Public R&D Spending and Cross-Sectional Stock Returns

Empirical findings on the wealth effect of public research and development (R&D) spending are mixed. We adopt an alternative approach by examining the effect of public R&D spending on stock returns. We find that firms located in states with a greater amount of public R&D spending earn higher abnormal stock returns. The effect persists after accounting for conventional pricing factors and state-level variables, and becomes stronger for firms with greater absorptive capabilities. The abnormal stock returns are not only related to the positive effects of public R&D on firm productivity and incoming spillovers, but are also related to the increased cash flow risk. Policymakers should be aware of this risk effect before making any changes in public R&D investment.

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G12, G14, O31

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Public R&D spending; Stock returns; R&D spillovers

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1. INTRODUCTION

Unlike other types of investment, research and development (R&D) investment shows substantial positive externalities. The literature suggests that the social rate of return of privately funded R&D is higher than its private rate of return (e.g., Scherer 1982; Bernstein and Nadiri 1998; Salter and Martin, 2001), which implies that private industries tend to underinvest in R&D when compared with the socially optimal level, and there is a room for public involvement. A common practice is that government directly funds R&D programs through contracts with companies, universities, and other not-for-profit institutions. In 2010, the U.S. public sector spends $166 billion on R&D investments, which accounts for 1.11% of the nation's gross domestic product (GDP).[1] However, the empirical findings regarding the wealth effect of public R&D spending are mixed.[2] For example, while Lerner (1999), Czarnitzki and Lopes-Bento (2013), Fritsch and Franke (2004), Takalo, Tanayama, and Toivanen (2013), and Hottenrott and Lopes-Bento (2014) find significant economic benefits of public-funded research programs, Lichtenberg (1993), Park (1995), Hu (2001), and Coe, Helpman, and Hoffmaister (2009) find no significant or negative effect of public R&D spending on GDP or productivity growth under the production function approach.

One main empirical challenge is the long lags involved in the relationship between public R&D spending and productivity growth. In this paper, we adopt an alternative approach by examining the effect of public R&D spending on stock returns for reasons below. The forward looking nature of stock prices allows us to potentially identify the effect of public R&D spending on productivity growth even when the effect occurs far in the future. Meanwhile, because stock returns embed risk premiums, this approach also allows

[1] Cohen, Diether, and Malloy (2013) indicate a shift in the composition of total R&D spending away from federal to private sector in the U.S. since the late 1980s, mainly driven by the decline in defense-related federal budget. However, when dividing R&D spending into three categories: basic research, applied research, and development, public spending on basic and applied research still dominates industry spending and grows faster after the late 1980s (Hourihan and Parkes, 2019). A possible reason is that the value attributable to in-house scientific research has dropped for large U.S. firms (Arora, Belenzon, and Patacconi 2018).
[2] Salter and Martin (2001) and van Elk et al. (2019) provide reviews of this literature.

us to examine the effect of public R&D spending on firm risk, which has been overlooked in the literature. Furthermore, the financial market plays an important role in a country. In the U.S., the market capitalizations of New York Stock Exchange (NYSE) and Nasdaq are about 24.2 and 14 trillion in 2018, and the aggregate market capitalization is almost twice the contemporaneous U.S. GDP, which is about 20.4 trillion. Thus, our approach helps advance knowledge of the economic impacts of public R&D spending and technology spillovers (e.g., David, Hall, and Toole 2000, Almus and Czarnitzki 2003, Hottenrott and Lopes-Bento 2014, and Oh 2017).

We propose a parsimonious production-based asset pricing model, which predicts that firms supported by more public R&D earn higher stock returns. Both the cost reduction in innovation due to public R&D and the positive spillover related to public R&D increase the productivity and the average cash flow of firms. However, a higher level of public R&D also makes a firm's cash flow more sensitive to exogenous profitability shocks. Firms located in states with higher public R&D investments can generate more cash flow when positive aggregate profitability shocks arrive, because they are in better position to take advantage of novel technologies and new growth opportunities. Conversely, when growth opportunities dry up, profits for these firms drop more than for others. Thus, more public R&D investment results in a higher covariance of firm cash flows and aggregate profitability shocks. This high covariance, also known as high cash flow risk, should be associated with a higher risk premium (Bansal, Dittmar, and Lundblad 2005, Belo and Yu 2013). Hence, firms operating in an environment of more public R&D earn higher expected stock returns in the cross-section.

Empirically, we use the level of public R&D spending scaled by GDP in each state as our primary measure of R&D investments made by the public sector. We assign this ratio to a firm according to the state in which it is headquartered. We use this measure because the NSF provides public R&D spending data only at the state level, and because firms' financial statements do not disclose the amount of R&D subsidies from the public sector. While R&D subsidies for each firm are not available, this state-level measure has the advantage of accounting for the potential spillover effects of public R&D. As public R&D

may allow transmission of know-how to a variety of private entities, ignoring spillover effects will underestimate the influence of public R&D on firm value.

In our sample of R&D active firms in U.S. over 1987–2010, we show that firms located in states with high public R&D spending earn significantly higher abnormal stock returns than firms in states with low public R&D spending. A hedge portfolio that is long stocks in the highest public R&D quintile and short stocks in the lowest public R&D quintile generates an average abnormal return of about 0.9% per month according to the Fama and French (2015) five-factor model. The *t*-statistic of is 3.54, which is greater than the requirement, a *t*-statistic greater 3.0, of Harvey, Liu and Zhu (2016). The hedge portfolio continues to produce significantly positive abnormal returns after accounting for the momentum factor of Carhart (1997), for the liquidity factor of Pástor and Stambaugh (2003), and for time-varying risks. As Chan, Lakonishok, and Sougiannis (2001) document that firms with higher R&D intensity earn higher abnormal returns, we also add an R&D factor constructed from firms' private R&D expenditures to the Fama and French five-factor model. We continue to find that the hedge portfolio constructed using public R&D information exhibits significantly positive abnormal returns, suggesting that the public R&D effect cannot be explained by firms' private R&D spending. Our conclusions remain valid when we use Fama and MacBeth (1973) regressions to control for the effect of firms' own R&D spending. Moreover, these regression analyses show that the effect of public R&D spending on cross-sectional stock returns cannot be explained by conventional asset pricing factors such as size, book-to-market, profitability, asset growth, momentum, patent citations, financial constraints, idiosyncratic volatility, or liquidity. Neither can state-level variables (such as labor income growth rates, unemployment rates, GDP growth rates, education of the population, capital expenditure, deficit, and labor income per capita) or industry effects explain the public R&D effect. Furthermore, we perform Heckman two-stage regressions to control for the selection of headquarters of firms, and continue to find a positive effect of public R&D spending on cross-sectional stock returns.

We construct a zero-cost factor-mimicking portfolio for public R&D spending. The Sharpe ratio of the public R&D factor-mimicking portfolio is 0.169. Further, we find that the mean mimicking portfolio returns are positive in most years. In our sample of 24 years, 19 exhibit positive mean returns associated with the public R&D factor.

We further find that firms associated with more public R&D spending tend to improve total factor productivity and enjoy more incoming R&D spillovers. The spillover effect comes mainly from public R&D spending within a state; public R&D spending of neighboring states produces little spillover impact. We examine the covariance of a firm's cash flows and aggregate profitability shocks. We find higher cash flow risk, measured as the sensitivity of cash flow to aggregate GDP growth, for firms with more public R&D spending. Finally, we show that the effect of public R&D spending on stock returns is stronger for firms with higher R&D intensity, which corroborates the model's prediction.

Our work contributes to the literature in several ways. First, we provide firm-level evidence on the productivity enhancement effect of public R&D spending, which adds to the literature examining this issue under the industry- or country-level production function framework (e.g., Nadiri and Mamuneas 1994, Mamuneas and Nadiri 1996, Guellec and van Pottelsberghe 2004, and Haskel and Wallis 2013). We also complement studies that show the beneficial effects of public-funded R&D investment in specific programs or surveys (e.g., Beise and Stahl 1999, Fritsch and Franke 2004, Czarnitzki and Lopes-Bento 2013, and Hottenrott and Lopes-Bento 2014). Our evidence based on the public R&D spending at state-level is less subject to the concern of sample selection bias. Second, we uncover a new facet of the economic consequences of public R&D spending. Previous papers emphasize the consequences of public R&D spending for economic growth, innovation performance, and technology spillover (e.g., Nadiri and Mamuneas 1994; Fritsch and Franke 2004, and Czarnitzki and Lopes-Bento 2013). It is apparent that the risk associated with public R&D spending remains a missing link in this research stream. Our results further fill this gap and suggest that public R&D spending makes firm's cash flow more sensitive to the exogenous shocks. Policymakers concerned about economic stability should consider this effect before making any changes in public R&D investment.

Third, the literature suggests that R&D investments can enhance a firm's ability to recognize, assimilate, and exploit external information (Cohen and Levinthal 1990;

Henderson and Cockburn 1996; Beise and Stahl 1999; Oh 2017). We provide supporting evidence for this notion by showing a stronger effect of public R&D spending on stock returns for firms with higher R&D intensity, which implies a complementary asset pricing effect between public and private R&D investments.[3] Fourth, the asset pricing literature focuses on how innovation funded by the private sector affects stock returns (e.g., Lev and Sougiannis 1996, Chan, Lakonishok, and Sougiannis 2001, Chambers, Jennings, and Thompson 2002, Eberhart, Maxwell, and Siddique 2004, Hsu 2009, Cohen, Diether, and Malloy 2013, Hirshleifer, Hsu, and Li 2013). We expand this literature by showing an asset pricing effect of public sector R&D spending. We also add to the literature that examines the effect of government expenditures on stock returns (e.g., Belo, Gala, and Li 2013, Belo and Yu 2013).

The remainder of this paper is organized as follows. In Section 2, we illustrate the relation between public R&D and expected return using the public R&D model. Section 3 describes our data, methodology, and summary statistics. Section 4 presents our empirical results and robustness checks. Section 5 tests the public R&D model and explores three tests of how public R&D spending affects stock returns. The final section concludes.

2. PUBLIC R&D SPENDING AND CASH FLOW RISK

We propose a simple production-based asset pricing model (Cochrane 1991; Liu, Whited, and Zhang 2009; Wu, Zhang, and Zhang 2010; Belo and Yu 2013) in Appendix 1 and derive the positive relation between public R&D spending and expected stock return. In this section, we briefly discuss the intuition behind the model. In the model, we assume that public R&D capital enhances a firm's profit for three reasons. R&D provided by public sectors directly subsidizes individual firms; public R&D improves the innovation environment; and public R&D causes positive spillovers to the private sector. Accordingly, we express the operating profit (cash flow) of firm j located in state s as

[3] The complementarity here means that private R&D amplifies the effect of public R&D on stock returns. Our approach and research focus differs from the literature examining whether public R&D investments complement (stimulate) or substitute for (crowd out) private R&D (e.g., David, Hall and Toole 2000, Cohen, Nelson, and Walsh 2002, Almus and Czarnitzki 2003, Toole 2007, and González and Pazó 2008).

$\pi_j = e^x A_s^{\alpha_j} k_j$, where x is the exogenous profitability shock resulted from demand or technology shocks; A_s is public R&D capital available in state s, which is exogenous to the firm; and k_j is private capital. $\alpha_j > 0$ represents the profitability enhancement effect of public R&D capital. We allow α_j to vary with firms because public R&D investments may not benefit all firms equally. In particular, we assume that α_j is positively related to firm j's absorptive capabilities. Studies suggest that firms with higher absorptive capabilities are more likely to internalize externally generated knowledge (Cohen and Levinthal 1990; Henderson and Cockburn 1996; Beise and Stahl 1999; Oh 2017), and thus would benefit more from public R&D investments.

The above setting of profit function implies that when holding α and k fixed, a higher public R&D capital (A) not only increases the profit of the firm, but also makes the profit more sensitive to the exogenous profitability shock (x). In other words, firms located in states with higher public R&D investments can generate more cash flow when positive aggregate profitability shocks arrive, because they are in better position to take advantage of novel technologies and new growth opportunities. Conversely, when growth opportunities dry up, profits for these firms drop more than for others. We show in Appendix 1 that more public R&D investment results in a higher covariance of firm profit and aggregate profitability shocks. This high covariance, also known as high cash flow risk (systematic risk), should be associated with a higher risk premium (Bansal, Dittmar, and Lundblad 2005, Belo and Yu 2013). Hence, firms operating in an environment of more public R&D earn higher expected stock returns in the cross-section. Moreover, because α_j is positively related to firm j's absorptive capabilities, the effect of public R&D on stock returns should be stronger for firms with higher absorptive capabilities.

3. DATA, METHODOLOGY, AND SUMMARY STATISTICS

3.1 Data

Data on public R&D spending allocated to each state are obtained from the National Science Foundation (NSF) (http://www.nsf.gov/statistics) and are available since 1987. Funders of public R&D spending include the federal government, local governments, universities and colleges, and not-for-profit organizations. Since public R&D data are reported every two years before 1997, data available from the previous year are used for years when there is no public report.[4] Because we use the lagged value of public R&D spending as the explanatory variable, the sample of public R&D spending ends in 2010.

