimate the long run effect of R&D on output or TFP with $\hat{\theta}_{PMG}$, and the estimates for ϕ, λ^*, and δ^* will capture the short-run effects and dynamics.[22] The PMG estimator not only 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. Testing shows that a dynamic specification of the form ARDL(1,1,1,1,1,1) is appropriate.[23]

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[20] In particular, $\theta = \sum_{j=0}^{q} \delta_{ij} / (1 - \sum_{j=1}^{p} \lambda_{ij})$ and is assumed in the PMG model to be constant across i.

[21] 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}.

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

[23] Lag length was selected based on the Schwarz Bayesian Information criterion (SBIC). We performed the test for each state in the sample and select the lag length that is appropriate in most states (we use the mode of the lag length test from all states, which was equal to zero according to the SBIC).

For the PMG estimator we require the existence of a long run relationship between the dependent variable and the control variables. Thus, the error-correcting speed of adjustment term for the long run relationship, ϕ_i, must be between zero and -2. We also will consider Hausman tests of the PMG and Mean Group (MG) estimates to test whether the assumption of a common long-run relationship is appropriate. The MG estimator (Pesaran and Smith, 1995) fits the model separately for each group, and the Hausman test looks for evidence that the restriction $\theta_i = \theta \; \forall \; i$ is invalidated by heterogeneity in the long run estimates.

V. Results

In this section, we present the empirical results for the testing of the econometric models' assumptions, the estimates from the baseline estimations, and the results of additional regressions designed to check the validity and robustness of our conclusions.

A. Tests for Nonstationarity and Order of Integration

The DOLS estimator requires that all the variables be I(1), while the PMG estimator requires that the variables be I(1) or I(0), with the order of *y* no greater than the order of the regressors. To test these assumptions, in Table 4 we shows the results of two different unit roots tests for the variables included in our baseline model. There are many tests for panel unit roots available; we choose two that are appropriate for large *N*, large *T* asymptotics and allow unbalanced panels. The unit root test of Im et al. (2003) has the null hypothesis that all panels are integrated and the alternative hypothesis that at least one panel is stationary.[24] The results for the variables before removing the time-means are in the first column of Table 4, and they

[24] In this test we use a number of lags chosen by the AIC criterion in constructing the test statistic, to account for serial correlation. The test was performed using the `xtunitroot ips` command in Stata 13 with the "`lags(aic 5)`" option.

show that the human capital variable may not have unit roots in each state. The conclusions are the same from the ADF-Fisher tests (Choi, 2001).[25] We next test the time-demeaned variables; results are in the middle pair of columns of Table 4. We fail to reject the null hypothesis of nonstationarity for any variable except TFP at the 5% level, although the null is still rejected for human capital at the 10% level. The ADF-Fisher tests fail to reject the null hypothesis for any variable. There is thus mixed evidence for the nonstationarity of TFP. If TFP is I(0), the DOLS estimator will fail but the PMG estimator is still consistent.

To make sure none of the variables is integrated at higher orders, we repeat the tests on the differenced form of the variables (results are in the last two columns of Table 4). The hypothesis of nonstationarity of all panels is convincingly rejected in each case. Thus, each series appears to be $I(1)$ in each state, except possibly TFP. In summary, the data appear to satisfy the assumptions of the DOLS and PMG estimators when SGDP is used as the dependent variable but satisfy only the assumptions of the PMG estimator with TFP as the dependent variable.

We also explore whether there is evidence of cointegration, as supposed by our estimation strategy. To test for cointegration we use a battery of residual-based tests for panel data from Pedroni (1999) and Kao (1999). We perform the cointegration test for the SGDP and TFP models using the baseline regression specification introduced in the next section. The results are shown in Table 5. The null hypothesis of no cointegration is rejected in the majority of cases overall, although the case is weaker for the TFP regression. The parametric panel t-statistic, which Örsal (2007) found to have the best size and power among the Pedroni statistics, rejects

25 Instead of constructing a single test statistic, the ADF-Fisher test instead combines the p-values from separate tests on each panel into an omnibus p-value (Choi, 2001). The test was performed using the `xtunitroot fisher` command in Stata 13 with five lags for serial correlation.

the null for all cases except the TFP regression with time-demeaned variables.[26] Given that failure to reject the null may merely indicate low power of a test, we interpret the mixed results as providing reasonable evidence for the existence of long-run relationships among the data, except perhaps for TFP with time-demeaned variables.

