Tax Policy Endogeneity: Evidence from R&D Tax Credits

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Abstract

Policymakers consider the state of the economy when setting taxes, which may lead to endogeneity bias in regression models that estimate relationships between economic variables and taxes. This paper quantifies the policy endogeneity bias and estimates the impact of R&D tax incentives on R&D expenditures at the U.S. state level. Identifying tax variation comes from changes in federal corporate tax laws that heterogeneously impact state-level R&D tax incentives due to the simultaneity of state and federal corporate taxes. With this exogenous variation, a representative estimate suggests a 1% increase in R&D tax incentives leads to a 2% increase in R&D. Alternatively, estimates that ignore the endogeneity bias indicate a 1% increase in R&D tax incentives leads to a 0.5% increase in R&D. These results support a political economy story of lawmakers implementing tax incentives to prevent economic downturns.

Keywords: Corporate Tax; Fiscal Policy; R&D Price Elasticity; Tax Credits; Policy Endogeneity

JEL Codes: H20; H25; H32; H71; K34; O38

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1 Introduction

Governments use the tax system to encourage long-run economic growth, promote investment, and smooth business cycle fluctuations. The United States has repeatedly adjusted its corporate income tax rate and built-up corporate income tax credits (e.g., the investment tax credit and the research and development tax credit) to attain favorable economic outcomes (Goolsbee, 1998). There is a deep-rooted belief held by policymakers and many economists about the efficacy of fiscal policy. Unfortunately, economic research estimating the real effects of tax incentives (Easterly and Rebelo, 1993; Goolsbee, 1998; Ramey and Shapiro, 1998; Burnside, Eichenbaum, and Fisher, 2004; Mountford and Uhlig, 2009; Romer and Romer, 2010; Ramey, 2011) must overcome the inherent endogeneity of tax policies. Among other factors, the state of the economy affects tax policies.

In this setting, endogeneity bias may lead regression models to either overestimate or underestimate the efficacy of tax policies. For example, in an Ashenfelter Dip (Ashenfelter, 1978) story, governments implement tax incentives when the economy is in a slump. A revitalized economy subsequent to the implementation of tax incentives could simply be mean and/or trend reversion. A difference-in-differences approach that ignores this endogeneity would attribute mean and/or trend reversion to an effect of tax policies on the economy and would bias estimates toward finding an effect. Another standard endogeneity story is policymakers foreseeing an economic slump and implementing tax incentives to keep economic growth high (Romer and Romer, 2010). Under policy foresight, econometricians could observe no effect of the tax policies when the true effect may have been to avoid a slowdown in economic growth and keep the economy at its mean/trend. In this second case, the bias would be toward finding no effect (attenuation bias).

To quantify the endogeneity bias driven by self-selection of tax policies and to investigate the impact of tax incentives, this paper estimates the elasticity of research and development (R&D) with respect to R&D tax incentives. I use the setting of U.S. states and their R&D tax incentives because of the availability of exogenous sources of variation in state-level R&D tax incentives: variation driven by changes in federal corporate tax laws. While state policymakers pay particular attention to their own state's economic conditions when tailoring their state-specific tax policies, the federal government is less attentive to idiosyncratic state conditions when forming uniform federal tax policies. If variation in state-level R&D tax incentives driven by federal corporate tax laws is uncorrelated with state-level factors that would otherwise drive state corporate tax policy and R&D, then using this variation removes endogeneity concerns caused by policymakers self-selecting tax incentives and can generate unbiased estimates.

In addition, changes in federal corporate tax laws have heterogeneous impacts on state-level R&D tax incentives as a function of preexisting state corporate tax laws, which allows for identification of the policy variable when including time dummies in the regressions. These preexisting features of state corporate tax laws include how states treat the deductibility of R&D expenditures, the basis for state taxable income, and the tendency for states to base their R&D tax credits on the federal R&D tax credit (also known as piggybacking). This identification strategy of using federal laws that generate treatment and control groups has been implemented in other contexts, such as analyzing minimum wages (Card, 1992). I follow the personal income tax literature (Gruber and Saez, 2002) to isolate the exogenous variation in state-level R&D tax incentives driven by federal corporate tax laws. In the literature on R&D tax incentives, this paper is closest to Wilson (2009).[1]

With corporate tax variation from only changes in federal laws, this paper estimates models that indicate an elastic response of R&D to R&D tax incentives, with an average elasticity estimate of 2.0 and a range of [1.6, 2.9]. The average estimate suggests if governments were to increase R&D tax incentives by 1%, then R&D would increase by 2%.