Our sample consists of U.S. listed firms covered by the Center for Research in Security Prices (CRSP) and Compustat. We exclude from the sample firms with a ratio of private R&D expenditures to assets lower than 1% and R&D expenditures lower than $1 million.[5] The final sample consists of 36,903 firm-year observations for 4,628 firms between 1987 and 2010.

Our primary measure of public R&D investments made by the public sector is the amount of public R&D spending scaled by GDP in each state, where data on state GDP are collected from the Bureau of Economic Analysis.[6] We assign this ratio to a firm by the state where its headquarters is located. We use this state-level measure because the NSF does not provide data on public R&D spending at the firm level. Further, R&D subsidies from public entities are not available in a firm's financial statements.[7] While we are unable to obtain data on public R&D subsidies for each firm, the use of state-level public R&D spending takes into account the potential spillover effects of public R&D.

3.2 Measuring Abnormal Stock Returns

According to the NSF data collection methods, on average there is a three-year lag between the data reference period and the data release date.[8] As investors will not have access to the state-level public R&D data until three years later on average, we allow for more than three years between the data reference period and the portfolio formation time. Specifically, we sort all 50 U.S. states into quintile portfolios according to the ratio of their

[4] We obtain similar results if the data available from the next year are used or if we restrict our sample to years when the public R&D data are available.

[5] We show later that the results remain unchanged if we include these firms.

[6] Results are unchanged if public R&D spending is scaled by aggregate sales of all firms in the same state.

[7] According to Compustat, R&D spending sponsored by the public sector is included in the top line of a firm's income statement, but income statements show only aggregate revenues without explicitly disclosing the amount of public R&D subsidies. The R&D expense reported in the income statement excludes government-sponsored R&D.

[8] For example, data on public R&D spending for year 2010 are not released until July 2013. Release dates can be found at the NSF website.

state-level public R&D spending in year $t-3$, and compute portfolio returns from the beginning of July of year $t+1$ through the end of June of year $t+2$. We sort all 50 U.S. states into quintile portfolios but do not sort all U.S. firms into quintile portfolios to ensure that top-quintile would not include two or three big states (e.g., California). For the public R&D data between 1987 and 2010, our return data are collected between July of 1991 and June of 2015. Thus, our proposed trading strategy does not have a look-ahead bias.

We use the Fama and French (2015) five-factor model to measure the average monthly abnormal stock return:[9]

$$R_{p\tau} - R_{f\tau} = \alpha + \beta(R_{m\tau} - R_{f\tau}) + sSMB_{\tau} + hHML_{\tau} + rRMW_{\tau} + cCMA_{\tau} + \varepsilon_{p\tau}. \tag{3}$$

We report results for a value-weighted investment strategy because this incurs lower rebalancing costs and is more appealing to the professional investment community. We test statistical significance using Newey and West (1987) corrected standard errors.

3.3 Summary Statistics

Table 1 presents summary statistics. Panel A shows that the average (median) amount of annual public R&D spending in each state during the sample period is \$2.3 (\$1.1) billion in 2010 prices. We further partition public R&D into four major parts: R&D with the federal government as both the funder and performer; R&D with the federal government as the funder and universities and colleges as the performers; R&D with non-industrial sectors as the funders and industrial firms as the performers; and all other.[10] The average proportions of public R&D spending among these four segments are almost equal. Panel A also shows that the amount of state-level public R&D spending accounts for 1.13% of state GDP on

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[9] We thank Kenneth French for making risk factors publicly available at his website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). $R_{p\tau}$ is the value-weighted monthly stock return on portfolio p in month τ; $R_{f\tau}$ is the return on one-month T-bills in month τ; $R_{m\tau}$ is the CRSP value-weighted market index return in month τ; SMB_{τ} is the difference in the returns of a portfolio of small and big stocks in month τ; HML_{τ} is the difference in the returns of a portfolio of high book-to-market stocks and low book-to-market stocks in month τ; RMW_{τ} is the difference in the returns of a portfolio of high operating profitability stocks and low operating profitability stocks in month τ; CMA_{τ} is the difference in the returns of a portfolio of low asset growth stocks and high asset growth stocks in month τ; and $\varepsilon_{p\tau}$ is the error term for portfolio p in month τ.

[10] The "all other" category includes (i) R&D with local governments as the funders and universities as the performers; (ii) R&D with universities as both the funders and performers; (iii) R&D with not-for-profit organizations as the funders and universities as the performers; (iv) R&D with the federal government as the funder and universities and federally funded R&D centers as the performers; and (v) other.

average.

Insert Table 1 Here

Figure 1 illustrates the geographic distribution of public R&D spending between 1987 and 2010. Panel A shows the average amount of annual public R&D spending in each state. California, Maryland, and Massachusetts are the states with the highest levels of public R&D spending, with an average annual public R&D spending of more than $7 billion in 2010 dollars. As Panel B shows, they are also among the states with a high public R&D ratio of more than 1.1%.

Insert Figure 1 Here

4. PUBLIC R&D AND STOCK RETURNS

4.1 Portfolio Returns Sorted by Public R&D Ratio

Table 2 shows average monthly raw returns sorted by the public R&D ratio. The mean value-weighted raw return for firms in the top public R&D quintile (quintile 5) is 1.02%, while the mean raw return for firms in the bottom public R&D quintile (quintile 1) is only 0.48%. A quintile-spread portfolio that buys firms with a high public R&D ratio and sells firms with a low public R&D ratio is associated with an average monthly raw stock return of 0.54%, which is statistically significant at the 1% level. Table 2 also presents average monthly abnormal returns based on the Fama and French (2015) five-factor model. The mean value-weighted abnormal return for firms in the top public R&D quintile is 0.63%, while the mean abnormal return for firms in the bottom public R&D quintile is −0.26%. The mean abnormal return spread between quintiles 5 and 1 is 0.89%, which is statistically significant at the 1% level.[11]

Insert Table 2 Here

We perform a number of robustness checks of the portfolio return results in Table 3. In Panel A, we compute abnormal returns using eight different factor models: (i) the Fama and French (1993) three-factor model; (ii) the Carhart (1997) four-factor model, which

[11] We also correct for a delisting bias for firms (Shumway 1997), and our results remain unchanged.

adds a momentum factor to the Fama and French (1993) three-factor model; (iii) a six-factor model that adds a momentum factor to the Fama-French five-factor (2015) model; (iv) a six-factor model that adds a private R&D factor to the Fama-French five-factor model, where the private R&D factor is constructed using a factor-mimicking portfolio that is calculated each month as the difference between stock returns in the highest private R&D quintile and stock returns in the lowest private R&D quintile; (v) a six-factor model that adds the Pástor and Stambaugh (2003) liquidity factor to the Fama-French five-factor model; (vi) a six-factor model plus market return volatility;[12] (vii) a model based on Arbitrage Pricing Theory (APT) of Chen, Roll, and Ross (1986); and (viii) a six-factor model that adds a mispricing factor to the Fama-French five-factor model, where the mispricing factor (UMO) is the difference in the returns of a portfolio of undervalued stocks and overvalued stocks (Hirshleifer and Jiang 2010; Hirshleifer, Hsu and Li 2013).[13] Mean abnormal returns on the hedge portfolio range from 0.49% to 1.90%, which are all statistically significant at the 1% level.

<u>Insert Table 3 Here</u>

Panel B of Table 3 reports the results of using different ways to construct portfolio abnormal returns. In Tests B1 and B2, we construct equal-weighted and log value-weighted portfolio returns, respectively, and then compute abnormal returns using the Fama-French (2015) five-factor model. As Berk, Green, and Naik (2004) document that R&D investment may result in a change in a firm's systematic risk, we take into account the effects of time-varying risk in the next two tests. In Test B3, we employ a method similar to that of Petkova and Zhang (2005), and estimate abnormal returns using the conditional Fama and French five-factor model, where the conditional variables include the dividend yield, the default

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[12] Da, Guo, and Jagannathan (2012) suggest that linear asset-pricing models like the CAPM are not able to capture differences in stock returns because of non-linearity due to the existence of real options. The market model with market return volatility is able to capture these uncontrolled features because they account for real options. Market return volatility is the variance of CRSP value-weighted index returns using past one-year monthly returns.

[13] The results from Panel A8 suggests that mispricing cannot explain the effect of public R&D. We thank Professor David Hirshleifer who makes the UMO factor publicly available at his website: http://sites.uci.edu/dhirshle/data/.

spread, the term spread, and the one-month T-bill rate, and each factor loading is a linear function of these four conditional variables. In Test B4, we follow Eberhart, Maxwell, and Siddique (2004) and estimate the Fama-French five-factor model using rolling regression estimates of each factor loading. The results in Panel B show that mean abnormal returns on the hedge portfolio range from 0.51% to 0.77% and remain statistically significant at the 1% level.

In Panel C of Table 3, we use different sampling methods to examine the public R&D effect. In Test C1, we expand the sample to all firms that have a positive amount of private R&D spending, regardless of the ratio of their private R&D expenditures to assets. The mean abnormal return on the hedge portfolio is 0.68%, which is statistically significant at the 1% level.[14] Since about 28% of our sample firms are located in California, we examine in Test C2 whether the public R&D effect persists after eliminating these firms. The mean abnormal return on the hedge portfolio is 0.62%, again statistically significant at the 1% level. We have assigned state-level R&D spending to a firm according to the location of its headquarters, even though a firm's headquarters and research centers may be located in different states. In some cases, a firm could benefit more from the public R&D spending of the state where its research centers are located rather than where its headquarters is located. To address this concern, we manually collect R&D center information from EDGAR (10Ks), and then exclude sample firms with at least one R&D center located in a state different from that in which the headquarters is located. Test C3 shows that our results are unchanged after eliminating these firms. In Tests C4 and C5, we partition the sample of public R&D spending into two subperiods (1987–1996 and 1997–2010); the public R&D effect obtains in both subperiods. Test C6 shows that the results hold when we exclude the internet bubble year 1999 (as in Baker and Wurgler 2006).[15]

Panel D presents Fama-French (2015) five-factor abnormal return results using

[14] We also compute abnormal returns for the sample that includes all firms with and without private R&D spending. The mean abnormal return on the hedge portfolio is 0.43% (*t*-value = 2.28), which is lower and less statistically significant. This is consistent with our model's prediction that the public R&D effect becomes weaker for firms with less absorptive capacities. See Section 5.4 for more evidence on this issue.

[15] Conclusions remain unchanged if we include in the sample only firms with an R&D-to-assets ratio of greater than 5% or exclude from the sample low-priced stocks (priced at less than $3).

different sorting methods. In Test D1, we sort all 50 U.S. states into quintile portfolios according to their public R&D ratio in year $t-1$. We measure the public R&D ratio in year $t-1$ in this test because that ratio is closer to the return formation year although a potential look-ahead bias may be present. The mean abnormal return on the hedge portfolio remains significantly positive at the 5% level. In Test D2, we sort all 50 U.S. states into quintile portfolios according to unscaled public R&D (i.e., the dollar amount of state-level public R&D spending) in year $t-3$. The mean abnormal return on the hedge portfolio is 0.71% (statistically significant at the 1% level), which is close to the mean abnormal return of 0.89% using scaled public R&D that we found in Table 2. In Test D3 we assign the public R&D ratio to a firm according to the state where its headquarters is located, and then sort all sample firms into quintiles according to their state-level public R&D ratio in year $t-3$. The mean abnormal return on the hedge portfolio remains significantly positive at the 1% level. In Test D4 we replace missing values of public R&D ratios (for years 1988, 1990, 1992, 1994 and 1996) with the estimated values obtained by linear interpolation. Once again, the mean abnormal return on the hedge portfolio are significantly positive at the 1% level. To reduce the concern that our paper mainly relies on the input-based R&D spending, in Tests D5 and D6, we sort states into quintiles based on two alternative state-level output-based measures of innovation performance in spirit of Janger, et al. (2017): (i) the shares of employees in high-tech industries to total employments in each state, where the definition of high-tech industries follows Eberhart, Maxwell, and Siddique (2004), and (ii) the number of patents applied and granted by public and industrial sectors to United States Patent and Trademark Office (USPTO) divided by state GDP. The mean abnormal return on the hedge portfolio under both measures have similar magnitude as our main results in Table 2, and both are significant at the 10% level in the one-tail test.

4.2 Regression Analyses

We perform Fama and MacBeth (1973) regressions of firm stock returns on public R&D spending and a set of control variables. We examine whether the public R&D effect is subsumed by other asset pricing variables such as firm size, book-to-market, operating profitability, asset growth, prior return, R&D intensity, patent citations, citations per R&D

dollar, financial constraints, idiosyncratic volatility, and illiquidity.[16] In particular, we measure R&D intensity by R&D capital-to-size ratio rather than R&D capital-to-sales because Chan, Lakonishok, and Sougiannis (2001) propose R&D capital-to-size ratio as a better return predictor than R&D capital-to-sales.[17] We also control for the potential effects of income growth and unemployment in each state and for industry-specific differences by including a state labor income growth rate variable, a state GDP growth rate variable, a state unemployment rate variable, and two-digit SIC dummies in the regression.[18] Detailed descriptions of the variables are given in Table 1 and Appendix 2.

Table 4 presents the results of the Fama-MacBeth regressions. The dependent variable is a firm's monthly stock returns from July of year $t + 1$ through June of year $t + 2$. Public R&D spending is measured in year $t - 3$; state-level economic indicators and variables about patent citations are measured in year t; and variables involving accounting data are measured as of the end of fiscal year t.[19] We report time-series averages of estimates.