B. Baseline Estimations

Table 6 presents the DOLS and PMG estimates for the baseline estimations. We begin with three DOLS specifications.[27] The first two estimations, for SGDP and TFP, respectively, use the raw data without removing the time means. The third DOLS estimation in Table 6 is for SGDP and uses the time-demeaned data. Regardless of which DOLS estimation is considered, we find that there is evidence of a positive effect of R&D on SGDP in the long run from R&D performed in the state. The long-run own-elasticity for R&D varies from 0.013 to 0.061 among the estimations. These elasticities fall within the range of results for R&D own-elasticity estimates from country-level panel data studies cited in Hall et al. (2010). We defer interpreting the magnitudes of the elasticities until our preferred PMG estimation.

The results for the impact from other-state R&D are mixed. In the first estimation, the other-elasticity is 0.050 and highly significant. The second estimate is about the same magnitude but insignificant. Recall that the dependent variable in this regression, TFP, may not be integrated within each state, which would lead to inconsistency in the DOLS estimates. The third estimate, from the time-demeaned data, is negative, a puzzling result. There are some other unexpected results that may indicate that the assumptions of the DOLS model are not satisfied. While capital and labor contribute positively and significantly to SGDP, the coefficient on

[26] We note that the same tests that fail to reject at the 5% level in the baseline R&D regressions of Bronzini and Piselli (2006) (the panel v-, and group and panel ρ-statistics) also fail to reject here. They nevertheless concluded, as we do here, that the evidence is for the existence of long-run relationships among the data.
[27] The number of leads and lags in each DOLS estimation was selected based on the SBIC.

capital is larger than (in column 1) or equal to (in column 3) the coefficient on labor.[28] Furthermore, human capital is not statistically significant in the first estimation, which is unexpected given the great importance this variable has been found to have in other growth and TFP regressions (Mankiw et al., 1992; Coe et al,, 2009; Bronzini and Piselli, 2009). The insignificance of human capital in the cointegrating relationship may be related to the evidence presented above that human capital may not in fact have a unit root in all panels before time-demeaning the variable.[29]

The varied performance of the DOLS approach leads us to examine the more general PMG estimator. The baseline PMG estimates are shown in Table 6, Columns 4 and 5 (long-run coefficients only). All PMG estimates use the time-demeaned data. 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 error correction term and its confidence interval are between zero and -2. Furthermore, the Hausman tests for the estimations shown in Columns 4 and 5 fail to reject the assumption of a common long-run relationship for all the states.[30]

Column 4, in Table 6, shows the estimates for the baseline model that uses SGDP as dependent variable. 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

[28] The conventional wisdom (and much empirical evidence) holds that labor's share of output is about twice capital's share of output in the US economy.
[29] The DOLS estimates shown in Table 6 are similar to results found when we use the Fully Modified Ordinary Least Squares (FMOLS). FMOLS, a competing estimator to DOLS, has been found to perform worse than DOLS when estimating cointegrated panel regressions, and we do not report the results here. See Baltagi (2008, p.299) for a discussion of the DOLS and FMOLS. FMOLS Results are available upon request.
[30] The p-values for the Hausman test of the consistency of the PMG estimates (vs. the MG estimates) are 0.69 and 0.89 for the estimations shown in Columns 4 and 5 of Table 6, respectively.

1.06, indicating that there are slightly increasing returns to scale to physical inputs.[31] These estimates are also close to the conventional wisdom regarding labor and capital shares in the US 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 US 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%.[32] 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 US in particular.[33] 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), in keeping with the practice in the literature. 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

[31] 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.
[32] 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.
[33] 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).