These estimates are large relative to results from previous literature on R&D tax incentives. Hall and Van Reenen (2000), Table 2, reviews studies of U.S. data and suggests existing research finds an average elasticity of 1.0 with a range of [0, 1.6]. To be comparable to previous studies, this paper also estimates models using corporate tax variation from both state and federal laws. This variation should give biased estimates due to states selecting their own tax incentives. The results

[1] For other studies on R&D tax incentives, see the review by Hall and Van Reenen (2000) and subsequent work by Bloom, Griffith, and Van Reenen (2002); Paff (2005); Wu (2005); Rao (2010); Czarnitzki, Hanel, and Rosa (2011); Lokshin and Mohnen (2012).

from using corporate tax variation from both state and federal laws give estimates consistent with existing literature, with an average elasticity estimate of 0.5 and a range of [0.2, 0.9]. Comparing the estimates from using exogenous federal law variation to estimates using endogenous state law variation suggests serious bias towards finding tax incentives are ineffective when ignoring the endogeneity of tax policies, which is consistent with the tax endogeneity bias found by Yang (2005); Romer and Romer (2010). The attenuation bias supports the endogeneity story of policymakers implementing preemptive tax incentives.

2 Data and Estimation

This paper estimates the following model with ordinary least squares:

$$RD_{it} = RD_{it-l} + \varphi_i + \lambda_t + RDSubsidyRate_{it} + X_{it}^{'}\beta + \varepsilon_{it} \tag{1}$$

where subscript i represents a state, subscript t is time, X is a matrix of controls, and the key regressor, $RDSubsidyRate$, is the R&D subsidy rate. With state fixed-effects φ and time dummies λ, ordinary least squares applied to equation (1) amounts to using the standard within estimator.

The dependent variable RD is state-year company-financed R&D expenditures from 1981-2006. These data come from the National Science Foundation's (NSF's) Survey of Industrial Research and Development (SIRD).[2] These data are biannual (odd year) observations of company-financed R&D up to 1997 and annual from 1997-2006.

The NSF censors observations if the disclosure of a state's R&D in a particular year reveals information about an individual firm's R&D. This censoring mechanism tends to eliminate observations from low R&D states and states where R&D is particularly concentrated among a few

[2] R&D data are available since 1963, but I focus on the period since the introduction of the federal R&D tax credit following previous studies of state R&D tax credits (Paff, 2005; Wu, 2005; Wilson, 2009). The introduction of the federal R&D tax credit in 1981 created strong incentives for firms to relabel expenditures as R&D and creates a potential measurement break between the pre-credit era and the post-credit era (Eisner, Albert, and Sullivan, 1986; Hall and Van Reenen, 2000). While subsequent revisions increasing the generosity of the federal R&D tax credit could strengthen the relabeling incentive, starting in 1981 firms already had the incentive to relabel their expenditures as R&D.

firms. As a result, I analyze the 21 high R&D states where I observe R&D expenditures consistently in the 1980s and 1990s. Observing states in the 1980s and 1990s is necessary because the identifying tax variation from federal laws comes in the 1980s and 1990s.[3]

Because the unit of analysis is a state-year, the controls capture state-level factors that could affect R&D. As R&D is procyclical, the model incorporates gross state product (GSP) from the Bureau of Economic Analysis (BEA) and the unemployment rate from the Bureau of Labor Statistics as proxies for business cycle effects.[4] Federal funding for R&D can either complement or substitute for company-financed R&D. For example, if a firm receives a federal R&D contract then it may undertake complementary R&D investments to help fulfill the contract. Conversely, firms may simply substitute private funds for the acquired public funds.[5] I control for federal funding with federally-financed R&D expenditures from the NSF's SIRD and data on federal obligations for R&D from the NSF's WebCASPAR database.[6] To control for other unobserved factors that could influence innovative activity, the model uses state expenditures on academic R&D. Data on academic R&D expenditures come from the NSF's WebCASPAR database. I convert all variables from nominal to real values with the BEA's GDP deflator.[7]

The lagged dependent variable captures the adjustment costs of R&D. To incorporate this lag, I impose a biannual structure over the entire sample period and use the first available lag of R&D ($t-2$). Imposing a biannual structure on the data drops observations when R&D data are available

[3]For 2000-2006 I observe nearly all states, although the NSF largely imputes data for low R&D states due to small survey sample sizes. The states in the sample are: Alabama, Arizona, California, Colorado, Connecticut, Florida, Illinois, Indiana, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Oregon, Pennsylvania, Texas, Virginia, and Wisconsin. This sample of high R&D states comprises 80-90% of R&D after 2000.

[4]See Barlevy (2007), Ouyang (2011), or Chang (Forthcoming) for research into macroeconomic determinants of R&D.

[5]There is a large literature debating whether public funds complement or substitute for private funds. See David, Hall, and Toole (2000) for a review.

[6]See the review in Brown, Plewes, and Gerstein (2005) for details on the differences between these two sources of data. The results report estimates using obligation data to maximize the sample size. The results are insensitive to both measurements of federal R&D expenditures.