Insert Table 4 Here

Model 1 in Table 4 includes the public R&D ratio, all the firm-level controls, and industry dummies. The coefficient on the public R&D ratio is 13.339, which is statistically significant at the 1% level. In Model 2, we add state-level economic indicators. The coefficient on the public R&D ratio is 11.300, again statistically significant at the 1% level. The evidence in Table 4 indicates that firms in states with more public R&D spending experience higher stock returns after accounting for other potentially influential factors.[20] In unreported results, we also examine the economic significance of each variable. As the

[16] Prior studies show that these variables can predict future returns. See Fama and French (1993, 2015), Jegadeesh and Titman (1993), Chan, Lakonishok, and Sougiannis (2001), Lamont, Polk, and Saá-Requejo (2001), Pástor and Stambaugh (2003), Ang, Hodrick, Xing, and Zhang (2006), Cooper, Gulen, and Schill (2008), He and Tan (2103), and Hirshleifer, Hsu, and Li (2013).

[17] Results are quantitatively similar if we measure R&D intensity by the ratio of R&D expenditures to sales or to book assets.

[18] Korniotis and Kumar (2013) suggest that state-level income growth and unemployment may influence the stock returns of firms in a state.

[19] Taking patent citations as the example, if a firm was granted three patents in 2010, and these patents respectively receive 8.8, 1.2, and 2 forward citations, then the number of variable patent citations for the firm in 2010 is 12. We relate this number to the firm's stock returns from July 2011 through June 2012.

[20] The results are similar if we also control for organization capital (Eisfeldt and Papanikolaou 2013), or control for the non-linearities of R&D intensity, firm age, and size.

public R&D ratio increases one standard deviation, we observe about a 7-8% increase in stock returns relative to the average monthly return (i.e., 1.278%), and the magnitude is higher than a number of other pricing factors in our study, including asset growth, prior return, R&D intensity, citations per R&D dollar, financial constraints, illiquidity, state GDP growth rate, and state unemployment rate.[21]

We further control for more state-level variables, including education of population, capital expenditure, deficit, and labor income per capita. In untabulated results, we find the coefficient on the public R&D ratio is 16.918, which is significant at the 1% level. State deficit is negatively related to cross-sectional stock returns, while there is little asset pricing effect for education of population, capital expenditure, and labor income per capita.[22] In another untabulated test, we control for the effect of local agglomeration economics of Dougal, Parsons, and Titman (2015) in the Fama and MacBeth regression analysis by incorporating the capital expenditures, R&D expenditures, equity issuance, and debt issuance of other firms in the same state as the right-hand-side variables in the regression. We continue to find that the public R&D ratio is positively related to future stock returns. In short, evidence from the Fama and MacBeth regression is consistent with evidence from the portfolio return analysis.[23]

We are concerned about the location choice and its effect on our findings. Based on

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[21] The coefficient of R&D intensity is insignificant in the Fama-MacBeth regressions. A possible explanation is that we include only firms with an R&D-to-asset ratio greater than 1% in the previous test, which reduces the cross-sectional variation in R&D intensity and the statistical power of the related test. In Table 11, we repeat the analysis with a sample including all firms with non-missing R&D expenditures, and find that the coefficients of R&D intensity become positive and significant at the 5% level.

[22] We do not tabulate this augmented regression model because sample size is considerably smaller due to data limitations. We measure the education of a population by the percentage of the population in the state with a college education, where the state-level education data are obtained from the U.S. Census Bureau. State-level capital expenditure and state government deficit (computed as revenue minus spending) are obtained and computed from http://www.usgovernmentrevenue.com/compare_state_revenue_1988bF0a and http://www.usgovernmentdebt.us/state_spend_gdp_population. Labor income per capita is the logarithm of labor salaries in a state.

[23] The Fama and MacBeth regressions allow us to examine the linear effect of public R&D ratio on returns while controlling for other firm and state characteristics that also affect returns. However, this firm-level approach imposes a potentially misspecified (linear) relation between the variables, puts heavy weight on small stocks relative to their size, and is sensitive to outliers (Novy-Marx, 2013). By contrast, the portfolio return analysis allows us to non-parametrically compare the returns between value-weighted portfolios with high and low public R&D ratio while controlling for the effect of other pricing factors. We thus use the results from the portfolio return analysis as our first piece of empirical evidence.

the literature of geographical economics and location theory (e.g., Feldman 1999), the geographical distribution of public R&D may affect the firm's headquarters location choice. This fact introduces potential endogenous bias. Therefore, we perform a Heckman two-stage regression (Heckman 1979; Branikas, Hong, and Xu 2017) to control for the headquarters location choice. In stage 1, we model a firm's location choice by estimating a conditional multinomial logit regression, where the dependent variable is a dummy that is equal to one if a firm's headquarters is located in a specific state and zero otherwise. The choice set of firms consists of all states with available information of public R&D spending. The main explanatory variables include the interaction terms of public R&D ratio with firm size, book-to-market, operating profitability, and R&D intensity. Other control variables include firm size, book-to-market, operating profitability, R&D intensity, patent citations, citations per R&D dollar, and industry dummies. In stage 2, we perform Fama-MacBeth regression as in Table 4 but additionally include the control function obtained from stage 1 to correct for the location choice. Under the linearity assumption of Dubin and McFadden (1984), Bourguignon, Fournier, and Gurgand (2007) show that the control function can be expressed as $-\gamma_s \ln(P_s) + \sum_{j \neq s} \gamma_j \left(\frac{P_j \ln(P_j)}{1\text{-}P_j}\right)$, where P_j is the estimated probability of a firm locating in state j from the stage 1 regression, s is the state where the firm's headquarters is located, and γ_js are parameters to be estimated in the stage 2 regression.

Table 5 reports results of the two-stage regressions. In state 1, we find that a state's public R&D spending indeed affects firms' location choice. The negative and significant coefficient on Public R&D ratio × Log(size) suggests that small firms are more likely to locate in states with higher public R&D spending. Similarly, the coefficients on other interaction terms indicate that states with higher public R&D spending also attract firms with low book-to-market ratio, low profitability, and high R&D intensity. More important, after controlling for this selection effect in stage 2, we continue to find positive effects of public R&D ratio on cross-sectional returns. In Model 1, the coefficient on the public R&D ratio is 28.821, which is statistically significant at the 1% level. In Model 2, we add state-level economic indicators as control variables. The coefficient on the public R&D ratio becomes 29.540, which is statistically significant at the 5% level.

Insert Table 5 Here

Table 6 reports several further robustness checks of the regression results, where all the firm-level and state-level control variables are the same as in Table 4. We report only the coefficients on the public R&D ratio for brevity. To assess whether our results are driven by small firms, we perform weighted least-squares (WLS) Fama-MacBeth (1973) regressions of firm stock returns using market capitalization (Panel A) or logarithm of market capitalization (Panel B) as the weight. The coefficients on the public R&D ratio remain significantly positive at the 5% level or better for both weightings and in both models. In Panel C, we perform Fama-MacBeth regressions at the state level. The dependent variable is the value-weighted monthly return of firms in each state. We group all the firm-level variables in the same state into a value-weighted portfolio to obtain portfolio characteristics at the state level. Coefficients on the state-level public R&D ratio are still significantly positive for both models. In Panel D, we also perform a panel regression of firm stock returns with *t*-statistics that are based on robust standard errors clustered by firm and year, as suggested by Petersen (2009). In Panel E, we drop firms that have changed their headquarters during our sample period, and then perform Fama-MacBeth regression with this reduced sample to mitigate the endogeneity concern that changes of public R&D ratio of each state over time would drive firms to relocate their headquarters. We lose 9.9% of the sample firms under this test. These results are similar to those in Table 3.[24]

Insert Table 6 Here

[24] One might ask whether political uncertainty accounts for the public R&D effect. Uncertainties associated with possible changes in public R&D policy depending on national election outcomes may have important implications for firm stock returns (Julio and Yook 2012, Bhattacharya et al. 2017). Some public entities may reduce or even suspend R&D investment during presidential election years. Therefore, firms in states with more public R&D spending may bear higher political risk and earn higher returns than firms in states with less public R&D spending. To test this conjecture, we use the political uncertainty (PU) index of Baker, Bloom, and Davis (2016) to account for the potential effect of political uncertainties. Baker, Bloom, and Davis (2016) note that since the PU index spikes around presidential elections, it represents a plausible way to measure uncertainty about what the government might do in the future. To measure a firm's exposure to political risk, we construct a PU beta by regressing stock returns on the PU index. We show that the public R&D effect is not significantly stronger for firms with a higher PU beta (i.e., higher exposure to political risk).

4.3 Factor-Mimicking Portfolios for Public R&D Spending

To better understand the asset pricing effect of public R&D, we construct a zero-cost factor-mimicking portfolio for public R&D spending. That is, at the end of June of year $t + 1$, we sort all 50 U.S. states into five groups according to their public R&D ratios in year $t - 3$. We assign the public R&D ratio to a firm according to the state where its headquarters is located, and compute value-weighted monthly returns on the five portfolios from July of year $t + 1$ through June of year $t + 2$. PRDHML is the portfolio return of stocks with the highest public R&D ratio minus the portfolio return of stocks with the lowest public R&D ratio. These return series track how monthly stock returns co-move with the public R&D ratio.

Panel A of Table 7 presents the means, standard deviations, time-series *t*-statistics, and ex post Sharpe ratios for PRDHML. PRDHML has a mean of 0.54% and a Sharpe ratio of 0.169. Panel A also presents summary statistics for the excess return on Fama and French's (2015) market proxy (RMRF) and Fama and French's factor-mimicking portfolios for size (SMB), book-to-market equity (HML), operating profitability (RMW), and asset growth (CMA). Panel B shows that PRDHML is positively correlated with RMRF and SMB, and negatively correlated with HML, RMW, and CMA. The absolute values of correlation coefficients between PRDHML and the market excess return and other factor-mimicking portfolios range from 0.335 to 0.558.

<u>Insert Table 7 Here</u>

Panel C shows the results of the analysis of variables (ANOVA), where we test the equality of the factor-mimicking portfolio returns. The F-value of ANOVA is 0.96, which fails to reject the null hypothesis that the mean returns of the six factor-mimicking portfolios (i.e., PRDHML, RMRF, SMB, HML, RMW, and CMA) are equal. Panel D shows the ANOVA of Sharpe ratios, and once again, we are not able to reject the null hypothesis that the Sharpe ratios of the six factor-mimicking portfolios are equal. Thus, the asset pricing effect of public R&D is comparable to market index and other conventional pricing factors.[25]

We plot mean annualized returns on factor-mimicking portfolios for public R&D spending over calendar years in Figure 2. The mean mimicking portfolio returns are positive in most years. Over the 24 years covered by our sample, in 19 years there are positive mean returns associated with the public R&D factor. Therefore, the effect of public R&D spending on stock return does not depend on specific years.

<u>Insert Figure 2 Here</u>

5. TESTS OF THE PUBLIC R&D MODEL

We have documented a positive relationship between public R&D spending and stock return in cross section. To confirm our argument, we further examine whether firms in states with more public R&D spending are likely to experience better productivity improvements and higher R&D spillovers. These two tests are aimed at confirming our assumption, $\alpha > 0$, in our public R&D model. Further, we test whether firms associated with more public R&D spending are subject to greater cash flow risks. Finally, we test the model's implication that the effect of public R&D on stock returns will be stronger for firms with a higher α.

5.1 Total Factor Productivity

Public R&D spending reduces a firm's innovation costs (Mamuneas and Nadiri 1996, Lerner 1999, Takalo, Tanayama, and Toivanen 2013). According to cost-production duality, a cost reduction implies production improvement. Thus, firms in states with more public R&D spending are likely to be more productive. We measure total factor productivity (TFP) using a Cobb-Douglas production function for each individual firm. We follow the literature and use Compustat data to compute firm TFP (Brynjolfsson and Hitt 2003, Keller and Yeaple 2009). Specifically, for all firms within the same two-digit SIC industry, we perform a regression for each calendar year:

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[25] Although PRDHML does not outperform other factor-mimicking portfolios, adding PRDHML into a portfolio of other factors can improve the efficiency of the overall portfolio because PRDHML has low correlations with other factors. For example, the Sharpe ratio of a portfolio with 60% on PRDHML and 40% on RMRF is 0.203, which is higher than the Sharpe ratio of RMRF alone (0.164).

$$\log(Y_i) = \alpha_i + a_K \log(K_i) + a_L \log(L_i) + e_i, \quad (4)$$

where Y_i is gross profit (sales minus cost of goods sold); K_i is property, plant, and equipment; L_i is number of employees; and e_i is the error term.[26] The regression residual is the total factor productivity for firm i, TFP_i^a. We then regress ΔTFP_i^a on public R&D spending, where public R&D spending is measured by the public R&D ratio in year $t-3$ and ΔTFP_i^a is the change in TFP_i^a over the period from year $t-3$ to year t. The control variables include firm size, book-to-market ratio, prior return, R&D intensity, state GDP, two-digit SIC dummies, and year dummies.[27] We report t-statistics using standard errors corrected for clustering by firm (Petersen 2009). We also treat a firm's own R&D spending as an additional input (Jaffe 1986, Chen et al. 2013) and estimate the equation:

$$\log(Y_i) = \alpha_i + a_K \log(K_i) + a_L \log(L_i) + a_R \log(RD_i) + e_i, \quad (5)$$

where RD_i is firm R&D expenditure. The regression residual provides another measure of total factor productivity for firm i, TFP_i^b, and ΔTFP_i^b is similarly defined.