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.[34]

Similarly, the impact of the R&D stock in other states 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 the out-of-state weighted R&D stock (which would require *each* other state to raise its R&D stock by one dollar) is 569%. Since the average weight of another state in the calculation of *RD_OTHER* 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 7 shows the own-state marginal returns to R&D, the returns spilled over to other states, [35] 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. Alaska and Hawaii are estimated to see less than 10% of total returns spill over to other states, while more than 90% of

[34] 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.

[35] 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*, $s_j = \sum_t b_{jt}Y_{jt}/RD\_OTHER_{jt}$ is the average output to out-of-state R&D ratio in the state, and b_{jt} is as defined in footnote 32.

total returns leave the borders of Connecticut, Delaware, Idaho, Michigan, New Jersey, and New Mexico.[36]

The 255 short run coefficients are not reported in the table (recall that the short run coefficients are allowed to vary freely among states in the PMG estimator). However, the results show that the average 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. Given that previous literature focused exclusively on the long-run relationship between R&D and growth, we do not have other results to which to compare this finding. However, it does emphasize 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.[37] 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.

We also estimate the impact of R&D on TFP using the PMG estimator, and the coefficients are shown in Column 5 of Table 6. 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.[38] Recall that the regressions for TFP require the assumption of constant returns to scale in labor and capital. Since the baseline estimation for SGDP formally

[36] Recall that the own-state and other-state R&D elasticities are the same for all states. Thus, differences in the returns and spillovers in Table 7 come from differences in the spatial weights and the SGDP to R&D stock ratios of the states.

[37] The average short-run coefficient for *rd_other* is, however, significant at the 10% level, but just barely: $p = 0.099$.

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

rejects this assumption, it may be that the elasticities from the TFP regression are biased.[39] 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 7).

C. 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. We use the PMG estimator with the dependent variable SGDP for all these additional regressions. 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 8. 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

[39] 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.

between domestic and foreign R&D stocks, the direct effect of R&D would likely be 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 US 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 8. 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 6. 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 lagged R&D replaces current-period R&D in equation (5). 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 8. The own-R&D elasticity of 0.074 is indeed more than five times higher than in the baseline estimation, but the other-R&D elasticity of 0.217 is lower.[40] However, neither of the changes in elasticity when lagging the R&D variables is statistically significant.[41]

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 level of economic development 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 rd_{it} and rd_other_{it} in these estimations. The long-run estimates from these models are shown in Table 9, 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-

[40] 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 8.

[41] The hypothesis test for equality of the coefficients on own-R&D from the estimations using current R&D and lagged R&D was performed using a panel bootstrap estimation of the standard error for the difference in coefficients (400 replications). The *p*-value from the *t*-test is 0.73. A similar test for other-R&D returns a *p*-value of 0.64.

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 9), 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 development. 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 development 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 development group do not perform enough R&D to affect SGDP measurably. The real R&D stock for the low-development group averages less than a third as much as for the middle group, and less than one-tenth as much as for the highest development group.[42] Finally, it may be the case that the states in the lowest development group do not have many multistate R&D

[42] 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.

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 9 show that states in all development 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 development 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.

VI. Conclusion

Our investigation of the relationship between investment in R&D capital and productivity allows us to draw the following conclusions. First, we observe in nearly all of the many specifications estimated that R&D performed within a state has a positive, significant effect on SGDP through TFP in the long run. The finding of a positive impact of R&D on SGDP is robust to the inclusion or exclusion of other-state R&D, to allowing the elasticity to change over time, and to the lag length chosen for R&D. The estimated contemporaneous marginal return within the state to R&D investment is 82% in our baseline estimation. 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 US state level. 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 US states. Our 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. 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, at the lowest level of state economic development 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 policy implications for the US and for developing countries. 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). Note that we cannot conclude from our research alone that the private incentives to perform R&D are deficient, due to the fact that most companies that perform R&D operate in multiple states (and, indeed, multiple countries).[43] R&D-performing multistate corporations are an important channel for the spillovers among states (Adams and Jaffe, 1996), and some of the spillovers among states will be internal returns to these firms.[44] Nevertheless, the large body of previous work on firm-level returns to R&D make it clear that positive externalities exist (Hall et