[7]The raw data for most of the variables are non-stationary. However, the time dummies and state fixed effects detrend all of the variables (Cameron and Trivedi, 2005). Panel unit root tests (Said and Dickey, 1984; Levin, Lin, and Chu, 2002) on the detrended variables support stationarity for all variables except GSP, and GSP has no effect on the main results.

on an annual basis, but has no effect on the results.[8]

The within estimator applied to equation (1) is consistent for a large time dimension. However, for a small time dimension the coefficient on the lagged dependent variable estimated by the within estimator is biased downward (Nickell, 1981). For the panel in this paper, the time dimension varies between 12-19 observations, which should reduce the bias from the within estimator. The main specifications use the within estimator because of its superior precision relative to instrumenting the lagged dependent variable with a generalized method of moments (GMM) estimator. The robustness checks section investigates the potential bias arising from the within estimator using the Blundell and Bond (1998) GMM estimator and a bias-corrected least squares (LSDVC) estimator (Bruno, 2005a,b).[9]

3 R&D Subsidy Rates

This section describes the calculation of state-level R&D subsidy rates. I then show pre-treatment plots that support this paper's identification strategy and review institutional details behind the federal and state corporate tax systems.

3.1 Computation of R&D Subsidy Rates

Because of the deductibility of R&D expenditures and R&D tax credits, a firm's marginal dollar of R&D reduces the firm's tax liability.[10] The decrease in tax liability from a marginal dollar of R&D is the government's effective R&D subsidy rate.

Let FT denote federal taxes, ST denote state taxes, RD^{tot} be total R&D expenditures, and r be the discount rate. I model the R&D subsidy rate for the representative firm,[11] $RDSubsidyRate$ as:

[8]Subsection 4.3.1 conducts this robustness check.

[9]The Blundell and Bond (1998) GMM estimator instruments the endogenous variable with lags of itself. The LSDVC estimators of Bruno (2005a,b) are unbiased under certain theoretical conditions in Bruno (2005a,b).

[10]Firms above their minimum taxable income amount can reduce their tax liability by increasing R&D because R&D is fully deductible.

[11]I model the representative firm because the NSF's R&D data are at the state level.

$$RDSubsidyRate_{it} = abs\left(\frac{\partial(ST_{it}+FT_{it})}{\partial RD_{it}^{tot}} + \sum_{m=1}^{M}\frac{1}{\prod_{s=1}^{m}(1+r_{t+s-1})}\frac{\partial(ST_{it+m}+FT_{it+m})}{\partial RD_{it}^{tot}}\right) \quad (2)$$

which is the reduction in taxes at time t for state i due to R&D at time t, plus the discounted changes in taxes for future periods.[12] I set the discount rate as the dividend-price ratio of the S&P 500 plus its long-term growth rate of 2.4%, following Chirinko, Fazzari, and Meyer (1999); Wilson (2009) with data from Shiller (2005).[13,14] Appendix A describes the computation in detail.

The primary source of data on state corporate tax policies is individual state session laws. When available, I also capitalize on state statutes, Commerce Clearing House's (CCH's) U.S. Master Multistate Corporate Tax Guide (Various Years), CCH's IntelliConnect, CCH's State Tax Handbook (Various Years), and data from Wilson (2009).

Equation (2) incorporates variation from both state and federal laws. The variation from state laws is likely endogenous because state policymakers may set R&D tax incentives as a function of unobserved state economic conditions. An abundance of anecdotal evidence documents that state lawmakers respond to state economic conditions when formulating tax policies. For example, Arizona Senator Barbara Leff, one of the sponsors of a bill to increase Arizona's R&D tax credit, wrote: "We should be the leader in manufacturing, research and development and headquarters but we are not. These jobs are going elsewhere because Arizona does not have specific incentives in place to attract these companies." (Leff, 2009). Similarly, when California was plagued with high unemployment in 1993, California Governor Pete Wilson made job creation the center of his political platform. In the Governor's 1993 State of the State address he asserted: "If we are to

[12]Taking into account the discounted sum of future changes in taxes is necessary because R&D tax credits are occasionally calculated as a credit amount over a M-year moving average base of previous R&D expenditures. This feature implies taking R&D tax credits in period t can affect the ability of a firm to take a credit in future periods.

[13]The theoretical rationale behind discounting future periods with the S&P 500 is the opportunity cost of a firm's funds. A firm deciding to undertake R&D could instead fund some outside investment, with the S&P being a representative indicator of the available market rate of return.

[14]Equation (2) discounts changes in the tax liability of future periods using the actual realized interest rate. The assumption behind this formulation is firms correctly anticipate the interest rate with certainty and follows Wilson (2009). As a robustness check, I also discount future periods by assuming firms in period t use the interest rate from period $t-1$ to form future expectations of the interest rate. This alternative formulation gives similar results.

create jobs, we have to cut taxes... I ask this new legislature to create new jobs. To put Californians back to work by enacting tax incentives and other changes to create jobs... I ask you to invest in the jobs of the future by enhancing the tax credit for research and development of new technologies, and I ask you to make it permanent." Empirically, a state's initial adoption of a R&D tax credit is correlated with observed state-level economic conditions (Miller and Richard, 2010). If state tax incentives are also correlated with unobserved state-level economic conditions, then the tax variation driven by state laws is endogenous.