Table 8 reports regression results of the change in TFP. Model 1 shows a coefficient of 10.614 on log(public R&D), which is statistically significant at the 1% level, when ΔTFP_i^a is used as the dependent variable. In Model 2 when ΔTFP_i^b is the dependent variable, we find similar results. The overall evidence in Table 8 suggests that firms in states with more public R&D spending tend to enjoy more improved productivity.[28]

<u>Insert Table 8 Here</u>

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[26] Following Schoar (2002), we include a constant term in the regression so that TFP includes only the idiosyncratic part of firm productivity. The results are similar if we do not allow for an intercept in the regression.

[27] Griffith, Redding, and Van Reenen (2004) and İmrohoroğlu and Tüzel (2014) suggest that firm size, book-to-market ratio, and R&D intensity affect firm productivity. We also include an R&D missing dummy in the regression (untabulated for brevity).

[28] We also perform two robustness checks. First, we estimate total factor productivity for each industry based on its three-digit SIC code or the Fama-French 48-industry classification scheme. Second, we use the translog production function in Christensen, Jorgenson, and Lau (1973) to estimate TFP. The results remain unchanged.

5.2 Public R&D Spillovers

By and large, public R&D spending at a state level generates technological knowledge that is spread to all the firms in the state, expanding their technological and market opportunities. This spillover effect could be driven by the positive externalities of public R&D spending through the movement of scientific personnel from government and research centers, and technical and scientific journal publication (Jaffe 1989, Cassiman and Veugelers 2002). The spillover of knowledge could also be contributed by formal R&D collaborations between public research institutes and private local firms (Scandura 2016). Universities are also likely to license innovations to local start-up companies and generate knowledge flows to individual firms. Thus, firms located in states with a higher level of public R&D spending are likely to enjoy more incoming R&D spillovers.

To estimate the incoming R&D spillover of firms, we use a stochastic frontier production method similar in spirit to that in Chen et al. (2013).[29] We use a production function to estimate the spillover because a firm's ability to absorb external knowledge is reflected in its output. Specifically, for each two-digit SIC industry in every year, R&D spillovers are obtained from u_i in a Cobb-Douglas production function:

$$\log(Y_i) = a_0 + a_1 \log K_i + a_2 \log L_i + a_3 \log RD_i + u_i + v_i, \tag{6}$$

where Y_i, K_i, L_i, and RD_i are as defined above. Residual u_i is assumed to be independent and identically distributed (i.i.d.) and to obey half-normal distribution |U|, given U ~ N(0, σ_u^2). Residual v_i is symmetric and assumed to be i.i.d. as N(0, σ_v^2). Because the random variable u_i captures the spillover effect, it is non-negative. The white noise v_i captures the impact of other random shocks.

Table 9 shows the regression analysis of the logarithm of the incoming R&D spillover effect, $\log(u_i)$, on public R&D spending and a set of control variables.[30] Public R&D spending is measured by the public R&D ratio in year $t-3$, and the incoming R&D

[29] Researchers have applied the stochastic frontier approach to examine various issues such as IPO underpricing, agency costs, and trading costs (see, e.g., Hunt-McCool, Koh, and Francis 1996, Habib and Ljungqvist 2005).

[30] Cassiman and Veugelers (2002) indicate that firm size and R&D intensity affect R&D spillovers.

spillover effect is the sum of u_i over the period from year $t - 2$ to year t.[31] We report t-statistics using standard errors corrected for clustering by firm. Model 1 shows a coefficient of 1.309 on the public R&D ratio, which is statistically significant at the 1% level. Consistent with expectation, firms in states with higher public R&D spending tend to experience more incoming spillovers.

Insert Table 9 Here

Public R&D in a state can creates spillovers not only for firms in the same state but also for firms in neighboring states. However, the ability to receive knowledge spillovers associated with R&D is inversely related to the distance from the knowledge source, because there may be geographic boundaries to knowledge spillovers or because the cost of transmitting knowledge rises with distance (Audretsch and Feldman 1996; Cabrer-Borras and Serrano-Domingo 2007). In addition, formal R&D collaborations are less common between research institutes (such as universities) and distant firms (Laursen, Reichstein, and Salter 2011; D'Este, Iammarino, and Guy 2013). We hence expect a firm to receive more of a spillover effect from public R&D spending within its state than from public R&D spending of neighboring states. In Model 2, we add the public R&D ratio of neighboring states (measured by the average public R&D ratio of bordering states) to Model 1.[32] The coefficient on the public R&D ratio remains significantly positive at the 1% level, and the coefficient on the public R&D ratio of neighboring states is not statistically significant. The evidence suggests that the spillover effect arises mainly from public R&D spending within the state.[33]

Finally, it is also possible that public R&D spending contributes to technology spillovers among firms, which would positively affect firm stock returns. Following Jaffe

[31] Our conclusion does not change if we measure the public R&D spillover effect as the sum of u_i over the period (i) from year $t - 2$ to year $t - 1$or (ii) from year $t - 3$ to year $t - 2$, $t - 1$, or t. Using the average u_i over each respective period also produces the same conclusion.

[32] For example, the public R&D ratio of neighboring states for California is the average of public R&D ratio of Oregon, Nevada and Arizona.

[33] We use various stochastic R&D spillover estimations to investigate the robustness of our results. We change the assumption for u_i by using an exponential or a truncated normal distribution. We also use the translog production function in Christensen, Jorgenson, and Lau (1973) to estimate the spillover effect. Our conclusions remain unchanged.

(1986), Bloom, Schankerman, and Van Reenen (2013), Qiu and Wan (2015) and Oh (2017), we measure technology spillovers for each individual firm using the patent-weighted average of all its rivals' R&D stock, where patent weights reflect pairwise spatial closeness in technology space.[34] We then repeat the analysis in Table 9 but replace the dependent variable with the technology spillovers. The results (untabulated) show that the coefficient on the public R&D ratio is 24.283, which is significantly positive at the 1% level. The coefficient on the public R&D ratio of neighboring states is not statistically significant.

5.3 Cash Flow Risk

Our model suggests that a higher level of public R&D investment makes a firm's cash flows more sensitive to exogenous profitability shocks. This higher cash flow risk, in turn, results in a higher risk premium. In this section, we provide evidence that links a firm's cash flow risk to public R&D investments.

We gauge cash flow risk as the sensitivity of cash flows of firms to aggregate profitability shock (McConnell and Perez-Quiros 2000, Belo and Yu 2013). More precisely, for each public R&D quintile, we calculate mean cash flows (proxied by earnings before extraordinary items and depreciation divided by total assets), size, B/M, asset growth, R&D intensity, dividend-to-price ratio, state labor income growth rate, and state unemployment rate across firms. We then regress average cash flows between t and $t-2$ on the average of country-level GDP growth rate between t and $t-2$ for each public R&D subgroup.[35] Cash flow risk is measured as the regression coefficient of the country-level GDP growth rate.

Table 10 presents results for cash flow risk. Panel A applies a simple regression, and Panel B employs multiple regression analysis that includes size, B/M, asset growth, R&D

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[34] Specifically, we first calculate the pairwise spatial closeness in technology space between firm i and firm j by $TECH_{i,j} = \frac{(T_i T_j')}{(T_i T_i')^{0.5}(T_j T_j')^{0.5}}$, where $T_l = (T_{l1}, T_{l2}, \ldots, T_{lK})$, $l = i, j$. T_{lk} is the share of patents of firm l in technology class k, $k = 1, 2, \ldots, K$. In other words, $TECH_{ij}$ is the uncentered correlation between T_i and T_j and is bounded between zero and one. We then calculate technology spillovers for firm i in year t by $\sum_{j, j \neq i} TECH_{i,j}\, RDS_{jt}$, where RDS is the R&D stock calculated using a perpetual inventory method, $RDS_t = RD_t + (1-\delta)RDS_{t-1}$. RD is the R&D expense and δ is the depreciation rate which is set to 15% following Hall, Jaffe, and Trajtenberg (2005).

[35] We follow the literature (e.g., Almeida, Campello, and Weisbach 2004) and use earnings before extraordinary items and depreciation divided by total assets as the measure of cash flows. We obtain quantitatively similar results when measure cash flow as the cash flow from operating activities.

intensity, dividend-to-price ratio, state labor income growth rate, and state unemployment rate as control variables. Panel A shows that coefficients of country-level GDP growth rate generally increase with public R&D ratios, meaning that firms headquartered in states with more public R&D spending are subject to higher cash flow risks. Panel B shows similar results after we control for firm-level and state-level variables. Therefore, firms receiving more benefit because of more public R&D spending also have higher cash flow risks, and the higher risks result in the higher excess returns that we find.[36]

Insert Table 10 Here

5.4 Effect of Firm R&D Expenditures

Our model implies that the effect of public R&D on stock returns will be stronger for firms with higher absorptive capabilities. To test this prediction, we conduct Fama-MacBeth regression similar to those in Table 4. We proxy a firm's absorptive capacity by its R&D intensity, defined as the ratio of R&D capital to firm size (Chan, Lakonishok, and Sougiannis 2001), because previous studies indicate that R&D investments can enhance a firm's ability to recognize, assimilate, and exploit new external information, and thus allow the firm to benefit more from R&D spillovers (Cohen and Levinthal 1989; Henderson and Cockburn 1996; Beise and Stahl 1999; Oh 2017).

Models 1 and 2 of Table 11 repeat the analyses in Table 4, but further include all firms with R&D intensity information to increase statistical power in the regression estimation. In addition, we incorporate an interaction term between the public R&D ratio and firm R&D intensity. The positive and significant coefficients on R&D intensity are consistent with the finding in the literature that firms with higher R&D intensity earn abnormal stock returns (Chan, Lakonishok, and Sougiannis 2001). In addition, we continue to find a positive and significant effect of the public R&D ratio on future stock returns. The coefficients of the interaction term are 4.522 and 3.949, respectively, and both are

[36] We perform two robustness checks on tests of cash flow risk. First, we follow Belo and Yu (2013) and use changes in cash dividend as the cash flow measure. Second, we replace country-level GDP growth rate with unexpected GDP, which is the residual of an autoregressive regression model of order one for country-level GDP (McConnell and Perez-Quiros 2000). Our results are similar for these two additional tests.

significant at the 5% level. The positive coefficients on the interaction term confirm the model's prediction that public R&D shows a stronger effect on stock returns for firms with higher absorptive capabilities. The results also imply a complementary asset pricing effect between public R&D and firm R&D investments.

6. Conclusion

Empirical research on the wealth effect of public R&D spending reports mixed results. We adopt an alternative approach by examining how public R&D spending affects stock returns. Our parsimonious production-based asset pricing model predicts that firms supported by more public R&D earn higher stock returns. Both the cost reduction in innovation due to public R&D and the positive spillover related to public R&D increase the productivity and the average cash flow of firms. Yet, a higher level of public R&D also makes a firm's cash flow more sensitive to the exogenous profitability shocks. This higher cash flow risk should result in a higher risk premium.

We empirically examine the model's predictions using a sample of U.S. firms between 1987–2010. We find that firms in states with greater amounts of public R&D spending earn significantly higher abnormal stock returns than firms in states with lower levels of public R&D spending. A hedge portfolio long stocks in the highest public R&D quintile and short stocks in the lowest public R&D quintile generates an average abnormal return of about 0.9% per month. The results persist after we account for time-varying risks, other asset pricing factors, state-level variables, and industry effects.

The results of additional tests show how public R&D spending positively affects stock returns through its impact on and interaction with firm fundamentals. Firms in states with higher levels of public R&D spending tend to experience greater improvement in productivity. They also enjoy more incoming R&D spillover, mainly from public R&D spending within a state rather than from public R&D spending of neighboring states. More important, cash flow risk is higher for firms when there is more public R&D spending. Finally, the effect of public R&D spending on stock returns is stronger when the firm has higher R&D intensity, implying a complementary asset pricing effect between public and private R&D investments. These additional tests confirm our argument and explain the positive relation between public R&D spending and cross-sectional stock returns.

Appendix 1

We use the following production-based asset pricing model to derive the positive relation between public R&D spending and expected stock return. Consider a two-period economy ($t = 0, 1$), where all firms are all equity financed. The operating profit (cash flow) of firm j located in state s can be expressed as

$$\pi_{jt} = e^{x_t} A_{st}^{\alpha_j} k_{jt} \tag{A1}$$

where x is the exogenous profitability shock; A_s is public R&D capital available in state s, which is exogenous to the firm; and k_j is firm j's private capital. $\alpha_j > 0$ represents the extent to which firm j can benefit from public R&D capital. We assume that α_j is larger for firms with better absorptive capabilities, because these firms are better able to internalize externally generated knowledge, thus benefitting more from public R&D investments.