[43] Around 80% of aggregate US industrial R&D was performed by multinational corporations in 1982 (Dunning, 1988).
[44] Adams and Jaffe (1996) find that within-firm R&D performed outside the state of a particular plant increases TFP at the plant, albeit not as much as when the R&D is performed in the same state.

al, 2010), and there is a potential role for government at both the state and federal level.[45] However, since we have shown that the lion's share of the benefits of R&D activities for output and productivity leak across state lines, 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.

Regarding implications for US state policy makers in particular, recent work has found that state R&D tax credits merely draw R&D activity from surrounding states, so that states play a nearly zero-sum game (Wilson, 2009). Thus, there may appear to be no scope for cooperation among states in a region in setting R&D policy. However, our results suggest that R&D spending contributes strongly to the economic growth of nearby states. Therefore, coordinated R&D incentives in a region across states, either from multistate policy cooperation or federal policies, can increase economic growth of the entire region. 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 STEM areas that are necessary for R&D.

Our findings also have implications for developing countries, particularly since the global distribution of R&D is beginning to shift toward emerging economies such as China (UIS, 2010). In many less-developed countries (LDCs) there is an uneven concentration of firms performing R&D, with most activity centered on an "innovation hub" or "innopolis" (UIS, 2010; Jung and Mah, 2013). Indeed, such regional variation is the norm (UIS, 2010). Some proponents thus

[45] 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. In this view, a careful comparative institutions approach and analysis of specific policies is necessary before concluding that the market underperforms relative to realistic alternatives.

advocate that governments in LDCs should promote R&D activity in lagging geographic areas to reduce regional inequality (Jung and Mah, 2013). However, our results show that (within the US) most benefits from R&D flow to other regions of the country anyway. Thus, perhaps more important than stimulating R&D in lagging areas of a country is the strengthening of the national system of innovation (Freeman and Soete, Ch. 12, 1997) so that all areas can benefit from R&D, wherever it is performed.

Our results suggest the importance of three particular aspects of building up an LDC's national system of innovation. The importance of human capital for reaping the benefits of R&D in the home region and from other parts of the country has already been noted above. Furthermore, since multinational corporations (MNCs) play a leading role in private-sector knowledge creation in many LDCs (Narula, 2005), attention must be paid to facilitating the linkages MNCs build with local economic agents. As Narula (2005) states, such "linkages constitute one of the ways in which skills and technological transfer is thought to disseminate to the rest of the economy. Thus [MNCs] can promote domestic enterprise and technological learning in the entire national system" (p.55). Thus trade liberalization and the encouragement of partnership between MNCs and domestic firms and public sector organizations such as universities are important for developing countries. These aspects are related, since human capital is one of the main determinants of the ability for an LDC to absorb spillovers from R&D performed by MNCs. Finally, deficient institutions and social capital—the "ground rules for interaction between economic actors"—can also decrease the absorptive capacity of an LDC (Narula, p. 49, 2005). Policymakers in LDCs can build social capital both by establishing stable and trustworthy public sector institutions and by firmly upholding the rule of law, intellectual property rights, and incentives for innovation in the private sector.

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. Even setting aside the question of whether publicly funded R&D crowds out privately funded R&D, many studies find the returns to publicly funded R&D to be lower than returns to privately funded R&D (Griliches, 1980a,b; see Hall et al. (2011) for others). Whether this is also true at the state level, and whether R&D funded by the state is more effective than R&D funded by the federal government is unknown. 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.