To get a measure of R&D subsidy rates free from the bias due to states selecting their own R&D tax incentives, I isolate the variation in equation (2) arising from only federal laws. Table 1 lists the laws this paper uses for federally driven variation in state-level R&D subsidy rates. This variation should be exogenous to unobserved state-level conditions that affect state-level R&D and state-level policies. State governments can tailor tax policies to respond to their own idiosyncratic state economic conditions, but the federal government sets uniform national R&D tax policies and is less attentive to idiosyncratic state conditions.

Let $\Delta RDSubsidyRate^{fed}$ be changes in the R&D subsidy rate driven by federal laws. The expression for $\Delta RDSubsidyRate^{fed}$ is:

$$\Delta RDSubsidyRate_{it}^{fed} = RDSubsidyRate(ST_{it-1},\ FT_{it}) - RDSubsidyRate(ST_{it-1},\ FT_{it-1}) \qquad (3)$$

which is the change in the R&D subsidy rate from a given change in federal tax laws holding state tax laws fixed. This strategy of isolating only the exogenous variation in R&D subsidy rates is analogous to the Gruber and Saez (2002) method of constructing exogenous personal income tax rates.[15] The R&D subsidy rate at time t from only federal laws is the sum of all previous changes in R&D tax incentives driven by federal corporate tax laws:

[15] Gruber and Saez (2002) isolate exogenous changes in personal income tax rates arising from variation in tax laws at time t by conditioning on the previous period's income. For this paper, I create exogenous R&D subsidy rates from variation in federal tax laws at time t by conditioning on the previous period's state tax laws.

$$RDSubsidyRate_{it}^{fed} = \sum_{n=1}^{t} \Delta RDSubsidyRate_{in}^{fed} + RDSubsidyRate_{i0} \tag{4}$$

A researcher may be concerned that state corporate tax policies are responding endogenously to federal corporate tax policies, which would lead to biased estimates even when using corporate tax variation from only federal corporate tax policies. Another worry is calculating R&D subsidy rates driven by federal corporate tax laws holding state corporate tax laws fixed may miss contemporaneous changes in state and federal corporate tax laws. An estimated coefficient on $RDSubsidyRate^{fed}$ may actually be picking up the effect of these contemporaneous state corporate tax law changes instead of the variation in exogenous federal corporate tax laws. To mitigate these concerns, as a robustness check I drop the two states (Illinois and Massachusetts) that enacted R&D tax credits within one year after a change in the federal R&D tax credit. Dropping these states gives similar results.[16]

Figure 1 plots summary statistics of per-dollar state-level R&D subsidy rates, calculated with both state and federal laws driving the variation (equation 2). Federal laws induce large shifts in state-level R&D subsidy rates. For example, the large increase in subsidy rates from 1981 to 1982 is due to the phase-in of the federal R&D tax credit. Similarly, the second large increase in subsidy rates, from 1989 to 1990, is the result of a reworking of the federal R&D tax credit. On net, federal laws place the average R&D subsidy rate at around 0.5 over the last 30 years. In addition, the introduction of state R&D tax incentives (the first state R&D tax credit was introduced in 1981, effective in 1982) increases the across-state variation in state-level R&D subsidy rates over time.[17]

Figure 2 plots summary statistics of per-dollar state-level R&D subsidy rates with only federal laws driving the variation (equation 4). The removal of variation from state laws decreases the across-state variation over time. However, because of the heterogeneous effects of federal laws on state-level R&D subsidy rates, the across-state variation in subsidy rates continues to increase over

[16] The robustness checks subsection 4.3.2 presents the results.

[17] With state fixed effects and time dummies, identifying variation comes from mean deviations in R&D subsidy rates, not from large shifts that affect all states equally. The robustness checks section confirms the main results are not sensitive to the large increase in R&D subsidy rates from the introduction of the federal R&D tax credit in 1981.

time.

3.2 Pre-treatment Plots and Selection Bias

Identification of the elasticity of R&D with respect to R&D tax incentives in the presence of time dummies relies on heterogeneous effects of federal laws on state-level R&D subsidy rates. One concern with this strategy is that the effects of federal laws on state-level R&D subsidy rates are selectively assigned. If states receive disproportionate tax incentives from federal laws due to some unobserved state-level factor that also affects R&D, then even the use of federal variation in subsidy rates would continue to cause inconsistent estimation.

To check for selection bias from federal laws, I perform a standard check in the difference-in-differences framework and plot the levels and trends of R&D for each state prior to the introduction of the federal R&D tax credit in 1981 (the first treatment law). If the levels and the trends of R&D for the treatment and control groups appear similar prior to the introduction of the federal R&D tax credit, then these graphs bolster the case for random assignment of the treatment.

A slight complication with these plots arises because the treatment is a series of laws that each treat all states, not just a single standard binary treatment/control setup. Therefore, I rank states based on their average value of R&D tax incentives (the mean of equation 4), with higher ranks indicating more generous tax incentives. I then plot pre-treatment R&D levels/trends against state tax incentive rank.