The depreciation rate of capital k for firm j is δ_j and the depreciation rate for public R&D capital is δ^A. Thus, the investment of firm j at $t = 0$ is $i_{j0} = k_{j1} - (1 - \delta_j)k_{j0}$. The public R&D investment in state s is $PRD_{s0} = A_{s1} - (1 - \delta^A)A_{s0}$. At $t = 1$, firm j has a liquidation value of $(1 - \delta_j)k_{j1}$. The investment in private capital involves adjustment cost $c(k_{j0}, i_{j0}) = \frac{c}{2}\left(\frac{i_{j0}}{k_{j0}}\right)^2 k_{j0}$. We assume no capital investment or public R&D investment at $t = 1$. The stochastic discount factor between time 0 and 1 is m. Following Berk, Green, and Naik (1999) and Zhang (2006), we assume $\log(m) = \log\beta + \gamma(x_0 - x_1)$, where $0 < \beta < 1$, and $\gamma > 0$.[37]

Firm j then chooses i_{j0} to maximize the sum of the discounted cash flows from the two periods:

$$\max_{\{i_{j0}\}} e^{x_0} A_{s0}^{\alpha_j} k_{j0} - i_{j0} - \frac{c}{2}\left(\frac{i_{j0}}{k_{j0}}\right)^2 k_{j0} + E_0[m(e^{x_1} A_{s1}^{\alpha_j} k_{j1} + (1 - \delta_j)k_{j1})]. \tag{A2}$$

[37] We do not explicitly model the decision problem of consumers and solve the general equilibrium, but directly parameterize the pricing kernel (m). The functional form of m is derived from the representative consumer with power utility and a relative risk averse coefficient, γ.

Specifically, the cash flows from $t = 0$ are equal to the operating profit minus the investment cost and the adjustment cost. The cash flows from $t = 1$ are equal to the operating profit plus the liquidation value. Taking the derivative of equation (A1) with respect to i_{j0}, we obtain

$$1 + c\left(\frac{i_{j0}}{k_{j0}}\right) = E_0\left[m(e^{x_1}A_{s1}^{\alpha_j} + (1-\delta_j))\right]. \tag{A3}$$

The left-hand side of equation (A3) is the marginal cost of capital investment, which is equal to one (the unit price of investment) plus the adjustment cost. The right-hand side of equation (A3) is the expected discounted value of the marginal benefit of investment at $t = 1$, which includes the incremental contribution of the profit at $t = 1$ ($e^{x_1}A_{s1}^{\alpha_j}$) and the liquidation value ($1 - \delta_j$). Equation (A3) means that, at the optimum level of investment, the marginal cost of investment should be equal to its marginal benefit.

Rearranging (A3), we have

$$1 = E_0[mr_1^I], \text{ where } r_1^I \equiv \left(\frac{e^{x_1}A_{s1}^{\alpha_j} + (1-\delta_j)}{1 + c\left(\frac{i_{j0}}{k_{j0}}\right)}\right). \tag{A4}$$

That is, the investment return, r_1^I, is defined as the ratio of marginal benefit to marginal cost of investment. Cochrane (1991) shows that under the assumption of constant returns to scale of the production function, the investment return (r_1^I) will be equal to the firm's stock return (r_1). Thus we have $1 = E_0[mr_1]$, which is the standard asset pricing equation.

Given $\log(m) = \log\beta + \gamma(x_0 - x_1)$, from the standard asset pricing equation we have

$$E_0\left[r_1 - r_f\right] \approx -\mathrm{Cov}_0(r_1, m)$$

$$= \mathrm{Cov}_0\left(\left(\frac{e^{x_1}A_{s1}^{\alpha_j} + (1-\delta_j)}{1 + c\left(\frac{i_{j0}}{k_{j0}}\right)}\right), -\beta e^{\gamma(x_0 - x_1)}\right) = \frac{\left[(1-\delta^A)A_{s0} + PRD_{s0}\right]^{\alpha_j}}{1 + c\left(\frac{i_{j0}}{k_{j0}}\right)}\mathrm{Cov}_0\left(e^{x_1}, -\beta e^{\gamma(x_0 - x_1)}\right). \tag{A5}$$

where r_f is the risk-free rate. The second equality follows because $A_{s1} = (1 - \delta^A)A_{s0} + PRD_{s0}$.

Since $\mathrm{Cov}_0\left(e^{x_1}, -\beta e^{\gamma(x_0\text{-}x_1)}\right) > 0$, equation (A5) indicates that holding the private capital investment rate ($\frac{i_{j0}}{k_{j0}}$) constant, the excess return of firm j is positively associated with the public R&D investment (A_{s0}). In addition, the positive relation between excess return and public R&D investment tend to be stronger for firms a larger absorptive capability (α_j). To understand the mechanism through which the model links the public R&D investment and risk premium, note that Equation (A1) indicates that a higher level of public R&D investment results in a higher covariance of a firm's cash flows and the aggregate profitability shock. Equation (A5) further suggests that this higher covariance, in turn, results in a higher risk premium, because the right-hand side of (A5) is proportional to the covariance between the operating profit (cash flow) at t = 1 of firm j and the aggregate productivity shock, $\mathrm{Cov}_0\left(e^{x_1}(\left(1-\delta^A\right)A_{s0}+PRD_{s0})^{\alpha_j}k_{j1}, e^{x_1}\right)$. This result implies the effect public R&D investment on risk premium is related to the cash flow risk (systematic risk) proposed by Belo and Yu (2013).

Appendix 2

Variable	Definition	References
Public R&D ratio	Public R&D ratio is the amount of public R&D spending scaled by state GDP at year $t - 3$, where data on annual public R&D spending allocated to each state are obtained from the National Science Foundation.	
State labor income growth rate	State-level labor income at year t divided by state-level labor income at year $t - 1$, and then minus one. Data are obtained from the Bureau of Labor Statistics.	Korniotis and Kumar (2013)
State GDP growth rate	State gross domestic product (GDP) at year t divided by state GDP at year $t - 1$, and then minus one. Data are obtained from the Bureau of Economic Analysis.	Korniotis and Kumar (2013)
State unemployment rate	State-level labor unemployment rate at year t. Data are obtained from the Bureau of Labor Statistics.	Korniotis and Kumar (2013)
Size	The market value of common equity in 2010 prices, which is measured at the end of June of year $t + 1$. Data are from CRSP.	Fama and French (1993, 2015)
B/M	The book-to-market ratio, which is the ratio of book value of common equity to market value of common equity. B/M is measured at year t. Raw data for this variable are from Compustat.	Fama and French (1993, 2015)
Operating profitability	Revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, all divided by book equity. Operating profitability is measured at year t. Raw data for this variable are from Compustat.	Fama and French (2015)
Asset growth	The past one-year asset growth rate, which is measured as the asset at year t divided by asset at year $t - 1$, and then minus one. Asset growth is measured at year t. Raw data for this variable are from Compustat.	Cooper, Gulen, and Schill (2008); Fama and French (2015)
Prior return	The past one-year return (skipping one month). For each month m, we perform the regression analysis for the stock returns; we then compute prior return as the returns between month $m - 2$ and $m - 12$. Raw data for this variable are from CRSP.	Jegadeesh and Titman (1993)
R&D intensity	The R&D capital-to-size ratio, where R&D capital is the cumulative R&D spending as: R&D expenditure_t + 0.8×R&D expenditure_{t-1} + 0.6×R&D expenditure_{t-2} + 0.4×R&D expenditure_{t-3} + 0.2×R&D expenditure_{t-4}. R&D intensity is measured at year t. Raw data for this variable are from Compustat.	Chan, Lakonishok, and Sougiannis (2001)

Variable	Definition	References
Patent citations	The sum of truncation-adjusted forward citations till 2016 across all patents granted to a firm at year *t*, where raw citation data are obtained from the EPO Worldwide Patent Statistical Database and truncation-adjusted forward citations are derived following Hall, Jaffe, and Trajtenberg (2001). For example, a firm was granted a mechanical related patent in 2010, and has received 3 forward citations till 2016. According to Hall, Jaffe, and Trajtenberg's Table 5, the adjust factor for a six-year-old patent is 0.341, and thus the truncation-adjusted forward citation is equal to 8.8 (= 3/0.341). If the firm was also granted another two patents in 2010, and respectively receive 1.2, and 2 truncation-adjusted forward citations, then the variable patent citations for the firm in 2010 is 12 (= 8.8 + 1.2 + 2).	Hirshleifer, Hsu, and Li (2013)
Citations per R&D	Patent citations divided by R&D expenditures, where patent citations are the sum of truncation-adjusted forward citations across all patents granted to a firm at year *t*. Raw data for this variable are from Compustat.	He and Tan (2013); Hirshleifer, Hsu, and Li (2013)
KZ index	The Kaplan and Zingales (1997) index, which is equal to: $-1.002(CF/TA) - 39.368(DIV/TA) - 1.315(CA/TA) + 3.139LEV + 0.283Q$, in which CF is earnings before extraordinary item and depreciation; TA is lagged book assets; DIV is cash dividends; CA is cash and short-term investments; LEV is total debt divided by book assets; Q is the ratio of the market value of the firm divided by book assets. KZ index is measured at year *t*. Raw data for this variable are from Compustat.	Lamont, Polk, and Saá-Requejo (2001)
Idiosyncratic volatility	The sum of the squared residuals of Capital Asset Pricing Model (CAPM) using the previous 36 monthly returns ending at June of year *t*+1. Idiosyncratic volatility is measured at year *t*. Raw data for this variable are from CRSP.	Ang, Hodrick, Xing, and Zhang (2006)
Illiquidity	The measure of stock illiquidity in Pástor and Stambaugh (2003), which is measured at year *t*. Data are from Professor Lubos Pástor's website: https://faculty.chicagobooth.edu/lubos.pastor/research/	Pástor and Stambaugh (2003)
Total factor productivity	The residual from the estimation of a Cobb-Douglas function for firms in the same two-digit SIC industry in each year.	
Market share	The fraction of the sales of a firm to aggregate sales in a two-digit SIC industry.	
Public R&D ratio of neighboring state	The average public R&D ratio of bordering states. For example, the public R&D ratio of neighboring states for California is the average of public R&D ratio of Oregon, Nevada and Arizona.	
Cash flow	The ratio of the earnings before extraordinary items and depreciation to total assets.	
Dividend-to-price ratio	The ratio of common stock dividend per share to stock price.	

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TABLE 1
Summary Statistics

Panel A: Public R&D Spending

Variable	Mean	SD	Min	Q1	Median	Q3	Max
Amount of public R&D spending ($ thousands):	2,328,151	3,731,571	30,488	412,086	1,144,377	2,841,539	35,289,332
(1) With federal government as both funder and performer	484,798	1,097,010	3,155	44,859	116,715	368,444	10,318,521
(2) With federal government as funder and universities and colleges as performers	451,348	612,635	9,454	89,775	243,455	518,064	4,766,000
(3) With non-industrial sectors as funders and industrial firms as performers	794,957	1,939,734	0	42,060	241,467	933,414	22,609,242
(4) All other	597,048	901,724	10,919	76,504	221,040	471,758	7,069,890
Public R&D ratio (%)	1.13	1.35	0.04	0.46	0.67	1.11	10.75

Panel B: Average Values of State-Level Variables

		Public R&D ratio				
Variable	All	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Public R&D ratio (%)	1.13	0.34	0.50	0.67	0.97	3.17
Amount of public R&D spending ($ thousands)	2,328,151	700,506	1,030,155	1,380,408	1,998,501	6,531,185
State labor income growth rate (%)	4.91	4.96	4.95	4.69	5.01	4.92
State GDP growth rate (%)	2.12	0.41	1.32	2.96	3.00	2.92
State unemployment rate (%)	5.25	5.04	5.09	5.46	5.30	5.40

Panel C: Average Values of Firm-Level Variables

		Public R&D ratio				
Variable	All	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Size ($ thousands)	3,449,482	5,182,279	3,542,889	3,947,231	3,226,767	2,836,414
B/M	0.54	0.56	0.58	0.57	0.56	0.50
Operating profitability	0.14	0.20	0.17	0.17	0.11	0.09
Asset growth	0.14	0.12	0.11	0.14	0.10	0.17
Prior return (%)	11.80	10.68	12.28	10.21	13.99	11.40
R&D intensity	0.10	0.09	0.09	0.09	0.11	0.11
Patent citations	105.65	106.74	81.48	107.65	109.20	115.34
Citations per R&D	2.88	3.21	2.60	3.42	2.76	2.77
KZ index	0.55	0.70	0.51	0.53	0.53	0.53
Idiosyncratic volatility	4.36	4.48	4.22	4.16	4.31	4.54
Illiquidity	-0.01	-0.02	-0.01	0.02	-0.07	0.01

TABLE 1 (continued)

This table presents summary statistics of public R&D spending, state-level variables, and firm-level variables. Panel A shows total and sector summary statistics of state-level public R&D spending between 1987 and 2010. Data on annual public R&D spending allocated to each state are obtained from the National Science Foundation. The dollar amount of public R&D spending is based on 2010 prices. Public R&D ratio is the amount of public R&D spending scaled by state GDP. Panel B shows average values of several state-level variables for the whole sample and for the subsamples based on the quintile ranking of public R&D ratios. Data on state-level economic indicators are obtained from the Bureau of Economic Analysis and the Bureau of Labor Statistics. Panel C shows average values of firm-level variables for the whole sample and for the subsamples based on the quintile ranking of public R&D ratios. Size is the market value of common equity in 2010 prices. B/M is the book-to-market ratio. Operating profitability is revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, all divided by book equity. Asset growth is the past one-year asset growth rate. Prior return is the past one-year return (skipping one month). R&D intensity is the R&D capital-to-size ratio. Patent citations are the sum of truncation-adjusted forward citations across all patents granted to a firm, where raw citation data are obtained from the EPO Worldwide Patent Statistical Database and truncation-adjusted forward citations are derived following Hall, Jaffe, and Trajtenberg (2001). Citations per R&D are patent citations divided by R&D expenditures. KZ index is a measure of financial constraint as defined in Lamont, Polk, and Saá-Requejo (2001). Idiosyncratic volatility is the sum of squared residuals from the Capital Asset Pricing Model (CAPM) in the past three years. Illiquidity is a measure of stock illiquidity as defined in Pástor and Stambaugh (2003). Public R&D spending is measured in year $t-3$; state-level economic indicators and variables about patent citations are measured in year t; variables involving accounting data are measured as of the end of fiscal year t; and variables involving stock market data are measured as of the end of June of year $t+1$.