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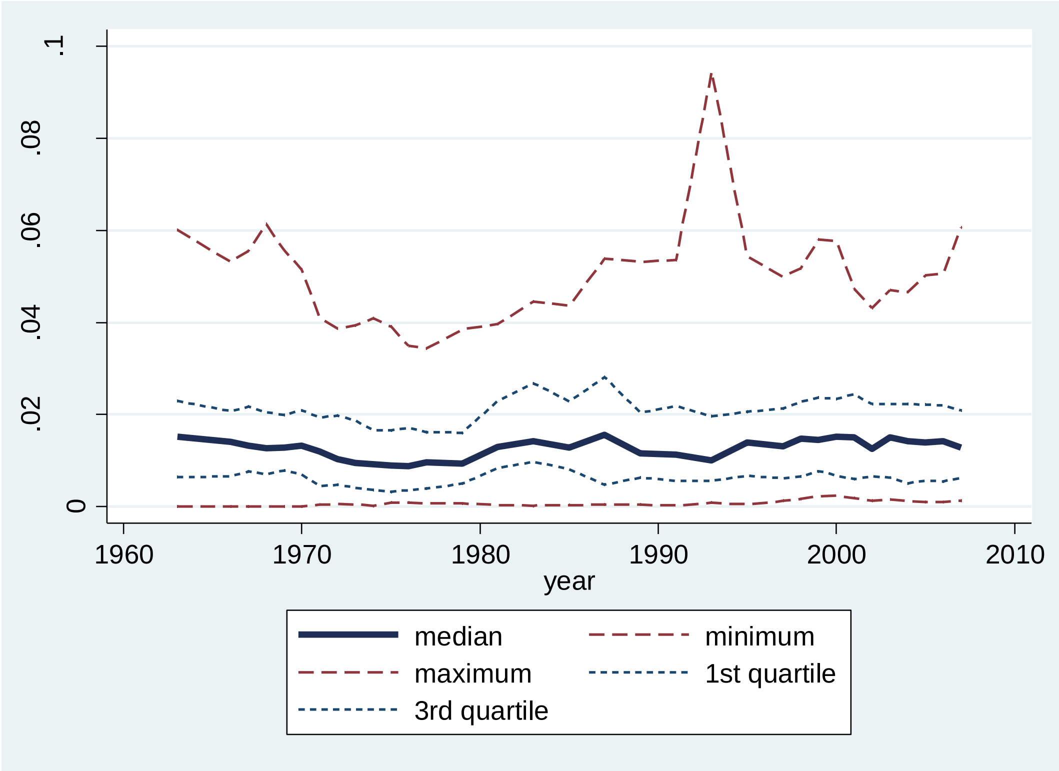
Figure 1: Industrial R&D as a fraction of GDP in US states, 1963-2007



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.

Table 1. Research and development expenditure as a percentage of GDP*

Country	00-04	05-09	2009	Country	00-04	05-09	2009
Israel	4.39	4.60	4.46	Portugal	1.64	0.74	1.21
Finland	3.38	3.61	3.93	Czech	1.48	1.17	1.44
Sweden	3.84	3.59	3.60	Estonia	1.43	0.73	1.17
Korea, Rep.	2.47	3.19	3.56	Spain	1.39	0.98	1.27
Japan	3.09	3.40	3.36	New Zealand	1.30	1.15	1.21
Denmark	2.49	2.69	3.06	Italy	1.26	1.09	1.17
United States	2.64	2.73	2.90	Russian	1.25	1.18	1.11
Germany	2.50	2.62	2.82	Hungary	1.17	0.91	1.02
Austria	2.12	2.56	2.72	Brazil	1.17	0.98	1.07
Singapore	2.04	2.40	2.43	Tunisia	1.10	0.61	1.00
France	2.18	2.14	2.26	Serbia	0.92	0.58	0.52
Belgium	1.94	1.91	2.03	Ukraine	0.86	1.04	0.93
Canada	2.03	1.96	1.92	Turkey	0.85	0.51	0.69
Slovenia	1.40	1.59	1.86	Lithuania	0.84	0.67	0.80
U.K.	1.76	1.78	1.86	Croatia	0.83	0.99	0.83
Netherlands	1.92	1.84	1.82	Hong Kong	0.79	0.61	0.78
Norway	1.63	1.59	1.78	Poland	0.67	0.58	0.59
Ireland	1.13	1.39	1.74	Belarus	0.64	0.66	0.74
China	1.06	1.46	1.70	Cuba	0.61	0.56	0.51
Luxembourg	1.64	1.61	1.66	Argentina	0.60	0.42	0.52

*Averages from 2000-2004 and 2005-2009, and value in 2009.
Source: World Development Indicators (World Bank, 2013).