Figure 3 graphs state R&D intensity, measured as state R&D to GSP, immediately prior to the introduction of the federal R&D tax credit against state treatment rank. This measure of R&D intensity is common in macroeconomic studies of R&D tax incentives, such as Bloom, Griffith, and Van Reenen (2002). One state (Michigan) has a much higher R&D intensity than other states. However, there does not appear to be a systematic relationship between R&D intensity and the magnitude of the treatment. The correlation between R&D intensity and treatment rank is only -0.05 (0.09 excluding Michigan).

Figure 4 plots average pre-treatment state R&D growth rates against state treatment rank. Similar to the R&D intensity plot, there is one outlier (Colorado) with a high R&D growth rate. More importantly for determining selection bias, visual inspection of Figure 4 indicates R&D growth rates appear to be uncorrelated with changes in state-level R&D subsidy rates from federal laws. The correlation between R&D growth rates and treatment rank is only 0.12 (0.11 excluding Colorado). The combined evidence from the R&D intensity plot in Figure 3 and the R&D growth plot of Figure 4 suggest the changes in state-level R&D subsidy rates driven by federal laws are uncorrelated with state R&D characteristics.

This paper uses federal laws as sources of variation in state-level R&D subsidy rates due to concerns about states selecting their own tax incentives. To check and see whether self-selection of R&D tax incentives is correlated with state characteristics, Figures 5 and 6 plot the levels and trends of R&D against state treatment rank, but with treatment rank determined using variation in subsidy rates from both state and federal laws (the mean of equation 2) instead of from only federal laws. If states select their own tax incentives as a function of state characteristics, then this measure of the subsidy rate should suffer from selection bias that can manifest itself in a correlation between R&D levels and/or trends and R&D tax incentives.

From the R&D growth plot in Figure 6, there does not appear to be a relationship between state tax incentives and pre-treatment R&D growth. The correlation between R&D growth and treatment rank is 0.04 (0.25 excluding Colorado). However, visual inspection of the R&D intensity plot in Figure 5 reveals a positive correlation between state treatment rank, which uses variation from both state and federal laws in R&D tax incentives, and R&D intensity. The correlation between R&D intensity and state treatment rank is 0.27, and this correlation increases to 0.71 when excluding Michigan. This evidence suggests that more R&D intensive states are also more likely to implement more favorable tax treatment for R&D. This relationship is absent from the plots using only variation from federal laws in subsidy rates, suggesting the use of federal variation will mitigate the bias stemming from states selecting their own R&D tax policies.

3.3 Institutional Details of Federal and State Taxes

The computations of federal and state corporate taxes are interdependent. A firm's federal tax liability depends on the firm's state tax liability and vice versa. The simultaneity between federal and state corporate taxes contributes to differential effects of federal laws on state-level R&D subsidy rates across states. I model the heterogeneous changes in R&D subsidy rates from federal laws by taking into account two broad classes of reductions in taxes: those relating to deductions for corporate income taxes paid and those relating to R&D tax credits.[18]

The federal government has allowed a deduction for state corporate income taxes since 1954. At the same time, some states allow deductions for federal and/or state corporate income taxes, while other states do not. This between-state variation in state tax policies implies any change in federal tax law that affects a firm's federal income tax liability will have differential effects on total tax liability across states.

For example, changes in the federal corporate income tax rate directly affects total taxes for all states. For states that allow federal corporate income taxes paid as a deduction, changes in the federal corporate income tax rate are dampened. The value of this deduction is proportional to the state corporate income tax rate. Suppose the federal government increases the federal corporate income tax rate from 0.4 to 0.5 and there are no R&D tax credits or state deductions for state corporate income taxes.[19] If a state does not allow a deduction for federal corporate income taxes paid, then the increase in taxes for firms would be ten cents per dollar of taxable income. If a state with a 5% corporate income tax allows a deduction for federal corporate income taxes paid, then the increase in taxes for firms would be 9.5 cents per dollar of taxable income. For every dollar of additional federal corporate income tax, firms can take an additional dollar of deduction on their state taxes. With a 5% state corporate income tax rate, each dollar of deduction from state taxable income is worth five cents. Therefore, changes in the federal corporate income tax rate have heterogeneous impacts on the value of deductions, and hence R&D subsidy rates due to

[18]These classes are themselves interdependent, but I separate them for exposition purposes.

[19]The presence of R&D tax credits and state deductions for state corporate income taxes complicates the intuition, but the main point is the same.

the deductibility of R&D expenditures, as a function of state corporate income tax rates and what proportion of federal corporate taxes states allow as a deduction.

Variation in the federal R&D tax credit also contributes to differential effects of federal laws on state-level R&D tax incentives. The largest source of variation comes from the passage of Public Law (PL) 101-239 on December 19, 1989, which increased the effective federal R&D tax credit and reduced allowable deductions for R&D expenditures starting on January 1, 1990. In 1989, the federal R&D tax credit was 20% of qualified research expenditures (QREs) in excess of a three-year moving average of QREs.[20] In addition, in 1989 firms were allowed to deduct 50% of their QREs claimed for computing the credit from their federal taxable income. PL 101-239 changed the base amount to a fixed base and disallowed the deduction for QREs used to calculate the credit (i.e., increased credit recapture).