TABLE 2
Public R&D Spending and Stock Returns

Public R&D ratio	Raw return	Abnormal return based on the Fama-French five-factor model					
		α	$R_m - R_f$	*SMB*	*HML*	*RMW*	*CMA*
Quintile 1	0.476	-0.260	0.953	-0.150	0.060	0.135	0.240
	(2.02)	(-2.45)	(34.75)	(-1.70)	(0.65)	(2.58)	(2.67)
Quintile 2	0.557	-0.213	0.957	0.175	-0.022	0.215	0.097
	(2.67)	(-1.55)	(25.79)	(3.58)	(-0.35)	(3.08)	(1.04)
Quintile 3	0.785	0.123	0.990	-0.120	-0.249	0.112	0.215
	(2.82)	(1.58)	(94.02)	(-4.35)	(-8.68)	(4.33)	(2.65)
Quintile 4	1.106	0.606	1.000	0.118	-0.443	-0.396	0.217
	(4.77)	(3.37)	(29.36)	(1.56)	(-6.15)	(-9.40)	(2.33)
Quintile 5	1.016	0.630	1.068	0.137	-0.450	-0.212	-0.477
	(2.63)	(3.20)	(45.76)	(4.13)	(-5.49)	(-5.75)	(-7.81)
Q5 – Q1	0.540	0.890	0.115	0.287	-0.511	-0.347	-0.717
	(2.83)	(3.54)	(2.61)	(2.86)	(-3.56)	(-5.53)	(-6.22)

This table presents average monthly raw and abnormal stock returns sorted by the public R&D ratio. We sort all 50 U.S. states into quintile portfolios according to the amount of their state-level public R&D spending scaled by state GDP in year $t-3$, where quintile 1 has the lowest and quintile 5 has the highest public R&D ratio. We assign the public R&D ratio to a firm according to the state where its headquarters is located, and compute value-weighted monthly portfolio returns from the beginning of July of year $t+1$ through the end of June of year $t+2$. We measure the average monthly abnormal stock return using the Fama and French (2015) five-factor model:

$$R_{p\tau} - R_{f\tau} = \alpha + \beta(R_{m\tau} - R_{f\tau}) + sSMB_\tau + hHML_\tau + rRMW_\tau + cCMA_\tau + \varepsilon_{p\tau},$$

where $R_{p\tau}$ is the value-weighted monthly return on portfolio p in month τ; $R_{f\tau}$ is the return on one-month T-bills in month τ; $R_{m\tau}$ is the CRSP value-weighted market index return in month τ; SMB_τ is the difference in the returns of a portfolio of small and big stocks in month τ; HML_τ is the difference in the returns of a portfolio of high book-to-market stocks and low book-to-market stocks in month τ; RMW_τ is the difference in the returns of a portfolio of high operating profitability stocks and low operating profitability stocks in month τ; CMA_τ is the difference in the returns of a portfolio of low asset growth stocks and high asset growth stocks in month τ; and $\varepsilon_{p\tau}$ is the error term for portfolio p in month τ. The estimated intercept (α) from the regression captures the average monthly abnormal return. Q5 – Q1 is a zero-cost hedge portfolio that buys stocks in quintile 5 and sells stocks in quintile 1. Newey-West (1987) adjusted t-statistics are reported in parentheses.

TABLE 3
Public R&D Spending and Stock Returns: Additional Evidence

	Quintile 1	Quintile 5	Q5 – Q1
Panel A: Different Factor Models			
A1. Fama-French (1993) three-factor model	-0.138	0.413	0.551
	(-2.37)	(2.32)	(2.70)
A2. Carhart (1997) four-factor model	-0.006	0.485	0.491
	(-0.07)	(2.82)	(2.89)
A3. Fama-French (2015) five-factor model plus momentum factor	-0.127	0.697	0.824
	(-1.39)	(3.74)	(4.26)
A4. Fama-French (2015) five-factor model plus R&D factor	-0.262	0.315	0.578
	(-2.45)	(5.14)	(4.66)
A5. Fama-French (2015) five-factor model plus liquidity factor	-0.296	0.666	0.962
	(-2.69)	(3.52)	(3.94)
A6. Fama-French (2015) five-factor model plus changes in market return volatility	-0.203	0.495	0.495
	(-1.92)	(3.11)	(3.11)
A7. Chen, Roll, and Ross (1986) model	0.943	2.846	1.903
	(4.77)	(3.47)	(2.59)
A8. Fama-French (2015) five-factor model plus mispricing factor	-0.218	0.612	0.830
	(-1.92)	(3.22)	(3.14)
Panel B: Different Ways to Construct Portfolio Abnormal Returns			
B1. Equal-weighted returns	0.493	1.003	0.510
	(5.15)	(4.53)	(2.96)
B2. Log value-weighted returns	0.380	0.897	0.517
	(5.21)	(4.67)	(3.25)
B3. Conditional Fama-French (2015) five-factor model	-0.229	0.544	0.773
	(-1.37)	(3.20)	(2.96)
B4. Fama-French (2015) five-factor model with rolling regression	-0.202	0.464	0.667
	(-2.01)	(2.85)	(2.79)
Panel C: Different Sampling Methods			
C1. Use all firms with a positive amount of private R&D	-0.238	0.438	0.677
	(-2.67)	(3.66)	(3.55)
C2. Remove California firms	-0.260	0.360	0.621
	(-2.45)	(3.29)	(4.10)
C3. Remove firms with at least one R&D center located in another state	-0.260	0.360	0.621
	(-2.45)	(3.29)	(4.10)
C4. Subsample period of public R&D sample: 1987–1996	-0.359	1.217	1.575
	(-1.88)	(5.48)	(4.26)
C5. Subsample period of public R&D sample: 1997–2010	-0.212	0.314	0.526
	(-1.34)	(4.19)	(2.66)
C6. Exclude the internet bubble year 1999	-0.203	0.552	0.755
	(-2.19)	(3.26)	(3.85)
Panel D: Different Sorting Methods			
D1. Sort states based on public R&D ratio at year $t-1$	-0.107	0.564	0.671
	(-0.92)	(2.39)	(2.37)
D2. Use unscaled public R&D in year $t-3$	-0.290	0.418	0.708
	(-2.02)	(2.59)	(2.94)
D3. Sort sample firms into quintiles according to their state-level public R&D ratio in year $t-3$	-0.280	0.637	0.917
	(-2.48)	(2.76)	(2.94)
D4. Sort public R&D spending using linear interpolation to estimate missing values of public R&D ratios	-0.039	0.668	0.707
	(-0.51)	(2.81)	(2.36)
D5. Sort states based on shares of employees in high-tech industries to total employments at year $t-1$	-0.093	0.701	0.794
	(-0.89)	(1.57)	(1.47)
D6. Sorts states based on aggregate patents to GDP ratio at $t-1$	-0.141	0.294	0.435
	(-0.73)	(3.00)	(1.65)

TABLE 3 (continued)

This table presents a number of robustness checks of average abnormal returns sorted by public R&D spending. In Panels A through C, we sort all 50 U.S. states into quintile portfolios according to the amount of their state-level public R&D spending scaled by state GDP in year $t - 3$, where quintile 1 has the lowest and quintile 5 has the highest public R&D ratio. We assign the public R&D ratio to a firm according to the state where its headquarters is located, and compute monthly portfolio returns from the beginning of July of year $t + 1$ through the end of June of year $t + 2$. In Panel A, we compute abnormal returns using eight different factor models: (i) the Fama and French (1993) three-factor model; (ii) the Carhart (1997) four-factor model; (iii) a six-factor model that adds a momentum factor to the Fama-French five-factor (2015) model; (iv) a six-factor model that adds a private R&D factor to the Fama-French five-factor model; (v) a six-factor model that adds the liquidity factor of Pástor and Stambaugh (2003) to the Fama-French five-factor model; (vi) a six-factor model that adds changes in market return volatility; (vii) a model based on the macroeconomic factors of Chen, Roll, and Ross (1986); and (viii) a six-factor model that adds a mispricing factor (UMO) to the Fama-French five-factor (2015) model, where UMO is obtained from Hirshleifer and Jiang (2010) and is the difference in the returns of a portfolio of undervalued stocks and overvalued stocks in month τ; where undervalued stocks are stocks with debt repurchases or equity repurchases, and overvalued stocks are stocks with initial public offerings (IPOs), seasoned equity offerings (SEOs), and debt issuances over the past 24 months. Panel B reports the results of using different ways to construct portfolio abnormal returns. In Tests B1 and B2, we construct equal-weighted and log value-weighted portfolio returns, respectively, and then compute abnormal returns using the Fama-French five-factor model. In Test B3, we estimate abnormal returns using the conditional Fama and French five-factor model, where the conditional variables include the dividend yield, the default spread, the term spread, and the one-month T-bill rate, and each factor loading is a linear function of these four conditional variables. In Test B4, we estimate the Fama-French five-factor model using rolling regression estimates of each factor loading. Specifically, we use the first 60 months of portfolio returns to estimate the factor loadings, and then obtain the expected portfolio return in month 61 by multiplying the factor loadings estimated over the previous 60 months by their respective month 61 factor returns. The abnormal return in month 61 is the difference between the actual portfolio return and the expected portfolio return. We repeat this step for every month. We then average the time series of monthly abnormal return estimates and perform a significance test based on the time-series volatility of these estimates. In Panel C, we use different sampling methods to examine the public R&D effect based on the Fama-French five-factor model. In Test C1, we expand the sample to all firms that have a positive amount of private R&D spending. In Test C2 we remove from the sample firms that are located in California. In Test C3, we exclude sample firms with at least one R&D center that is located in a state different from that in which the headquarters is located. In Tests C4 and C5, we partition the sample of public R&D spending into two subperiods (1987–1996 and 1997–2010). In Test C6, we exclude the internet bubble year 1999. Panel D presents Fama-French (2015) five-factor abnormal returns using different sorting methods. In Test D1, we sort all 50 U.S. states into quintiles according to the public R&D ratio in year $t - 1$. In Test D2, we sort all 50 U.S. states into quintiles according to unscaled public R&D in year $t - 3$. In Test D3 we assign the public R&D ratio to a firm by the state where its headquarters is located, and then sort sample firms into quintiles according to their state-level public R&D ratio in year $t - 3$. In Test D4 we replace missing values of public R&D ratios from estimated value using the linear interpolation method. In Test D5, we sort states by shares of employees in high-tech industries to total employment of a state, where the definition of high-tech industries follows Eberhart, Maxwell, and Siddique (2004). In Test D6, we sort states by the number of patents applied and granted by public and industrial sectors to United States Patent and Trademark Office (USPTO) divided by state GDP. For brevity, we present only the results on average monthly abnormal returns for quintiles 1 and 5 and for Q5 − Q1, which is a zero-cost hedge portfolio that buys stocks in quintile 5 and sells stocks in quintile 1. Newey-West (1987) adjusted t-statistics are reported in parentheses.

TABLE 4
Fama and MacBeth Regressions

Variable	Model 1	Model 2
Intercept	1.658	1.174
	(5.15)	(1.91)
Public R&D ratio	13.339	11.300
	(3.18)	(3.28)
Log(size)	-0.051	-0.050
	(-1.56)	(-1.50)
B/M	0.488	0.501
	(6.58)	(6.79)
Operating profitability	0.247	0.249
	(5.69)	(5.47)
Asset growth	-0.131	-0.125
	(-2.19)	(-2.00)
Prior return	0.001	0.001
	(0.27)	(0.24)
R&D intensity	0.149	0.137
	(0.19)	(0.19)
Log(1 + patent citations)	0.074	0.071
	(4.58)	(4.44)
Log(1 + citations per R&D)	-0.009	-0.014
	(-0.07)	(-0.11)
KZ index	0.011	0.012
	(0.47)	(0.50)
Idiosyncratic volatility	-0.042	-0.041
	(-2.00)	(-2.07)
Illiquidity	-0.147	-0.134
	(-1.41)	(-1.35)
State labor income growth rate		0.043
		(1.97)
State GDP growth rate		0.003
		(0.86)
State unemployment rate		0.086
		(0.42)
Industry dummies	Yes	Yes
Adj. R-sq	0.055	0.056

This table presents Fama and MacBeth (1973) regressions of firm stock returns on public R&D spending and a set of control variables. The dependent variable is a firm's monthly stock returns from July of year $t + 1$ through June of year $t + 2$. Public R&D ratio is the ratio of public R&D spending to state GDP assigned to a firm according to the state where its headquarters is located. Control variables are defined in Table 1. Public R&D spending is measured in year $t - 3$; state-level economic indicators and variables about patent citations are measured in year t; variables involving accounting data are measured as of the end of fiscal year t; and variables involving stock market data are measured as of the end of June of year $t + 1$. Industry dummies are based on two-digit SIC codes. Newey-West (1987) adjusted t-statistics are reported in parentheses.