Table 2. Average of R&D expenditure as percentage of GDP, 1963- 2007

State Code	R&D intensity	State Code	R&D intensity	State Code	R&D intensity
Alabama	1.10	Kentucky	0.50	N. Dakota	0.60
Alaska	0.10	Louisiana	0.40	Ohio	1.80
Arizona	1.90	Maine	0.50	Oklahoma	0.70
Arkansas	0.30	Maryland	1.80	Oregon	1.60
California	3.60	Massachusetts	4.00	Pennsylvania	2.20
Colorado	1.90	Michigan	4.30	Rhode Island	1.80
Connecticut	3.90	Minnesota	2.20	S. Carolina	0.80
Washington, DC	2.90	Mississippi	0.20	S. Dakota	0.30
Delaware	0.70	Missouri	1.50	Tennessee	1.10
Florida	1.10	Montana	0.30	Texas	1.30
GA	0.70	Nebraska	0.40	Utah	1.50
Hawaii	0.30	Nevada	0.80	Vermont	1.90
Idaho	2.80	New Hampshire	2.30	Virginia	1.20
Illinois	1.60	New Jersey	3.70	Washington	3.80
Indiana	1.80	New Mexico	3.00	W. Virginia	0.80
Iowa	1.00	New York	1.60	Wisconsin	1.30
Kansas	1.20	N. Carolina	1.20	Wyoming	0.20

Source: National Science Foundation (2013).

Table 3. Summary statistics for the estimation sample

	Mean	Std. Dev.	Min	Max
Value in Levels				
SGDP, millions 2005 $	1,425.77	1,777.06	45.12	15,704
TFP	0.15	0.04	0.07	0.53
Physical capital, millions 2005 $	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, millions 2005 $, δ = 5%	21,586	42,089	6.56	538,478
R&D Stock, millions 2005 $, δ = 15%	10,706	21,757	6.56	293,792
Other states wgtd. ave. R&D stock, millions 2005 $, δ = 5%	21,478	11,554	5,598	85,625
Values in Logarithms				
ln(SGDP)	6.72	1.05	3.81	9.66
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(R&D Stock, δ = 5%)	8.01	1.85	1.88	12.59
ln(Other states average R&D stock, δ = 5%)	9.84	0.53	8.63	11.36

Notes: Summary statistics for annual observations for the period 1963-2010 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 4. P-values from panel tests for unit roots

	Variables in Levels		Time-Demeaned Variables in Levels		Time-Demeaned Variables in Differences	
	Im, Pesaran & Shin Test	ADF-Fisher Test	Im, Pesaran & Shin Test	ADF-Fisher Test	Im, Pesaran & Shin Test	ADF-Fisher Test
Ln(SGDP)	1.000	1.000	0.308	0.205	0.000	0.000
Ln(TFP)	0.999	1.000	0.020	0.258	0.000	0.000
Ln(Labor force)	0.100	1.000	0.845	0.358	0.000	0.000
Ln(Physical capital)	1.000	0.959	0.866	0.919	0.000	0.000
Ln(Human capital)	0.000	0.000	0.071	0.750	0.000	0.000
Ln(R&D Stock)	1.000	1.000	0.997	0.345	0.000	0.000

Figures are *p*-values from the test stated in the column subheading, where the variable tested is given in the row heading and is in levels or differences as specified in the column superheading. The specified lags for serial correlation in the test statistics is five. The null hypothesis of each test is that each time series in the panel contains unit roots (i.e., that each states' time-series is non-stationary), while the alternative hypothesis is that at least one time series in the panel is stationary. For the ADF-Fisher test, an inverse chi-squared transformation that is suitable for large *N* is used to combine the *p*-values from the panels (Choi, 2001).