Changing the base amount from a moving average to a fixed base dramatically increased the effective credit rate (Hall, 1993; Wilson, 2009). Under the three-year moving average base amount, for each dollar of credit claimed a firm had to lower its future claimed credit by a third of a dollar for each of the next three years. With the fixed base, this opportunity cost was eliminated. At the same time, the disallowance of the 50% QRE deduction decreased the effective credit rate as firms could no longer take both a deduction and a credit for the same QREs. The heterogeneous effects on state-level R&D subsidy rates from PL 101-239 arose from two factors: 1) how states structured their R&D tax credits and 2) how states computed state taxable income (state taxable income basis).

A common feature of state R&D tax credits is piggybacking on the federal R&D tax credit. States offer R&D tax credits computed with the same method as the federal R&D tax credit and have this computation method linked directly to the Internal Revenue Code (IRC), which documents U.S. federal tax law. For example, Oregon Revised Statues § 317.152, which authorizes a R&D tax credit for Oregon QREs, states "A credit against taxes otherwise due under this chapter shall be allowed to eligible taxpayers for increases in qualified research expenses... the credit shall

[20]See Guenther (2006) for a review of the federal R&D tax credit.

be determined in accordance with section 41 of the Internal Revenue Code."

This piggybacking feature implies any change in the computation of the federal R&D tax credit automatically updates how piggybacking states calculate their R&D tax credits: federal law drives changes in effective state tax law and state policymakers do not dictate these changes. In 1989, California, Indiana, Iowa, Minnesota, North Dakota, Oregon, and Wisconsin piggybacked on the federal R&D tax credit. All else equal, for these seven states PL 101-239 increased both the effective federal R&D tax credit *and the effective state R&D tax credit*, which caused a disproportionally large increase in R&D subsidy rates relative to states without R&D tax credits. For states without R&D tax credits, PL 101-239 caused an increase in R&D subsidy rates of between nine and thirteen cents per dollar of R&D. The increase in subsidy rates for states with piggybacked R&D tax credits was approximately 50% greater than for states without R&D tax credits.

The basis for state taxable income also helped foster heterogeneous effects of PL 101-239 on state-level R&D subsidy rates. In general, states either use income from all sources (gross receipts) or federal taxable income as a starting point for computing state taxable income. States that incorporate federal taxable income as a starting point automatically apply federal-specific deductions and exemptions to form state taxable income. For these states, changes in the IRC cause automatic updates in state tax codes. On the other hand, states that form state taxable income starting with income from all sources do not incorporate federal-specific deductions and exemptions so that alterations to the IRC have no effect on their state tax codes. PL 101-239 disallowed the 50% QRE deduction allowed prior to 1990 when taking the federal R&D tax credit (IRC § 280C(c)). Therefore, for states with federal taxable income as a base, PL 101-239 caused an automatic increase in the state income base (i.e., a decrease in the effective federal R&D tax credit) and had no effect for states that used income from all sources as a base, which again contributes to differential effects of federal laws on state-level R&D subsidy rates.[21]

[21] In the interest of brevity I simplified this discussion slightly. States occasionally have specific provisions that override what the base would predict. See Appendix A for details.

4 Results

The main result of this paper is estimating the elasticity of R&D with respect to R&D tax incentives by exploiting only exogenous variation in tax incentives driven by federal laws yields an average estimate of 2.0 and a range of [1.6, 2.9]. The average estimate suggests a 1% increase in R&D tax incentives would lead to a 2% increase in R&D expenditures.[22] These estimates are larger than the results from previous literature, which tends to find an elasticity around 1.0. The review by Hall and Van Reenen (2000) places previous estimates between [0, 1.6]. Subsequent macroeconomic studies also find elasticities in this range (Bloom, Griffith, and Van Reenen, 2002; Wilson, 2009).

To be comparable to previous studies, this paper also estimates models with the R&D subsidy rate that incorporates variation in tax incentives from both state and federal laws. These models should suffer from endogeneity bias driven by states self-selecting their tax policies. With variation from both state and federal laws, this paper estimates an average elasticity of 0.5 and a range of [0.2, 0.9]. The results from using endogenous tax variation are similar to estimates from previous studies of R&D tax credits. The bias towards finding that tax incentives are ineffective at stimulating economic activity is consistent with research by Yang (2005); Romer and Romer (2010). This bias suggests policymakers implement tax incentives to prevent economic slowdowns.