TABLE 5

Fama and MacBeth Regressions- Controlling for the Headquarters Location Choice

Stage 1		Stage 2		
Variable		Variable	Model 1	Model 2
Public R&D ratio × Log(size)	-1.149	Intercept	0.894	4.835
	(-2.30)		(1.77)	(2.27)
Public R&D ratio × B/M	-18.896	Public R&D ratio	28.821	29.540
	(-7.47)		(2.53)	(2.24)
Public R&D ratio × Operating profitability	-9.642	Log(size)	-0.018	0.008
	(-6.30)		(-0.58)	(0.21)
Public R&D ratio × R&D intensity	81.694	B/M	0.486	0.462
	(7.50)		(3.30)	(3.25)
		Operating profitability	0.246	0.204
			(4.29)	(2.97)
		Asset growth	-0.223	-0.214
			(-1.39)	-(1.40)
		Prior return	-0.002	-0.002
			(-0.91)	-(0.94)
		R&D intensity	-0.929	-0.485
			(-1.73)	-(1.04)
		Log(1 + patent citations)	0.049	0.068
			(2.64)	(3.99)
		Log(1 + citations per R&D)	0.070	-0.088
			(0.31)	-(0.49)
		KZ index	0.014	0.018
			(0.51)	(0.65)
		Idiosyncratic volatility	-0.030	-0.030
			(-1.05)	-(1.08)
		Illiquidity	-0.225	-0.217
			(-1.33)	-(1.32)
		State labor income growth rate		0.202
				(3.11)
		State GDP growth rate		-3.017
				-(3.25)
		State unemployment rate		0.013
				(0.44)
Other controls	Yes	Control function	Yes	Yes
Industry dummies	Yes	Industry dummies	Yes	Yes
Log-likelihood	-2,572.7	Adj. R-sq	0.056	0.058

This table presents the results of Fama and MacBeth Regressions of firm stock returns on public R&D spending after controlling for firms' headquarters location choice. In the first stage, we run an conditional multinomial logit model where the dependent variable is a dummy that is equal to one if a firm's headquarters is located in a specific state and zero otherwise. The choice set of firms consists of all states with available information of public R&D spending. Other controls include firm size, book-to-market, operating profitability, R&D intensity, patent citations, and citations per R&D dollar. In the second stage, we perform Fama and MacBeth (1973) regressions of firm stock returns on public R&D spending, all control variables in Table 4, and the control function obtained from the first state regression to correct for firms' location choice of headquarters. The dependent variable in the second stage regression is a firm's monthly stock returns from July of year $t + 1$ through June of year $t + 2$. Public R&D ratio is the ratio of public R&D spending to state GDP assigned to a firm according to the state where its headquarters is located. Other control variables are defined in Table 1. Public R&D spending is measured in year $t - 3$; state-level economic indicators and variables about patent citations are measured in year t; variables involving accounting data are measured as of the end of fiscal year t; and variables involving stock market data are measured as of the end of June of year $t + 1$. Industry dummies are based on two-digit SIC codes. Newey-West (1987) adjusted t-statistics are reported in parentheses.

TABLE 6
Cross-Sectional Regressions of Stock Returns: Robustness Checks

Variable	Model 1	Model 2
Panel A: WLS Fama-MacBeth Regressions Using Market Capitalization as a Weight		
Intercept	1.476	1.282
	(1.52)	(0.92)
Public R&D ratio	13.431	10.277
	(3.12)	(2.35)
Firm-level controls	Yes	Yes
State-level controls	No	Yes
Industry dummies	Yes	Yes
Adj. R-sq	0.310	0.329
Panel B: WLS Fama-MacBeth Regressions Using Logarithm of Market Capitalization as a Weight		
Intercept	1.657	1.103
	(4.71)	(1.57)
Public R&D ratio	13.358	10.782
	(3.24)	(3.31)
Firm-level controls	Yes	Yes
State-level controls	No	Yes
Industry dummies	Yes	Yes
Adj. R-sq	0.057	0.059
Panel C: Fama-MacBeth Regressions at the State Level		
Intercept	2.052	1.648
	(0.90)	(0.81)
Public R&D ratio	7.211	7.928
	(2.43)	(2.00)
Firm-level controls	Yes	Yes
State-level controls	No	Yes
Industry dummies	No	No
Adj. R-sq	0.315	0.324
Panel D: Panel Regressions with Robust Standard Errors Clustered by Firm and Year		
Intercept	-0.165	1.149
	(-0.18)	(0.49)
Public R&D ratio	18.780	20.010
	(1.86)	(2.10)
Firm-level controls	Yes	Yes
State-level controls	No	Yes
Industry dummies	Yes	Yes
Adj. R-sq	0.002	0.003
Panel E: Fama and MacBeth Regressions- Drop Firms Changing Their Headquarters		
Intercept	1.869	1.549
	(4.89)	(2.17)
Public R&D ratio	12.533	10.348
	(2.39)	(2.38)
Firm-level controls	Yes	Yes
State-level controls	No	Yes
Industry dummies	Yes	Yes
Adj. R-sq	0.058	0.059

TABLE 6 (continued)

This table presents several robustness checks of cross-sectional regressions of stock returns on public R&D spending and a set of control variables. The dependent variable is monthly stock returns from July of year $t + 1$ through June of year $t + 2$. Public R&D ratio is the ratio of public R&D spending to state GDP assigned to a firm according to the state where its headquarters is located. All the firm-level and state-level control variables are the same as in Table 4. Public R&D spending is measured in year $t - 3$; state-level economic indicators and variables about patent citations are measured in year t; variables involving accounting data are measured as of the end of fiscal year t; and variables involving stock market data are measured as of the end of June of year $t + 1$. Industry dummies are based on two-digit SIC codes. In Panels A and B, we perform weighted least-squares (WLS) Fama and MacBeth (1973) regressions of firm stock returns using market capitalization or the logarithm of market capitalization as weights, respectively. In Panel C, we perform the Fama-MacBeth regressions at the state level. The dependent variable is the value-weighted monthly return of firms in each state. We group all the firm-level variables in the same state into a value-weighted portfolio to obtain portfolio characteristics at the state level. Newey-West (1987) adjusted *t*-statistics are reported in parentheses in Panels A through C. In Panel D, we perform panel regressions of firm stock returns with *t*-statistics that are based on robust standard errors clustered by firm and year. In Panel E, we remove firms that change their headquarters during the sample period from the regression analysis. We report only the coefficients on the public R&D ratio for brevity.

TABLE 7

Factor-Mimicking Portfolios

	PRDHML	RMRF	SMB	HML	RMW	CMA
Panel A: Summary Statistics						
Mean	0.540	0.662	0.227	0.288	0.331	0.321
SD	3.204	4.031	2.306	2.360	1.652	1.827
t-statistic	2.831	2.760	1.650	2.048	3.366	2.953
Ex post Sharpe ratio	0.169	0.164	0.098	0.122	0.200	0.176
Panel B: Correlation Coefficients						
PRDHML	1.000					
RMRF	0.341	1.000				
SMB	0.335	0.208	1.000			
HML	-0.558	-0.233	-0.182	1.000		
RMW	-0.436	-0.421	-0.501	0.442	1.000	
CMA	-0.492	-0.352	-0.034	0.674	0.200	1.000

Panel C: ANOVA of hedge portfolio returns

	Sum of squared	*df*	Mean Squared	F-value	P-value
Between	61.95	5	12.39	0.96	0.44
Within	21,705.87	1,686	12.87		
Total	21,767.82	1,691			
Panel D: ANOVA of Sharpe ratios					
Between	40.03	5	8.01	1.11	0.36
Within	12,213.33	1,686	7.24		
Total	12,253.35	1,691			

This table presents the summary statistics and correlation matrix of factor-mimicking portfolios. At the end of June of year $t + 1$, we sort all 50 U.S. states into five groups according to their public R&D ratios in year $t - 3$. We assign the public R&D ratio to a firm according to the state where its headquarters is located, and compute value-weighted monthly returns on the five portfolios from July of year $t + 1$ through June of year $t + 2$. PRDHML is the monthly portfolio return of stocks with the highest public R&D ratio minus the monthly portfolio return of stocks with the lowest public R&D ratio. RMRF, SMB, HML, RMW, and CMA are, respectively, the excess return on Fama and French's (2015) market proxy and Fama and French's factor-mimicking portfolios for size, book-to-market equity, operating profitability, and asset growth. Panel A shows means, Newey-West (1987) adjusted standard deviations, time series *t*-statistics, and ex post Sharpe ratios, and Panel B shows correlation coefficients. Panel C and Panel D present analysis of variance (ANOVA) of hedge portfolio returns and Sharpe ratios. Panel C tests the null hypothesis that six factor-mimicking portfolio mean returns (i.e., PRDHML, RMRF, SMB, HML, RMW, and CMA) in Panel A are statistically equal. Panel D tests the null hypothesis that six factor mimicking portfolio Sharpe ratios are statistically equal.

TABLE 8
Regressions of Changes in Total Factor Productivity

Variable	Model 1 Dependent variable: ΔTFP_i^a	Model 2 Dependent variable: ΔTFP_i^b
Intercept	4.873	2.589
	(0.88)	(0.63)
Public R&D ratio	10.614	9.197
	(2.68)	(2.30)
Log(size)	-0.174	-0.163
	(-10.59)	(-10.13)
B/M	-0.001	-0.001
	(-4.30)	(-3.93)
Operating profitability ($\times 10^{-1}$)	-0.001	-0.002
	(-0.19)	(-0.42)
Asset growth	0.122	0.106
	(1.87)	(1.68)
R&D intensity	0.008	
	(0.47)	
Market share	1.702	1.714
	(2.62)	(2.66)
State labor income growth rate	0.049	0.053
	(2.65)	(2.85)
State GDP growth rate	0.485	0.453
	(2.83)	(2.64)
State unemployment rate	-0.637	-1.301
	(-0.40)	(-0.82)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Adj. R-sq	0.040	0.035

This table presents regression analyses of changes in total factor productivity (TFP) on public R&D spending and a set of control variables. We measure TFP using a Cobb-Douglas production function. For all firms within the same two-digit SIC industry, we perform a regression for each calendar year:

$$\log(Y_i) = \alpha_i + a_K \log(K_i) + a_L \log(L_i) + e_i,$$

where Y_i is gross profit; K_i is property, plant, and equipment; L_i is number of employees; and e_i is the error term. The regression residual is the total factor productivity for firm i, TFP_i^a. We then regress ΔTFP_i^a on public R&D spending, where public R&D spending is measured by the public R&D ratio in year $t-3$ and ΔTFP_i^a is the change in TFP_i^a over the period from year $t-3$ to year t. Public R&D ratio is the ratio of public R&D spending to state GDP assigned to a firm according to the state where its headquarters is located. We also treat a firm's own R&D spending as an additional input and estimate the equation:

$$\log(Y_i) = \alpha_i + a_K \log(K_i) + a_L \log(L_i) + a_R \log(RD_i) + e_i,$$

where RD_i is firm R&D expenditure. The regression residual provides another measure of total factor productivity for firm i, TFP_i^b. ΔTFP_i^b is similarly defined. Market share is the fraction of the sales of a firm to aggregate sales in a two-digit SIC industry. Other control variables are defined in Table 1. An R&D missing dummy is included in the regression (unreported for brevity). We report t-statistics in parentheses using standard errors corrected for clustering by firm (Petersen 2009).

TABLE 9
Regressions of Public R&D Spillovers

Variable	Model 1	Model 2
Intercept	0.732	0.743
	(12.51)	(12.20)
Public R&D ratio	1.309	1.342
	(2.68)	(2.71)
Public R&D ratio of neighboring states		-0.690
		(-1.32)
Log(size)	-0.044	-0.044
	(-20.79)	(-20.76)
B/M ($\times 10^{-1}$)	-0.001	-0.001
	(-1.78)	(-1.86)
Operating profitability ($\times 10^{-1}$)	0.001	0.001
	(0.90)	(0.87)
Asset growth	0.037	0.037
	(6.05)	(6.02)
R&D intensity	-0.045	-0.046
	(-2.74)	(-2.76)
Patent reference count ($\times 10^{-2}$)	0.001	0.001
	(0.94)	(0.88)
State labor income growth rate	0.002	0.002
	(1.73)	(1.84)
State GDP growth rate	0.046	0.043
	(2.60)	(2.36)
State unemployment rate	0.076	0.083
	(0.60)	(0.65)
Year dummies	Yes	Yes
Industry dummies	Yes	Yes
Adj. R-sq	0.322	0.322

This table presents regression analyses of public R&D spillovers on public R&D spending and a set of control variables. For each two-digit SIC industry in every year, R&D spillovers are obtained from u_i in a Cobb-Douglas production function:

$$\log(Y_i) = a_0 + a_1 \log K_i + a_2 \log L_i + a_3 \log RD_i + u_i + v_i,$$

where Y_i is gross profit; K_i is property, plant, and equipment; L_i is number of employees; and RD_i is firm R&D expenditure. Residual u_i obeys half-normal |U| given U~N(0, σ_u^2), and residual v_i obeys Normal N(0, σ_v^2). In Model 1, the dependent variable is the logarithm of sum of u_i over the period from year $t-2$ to year t. Public R&D spending is measured by the public R&D ratio in year $t-3$, which is the ratio of public R&D spending to state GDP assigned to a firm according to the state where its headquarters is located. Patent reference count is the number of backward citations of a firm's patents. Other control variables are defined in Table 1. In Model 2, we add the public R&D ratio of neighboring states (measured by the average public R&D ratio of bordering states) to Model 1. An R&D missing dummy is included in the regression (unreported for brevity). We report t-statistics in parentheses using standard errors corrected for clustering by firm (Petersen 2009).