Table 5. P-values from panel tests for cointegration

	Non-Time-Demeaned Variables		Time-Demeaned Variables	
Specification:	SGDP	TFP	SGDP	TFP
Pedroni tests				
Panel v-statistic	0.239	0.078	0.448	0.750
Panel ρ-statistic	0.942	0.934	0.949	0.997
Panel t-statistic (nonparametric)	0.000	0.547	0.008	0.997
Panel t-statistic (parametric)	0.000	0.004	0.000	0.755
Group ρ-statistic	1.000	1.000	0.996	1.000
Group t-statistic (nonparametric)	0.000	0.562	0.000	0.999
Group t-statistic (parametric)	0.000	0.000	0.000	0.006
Kao Tests				
ADF statistic	0.000	0.000	0.000	0.000
t_{ADF} statistic	0.000	0.000	0.000	0.000

Figures are the *p*-values from the regression-based hypothesis tests for no cointegration from Pedroni (1999) and Kao (1999); refer to these sources for the formulae for the test statistics. The regression specification is the baseline specification as in Table 6. Rejection of the null in favor of the alternative hypothesis of cointegration is evidence in favor of the existence of long run relationships among the regressors. Lag length selection is based on AIC; results based on SIC were nearly identical.

Table 6. Baseline DOLS and PMG estimation results

Dependent Variable:	SGDP	TFP	SGDP	SGDP	TFP
Estimator:	DOLS	DOLS	DOLS	PMG	PMG
	(1)	(2)	(3)	(4)	(5)
Long run coefficients					
R&D Stock	0.032***	0.061***	0.013***	0.056***	0.143***
	(0.006)	(0.011)	(0.005)	(0.005)	(0.012)
Other States' R&D Stock	0.050***	0.041	-0.086**	0.313***	0.531***
	(0.016)	(0.027)	(0.034)	(0.039)	(0.080)
Years of Schooling	-0.009	0.843***	0.423***	1.257***	2.811***
	(0.077)	(0.124)	(0.128)	(0.124)	(0.121)
Physical Capital Stock	0.648***		0.566***	0.334***	
	(0.033)		(0.039)	(0.039)	
Labor Force	0.484***		0.571***	0.729***	
	(0.030)		(0.037)	(0.039)	
Error Correction (ϕ)				-0.181***	-0.107***
				(0.025)	(0.017)
All variables time-demeaned	No	No	Yes	Yes	Yes
No. States	51	51	51	51	51
No. Obs.	1,615	1,762	1,619	1,842	1,842
R-squared	0.999	0.909	0.999		
Log Likelihood				5,021	4169.3

***, **, 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. Estimations include observations for 44 years during the period 1963-2007. Estimations include a minimum of 12 observations per state and a maximum of 44, with an average number of observations per state of 36.