4.1 Main Specifications

Table 2 presents estimates with the R&D subsidy rate calculated with only exogenous variation driven by federal laws, $RDSubsidyRate^{fed}$. The table reports coefficients as elasticities. All specifications indicate an elastic response of R&D to its subsidy rate of at least 2.0. Columns (1) and (2) present results from static specifications, which omit the lagged dependent variable. Column (1), a specification that only includes $RDSubsidyRate^{fed}$ with state fixed effects and time dummies, indicates an elasticity (standard error) of 4.07 (2.33). Column (2) adds lagged federal R&D following Wilson (2009) as well as academic R&D and the unemployment rate as controls. The

[22]Recent research on the elasticity of foreign direct investment with respect to its marginal tax rate also finds an elastic response, with point estimates even larger in magnitude (de Mooij and Ederveen, 2008; Zodrow, 2010).

coefficient (standard error) of $RDSubsidyRate^{fed}$ remains elastic at 4.37 (2.66). Among the control variables, only federal R&D is statistically significant. The positive coefficient on federal R&D suggests complementarity between federal R&D and company-financed R&D.

If the lagged dependent variable belongs in the model, then omitting it leads to inconsistent estimates. I prefer to include the lagged dependent variable due to R&D's high adjustment costs. Columns (3) - (5) estimate dynamic specifications that include the lagged dependent variable. The lagged dependent variable attenuates the elasticity estimate of R&D to its subsidy rate, but improves its precision.[23] Furthermore, the results continue to indicate a 1% increase in R&D tax incentives leads to at least a 2% increase in R&D. The estimates are also statistically significant at standard levels. Column (3) of Table 2, which uses only $RDSubsidyRate^{fed}$, the lagged dependent variable, and fixed effects, implies an elasticity estimate (standard error) of 2.63 (1.00). The coefficient (standard error) on the lagged dependent variable is 0.52 (0.11), confirming the presence of adjustment costs for R&D.

Column (4) of Table 2 includes a full set of control variables. The coefficient (standard error) of $RDSubsidyRate^{fed}$ is still large at 2.85 (1.02). GSP enters the model as positive and large, consistent with the procyclicality of R&D. The coefficients on the other control variables have a similar interpretation to the static specification in column (2), although the coefficient on academic R&D is now negative. Column (5) removes GSP so that the model includes only stationary variables. This specification gives similar results to column (4) and continues to indicate an elastic response of R&D to tax incentives. Academic R&D in column (5) is once again insignificant.

Table 3 presents results from equation (1) with the key regressor as the potentially endogenous R&D subsidy rate (state and federal laws driving the tax variation) and coefficients as elasticities. The use of endogenous variation in tax policies makes Table 3's specifications analogous to specifications from the existing literature on R&D tax incentives. The estimates from Table 3 should be biased due to states self-selecting their R&D tax policies.

Using the endogenous tax variation, all specifications in Table 3 indicate an inelastic response

[23] Attenuated estimates with improved precision when including the lagged dependent variable is consistent with Bloom, Griffith, and Van Reenen (2002)'s cross-country study of R&D tax credits.

of R&D to its subsidy rate. Columns (1) and (2) present results from static models, which omit the lagged dependent variable. The specification in column (1) includes only the endogenous subsidy rate, *RDSubsidyRate*, and fixed effects. This specification indicates a 1% increase in the R&D subsidy rate causes a 0.84% increase in company-financed R&D. In column (2), I retain the static model and add control variables. The response of R&D to its subsidy rate remains almost unchanged.

Table 3, columns (3) - (5) present results from dynamic specifications. The estimates from these dynamic specifications continue to indicate an inelastic response of R&D to its subsidy rate, with a range between 0.24 and 0.55. These estimates are well within the range of estimates provided by the existing literature. The precision of the dynamic specifications continues to be superior to the static specifications (standard errors are halved) and the control variables have the same interpretation as the controls from Table 2.

The difference between the results in Tables 2 and 3 suggests ignoring the endogeneity of tax policies leads to attenuated estimates of the response of R&D to tax incentives. Because the estimates of the response of R&D to tax incentives with exogenous variation in incentives are larger than the estimates with endogenous variation, the results are consistent with policymakers implementing R&D tax incentives to prevent the loss of R&D expenditures. For example, if firms plan to relocate R&D activity to another region, then lawmakers may offer the firm tax incentives to keep the firm's R&D activity from changing location. This preemptive offering of R&D tax incentives would cause researchers to observe no effect of the self-selected tax policies when their true effect was to prevent a drop in R&D. Therefore, the presence of this prevention mechanism would bias regression models towards finding no effect of tax policies on R&D.

4.2 Estimate Precision and Wild Cluster Bootstrap-t

Turning to the precision of the estimates, Tables 2 and 3, as well as other estimation results using the within estimator, present clustered standard errors by state. The tables indicate statistical significance of the two-sided tests $H_0: \beta = 0$ vs. $H_A: \beta \neq 0$. For the case of the key regressor

$RDSubsidyRate^{fed}$, these two-sided tests may be too conservative in favor of the null hypothesis (lead to under-rejection). An increase in the R&D subsidy rate should lead to either an increase or no change in R&D. There is no plausible reason to believe a subsidy would lead firms to conduct less R&D. Therefore, economic theory better supports one-sided hypothesis tests.