TABLE 10
Cash Flow Risk

Public R&D ratio	Intercept	Country-level GDP growth rate	Log(size)	B/M	Asset growth	R&D intensity	Dividend-to-Price ratio	State labor income growth rate	State unemployment rate	Adj. R-sq
Panel A: Simple Regression Analysis										
Quintile 1	0.071	-0.005								-0.027
	(4.57)	(-0.77)								
Quintile 2	0.020	0.008								0.096
	(2.74)	(2.11)								
Quintile 3	0.023	0.005								-0.007
	(1.80)	(0.93)								
Quintile 4	-0.050	0.019								0.226
	(-1.90)	(3.16)								
Quintile 5	-0.393	0.067								0.420
	(-4.23)	(4.14)								
Panel B: Multiple Regression Analysis										
Quintile 1	1.022	-0.004	-0.070	-0.001	0.113	-0.143	-0.015	0.004	0.066	0.501
	(1.87)	(-0.42)	(-2.36)	(-0.04)	(1.22)	(-0.54)	(-0.83)	(1.08)	(0.88)	
Quintile 2	0.579	0.007	-0.043	-0.001	0.137	-0.003	0.011	-0.001	0.024	0.589
	(4.26)	(1.12)	(-5.03)	(-0.05)	(1.14)	(-0.04)	(1.28)	(-0.19)	(1.04)	
Quintile 3	-0.015	0.001	-0.012	-0.007	0.126	0.285	-0.010	0.004	0.106	0.514
	(-0.04)	(0.13)	(-0.41)	(-3.15)	(1.96)	(1.07)	(-1.20)	(0.96)	(4.66)	
Quintile 4	0.559	0.038	-0.070	-0.001	0.023	-0.169	0.033	-0.003	0.169	0.524
	(1.36)	(2.31)	(-2.23)	(-0.48)	(0.18)	(-1.33)	(1.19)	(-0.56)	(2.55)	
Quintile 5	-2.294	0.123	0.045	0.021	0.119	0.485	-0.058	-0.008	0.468	0.633
	(-2.39)	(4.03)	(1.05)	(1.49)	(1.20)	(1.43)	(-2.87)	(-0.48)	(2.99)	

This table presents cash flow risk sorted by the public R&D ratio. We sort all 50 U.S. states into quintile portfolios according to the amount of their state-level public R&D spending scaled by state GDP in year $t-3$, where quintile 1 has the lowest and quintile 5 has the highest public R&D ratio. We assign the public R&D ratio to a firm according to the state where its headquarters is located. For each public R&D subgroup, we calculate mean cash flows (i.e., earnings before extraordinary items and depreciation divided by total assets), size, B/M, asset growth, R&D intensity, dividend-to-price ratio, state labor income growth rate, and state unemployment rate. We then regress average cash flows between t and $t-2$ on the average of country-level GDP growth rate between t and $t-2$ for each public R&D subgroup. Cash flow risk is measured as the regression coefficient of country-level GDP growth rate. Panel A shows simple regression analysis, while Panel B shows multiple regression analysis. Newey-West (1987) adjusted *t*-statistics are reported in parentheses.

TABLE 11

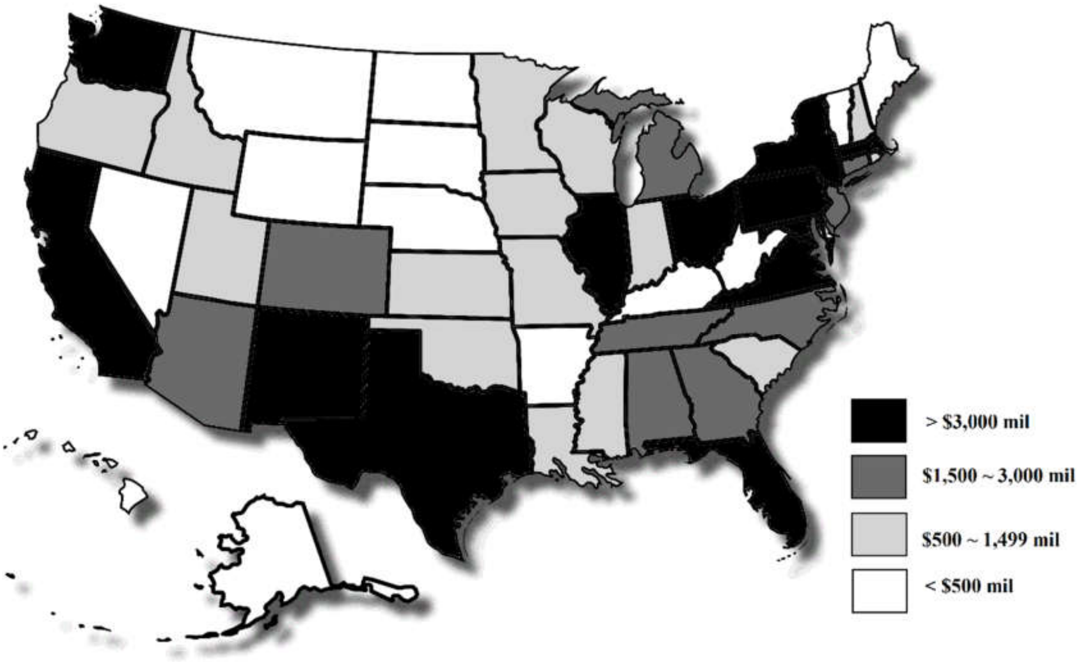
Fama and MacBeth Regressions- Using the Sample with Non-Missing R&D

Variable	Model 1	Model 2
Intercept	3.170	2.380
	(5.81)	(3.49)
Public R&D ratio	24.376	20.049
	(2.34)	(2.24)
R&D intensity	1.379	1.410
	(1.72)	(1.79)
Public R&D ratio × R&D intensity	4.522	3.948
	(2.24)	(2.05)
Firm-level controls	Yes	Yes
State-level controls	No	Yes
Industry dummies	Yes	Yes
Adj. R-sq	0.054	0.055

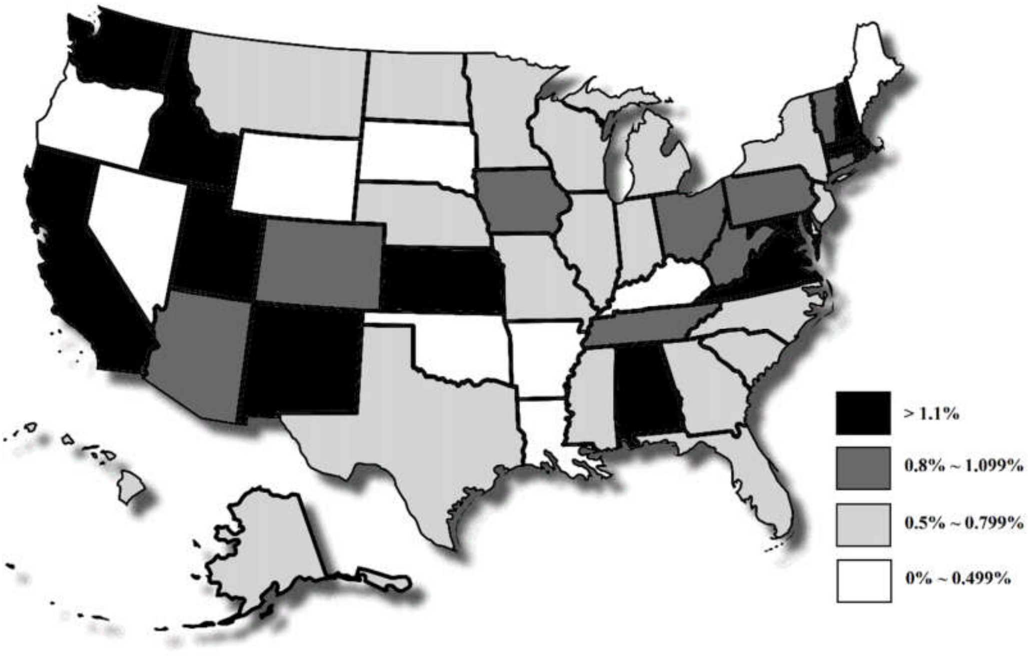
This table presents Fama and MacBeth (1973) regressions of firm stock returns on public R&D spending, firm R&D intensity, and all control variables in Table 4. We use a sample with firms whose R&D expenditures are non-missing in year t. The dependent variable is a firm's monthly stock returns from July of year $t + 1$ through June of year $t + 2$. Public R&D ratio is the ratio of public R&D spending to state GDP assigned to a firm according to the state where its headquarters is located. R&D intensity is the R&D capital-to-size ratio. Public R&D spending is measured in year $t - 3$; state-level economic indicators and variables about patent citations are measured in year t; variables involving accounting data are measured as of the end of fiscal year t; and variables involving stock market data are measured as of the end of June of year $t + 1$. Industry dummies are based on two-digit SIC codes. Newey-West (1987) adjusted t-statistics are reported in parentheses.

FIGURE 1
Public R&D Spending in Each State

Panel A. Amount of Public R&D Spending

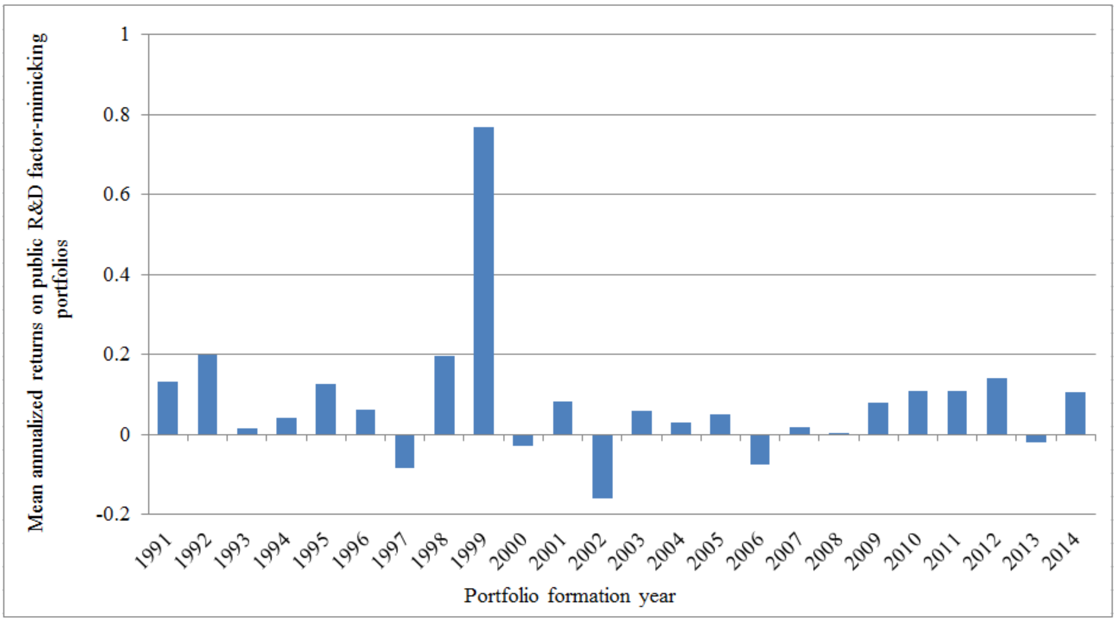


Panel B. Public R&D Ratio



Panel A describes the average amount of annual public R&D spending in each state between 1987 and 2010. The dollar amount of public R&D spending is based on 2010 prices. Panel B presents the average public R&D ratio in each state (the amount of public R&D spending scaled by state GDP). Data are obtained from the National Science Foundation.

FIGURE 2
Mean Annualized Returns on Zero-Cost Factor-Mimicking Portfolios for Public R&D Spending in Calendar Time



At the end of June of year $t + 1$, we sort all 50 U.S. states into five groups according to the public R&D ratio in year $t - 3$. We assign the public R&D ratio to a firm according to the state where its headquarters is located, and compute value-weighted monthly returns on the five portfolios from July of year $t + 1$ through June of year $t + 2$. The return on the public R&D factor-mimicking portfolio is the portfolio return of stocks with the highest public R&D ratios minus the portfolio return of stocks with the lowest public R&D ratios.