Table 7. Marginal returns to R&D investment, within state and spillovers

	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction
	(1)	(2)	(2)/(1)	(2)/[(1) + (2)]
SGDP-Weighted Average*	0.823	1.992	4.902	0.767
Alabama	0.689	2.332	3.386	0.772
Alaska	9.712	0.655	0.067	0.063
Arizona	0.490	2.078	4.240	0.809
Arkansas	6.788	2.363	0.348	0.258
California	0.230	0.866	3.758	0.790
Colorado	0.473	1.860	3.935	0.797
Connecticut	0.210	2.612	12.412	0.925
Delaware	0.245	2.793	11.401	0.919
Washington, DC	1.088	3.173	2.917	0.745
Florida	0.748	1.379	1.842	0.648
GA	1.476	2.192	1.485	0.598
Hawaii	7.554	0.499	0.066	0.062
Idaho	0.167	1.818	10.905	0.916
Illinois	0.519	2.350	4.526	0.819
Indiana	0.423	2.778	6.566	0.868
Iowa	0.805	2.299	2.855	0.741
Kansas	0.909	2.214	2.435	0.709
Kentucky	1.942	2.602	1.340	0.573
Louisiana	1.358	2.054	1.512	0.602
Maine	2.609	1.599	0.613	0.380
Maryland	0.434	2.800	6.448	0.866
Massachusetts	0.211	1.957	9.274	0.903
Michigan	0.186	2.265	12.196	0.924
Minnesota	0.395	1.876	4.754	0.826
Mississippi	7.775	2.334	0.300	0.231
Missouri	0.443	2.315	5.224	0.839
Montana	2.546	1.600	0.628	0.386
Nebraska	4.431	2.097	0.473	0.321
Nevada	2.666	3.389	1.271	0.560
New Hampshire	0.642	2.180	3.395	0.772
New Jersey	0.198	2.755	13.917	0.933

Table continued	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction
	(1)	(2)	(2)/(1)	(2)/[(1) + (2)]
New Mexico	0.113	1.955	17.291	0.945
New York	0.385	2.242	5.831	0.854
N. Carolina	0.836	2.176	2.603	0.722
N. Dakota	2.924	1.646	0.563	0.360
Ohio	0.378	2.423	6.412	0.865
Oklahoma	0.945	2.258	2.389	0.705
Oregon	1.165	1.728	1.483	0.597
Pennsylvania	0.323	2.484	7.694	0.885
Rhode Island	0.917	2.642	2.880	0.742
S. Carolina	1.127	2.327	2.064	0.674
S. Dakota	10.417	1.891	0.182	0.154
Tennessee	0.672	2.428	3.614	0.783
Texas	0.721	1.537	2.132	0.681
Utah	0.535	2.043	3.819	0.792
Vermont	0.603	1.961	3.254	0.765
Virginia	0.804	2.347	2.918	0.745
Washington	0.265	1.394	5.258	0.840
W. Virginia	1.269	2.616	2.061	0.673
Wisconsin	0.613	2.334	3.806	0.792
Wyoming	15.199	1.857	0.122	0.109

*For the weighted averages, the figures in the row are calculated first at the state level using the formula in the column heading and then are averaged across states.

Notes: Figures in columns (1) and (2) 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 baseline PMG estimation for SGDP (column 3 in Table 6).

Table 8. Additional PMG estimation results

Y = SGDP	Without other-state R&D (1)	Period-specific R&D Elasticity (2)	Lagged R&D (3)
Long Run Coefficients			
R&D Stock	0.076	0.050	
	(0.006)***	(0.005)***	
R&D Stock, later period		0.008	
		(0.002)***	
R&D Stock, lagged			0.074
			(0.006)***
Other States' R&D Stock		0.215	
		(0.035)***	
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
	(0.139)***	(0.112)***	(0.129)***
Physical Capital Stock	0.436	0.347	0.508
	(0.029)***	(0.036)***	(0.028)***
Labor Force	0.657	0.755	0.532
	(0.028)***	(0.037)***	(0.030)***
Error Correction (ϕ)	-0.182	-0.204	-0.189
	(0.031)***	(0.026)***	(0.037)***
All variables time-demeaned	Yes	Yes	Yes
Short run coefficients omitted in table			
No. States	51	51	51
No. Obs.	1,842	1,842	1,791
Log Likelihood	4,958.9	5,087.4	4,935.6

***, **, 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. Estimations in columns (1) and (2) have a minimum of 12 observations per state and a maximum of 44 (average = 36). The estimation in column (3) has a minimum of 11 observations per state and a maximum of 43 (average = 35).

Table 9. 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, Low Group	0.081	0.308***
	(0.081)	(0.098)
Other States R&D Stock, Medium Group	0.160***	0.297***
	(0.040)	(0.082)
Other States R&D Stock, 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.