The asymptotics behind the rejection rates of clustered standard errors assumes the number of clusters is large. In this paper, there are $N = 21$ states (clusters). Clustering at the state level allows for arbitrary within-state correlation and heteroskedasticity. The tables use standard rejection rates from a $T(N-1) = T(20)$ distribution instead of a normal distribution, a common finite-sample correction because general finite-sample rejection results for clustered standard errors are not possible (Cameron, Gelbach, and Miller, 2008).

When the number of clusters is small, clustered standard errors can give incorrect rejection rates. This bias usually leads to over-rejection of the null hypothesis even when using a t-distribution instead of a normal distribution to compute p-values. Simulation evidence from Bertrand, Duflo, and Mullainathan (2004), Table 8, suggests 20 clusters gives correct inference, in which case the standard errors presented thus far are valid. However, Cameron, Gelbach, and Miller (2008)'s simulations infer 30 or more clusters is necessary and suggest with 20 clusters, tests of size 0.05 actually reject with probabilities between 0.08 and 0.09 (Cameron, Gelbach, and Miller, 2008, Tables 2 and 3).

Following the recommendation of Cameron, Gelbach, and Miller (2008), I also conduct the hypothesis tests by bootstrapping the t-statistic using the wild cluster bootstrap-t procedure.[24] This procedure leads to asymptotic refinement of the standard errors, which may lead to improved rejection rates (Brownstone and Valletta, 2001; Cameron, Gelbach, and Miller, 2008).[25] Applying this procedure to two-sided tests of $H_0 : RDSubsidyRate^{fed} = 0$ vs. $H_A : RDSubsidyRate^{fed} \neq 0$ yields coefficients that range from significant at the 5% level to marginally insignificant (the largest $p = 0.19$). Therefore, one-sided tests, which are better supported by theory as an increase in the

[24] I use Rademacher weights with 1000 replications for each test.

[25] While the wild cluster bootstrap-t improves the convergence rate of rejection rates to their asymptotic ideals (leads to asymptotic refinement), the direction of finite-sample bias cannot be signed. Rejection rates may still be either too high or too low.

R&D subsidy rate should increase R&D, yield rejection of $H_0 : \mathit{RDSubsidyRate}^{fed} = 0$ at the 10% level or higher in all cases.

4.3 Robustness Checks

In this subsection, I present additional robustness checks on the main results from Table 2.

4.3.1 Additional Controls and Sample Restrictions

A researcher may be concerned the control variables in Tables 2 and 3 are insufficiently rich. Therefore, I experiment with a more saturated specification of controls that utilizes contemporaneous, one lag, and two lags of all control variables. The R&D subsidy rate driven only by federal laws generates an estimate (standard error) of 3.85 (1.09). This estimate continues to indicate a large response of R&D to tax incentives consistent with the more simple specifications of Table 2. This more saturated specification gives an elasticity estimate (standard error) of 0.31 (0.57) for the endogenous R&D subsidy rate driven by both state and federal laws, which is in line with the parsimonious specifications in Table 3.[26,27]

Table 4 considers models subject to various sample modifications. Starting with the specification in column (5) of Table 2, in column (1) of Table 4 I trim the 2% of observations with the largest residuals, removing 1% of the sample from each tail.[28] Column (2) estimates the model with data starting in 1985 to remove the effect of the introduction of the federal R&D tax credit, which causes the large increase in R&D subsidy rates from 1981-1982 in Figures 1 and 2. In column (3), I estimate the model only with data up to 1999 because the variation in R&D subsidy rates driven by federal laws comes exclusively from the 1980s and 1990s. In column (4), I use all of the available R&D data by abandoning the biannual structure used so far. This strategy changes the model from biannual to annual observations from 1997-2006 and addresses concerns

[26]The results are also robust to adding state-specific linear time trends as controls.

[27]The endogenous R&D subsidy rate driven by both state and federal laws gives inelastic point estimates for all robustness checks.

[28]A 5% sample trim (2.5% from each tail) yields similar estimates.

over potential loss of precision from dropping observations in the latter part of the sample.[29]

The models subject to these sample modifications continue to suggest an elastic response of R&D to tax incentives. The smallest estimate comes from removing outliers in column (1), which indicates if governments were to increase R&D tax incentives by 1%, then R&D would increase by 2.20%.

Estimating the model with data starting in 1985 yields an estimate almost identical to the main results in Table 2. Therefore, the main results are not driven by the phase-in of the federal R&D tax credit, which causes the large increase in R&D subsidy rates from 1981 to 1982 shown by Figures 1 and 2.

Dropping observations after 1999 in column (3) imposes the largest sample reduction and also has the largest effect on the estimates. The estimate of the price elasticity (standard error) is now much more elastic at 4.70 (1.31). This large increase in magnitude is likely due to the increased downward bias on the lagged dependent variable from the within estimator. The coefficient on the lagged dependent variable is down to 0.21 (0.05) from 0.48 (0.10) in Table 2, column (5). This bias on the lagged dependent variable renders the other coefficients inconsistent, so the estimates from column (3) should be taken with a dose of suspicion.

The final sample modification in column (4), using annual observations from 1997-2006 instead of biannual observations, gives a similar estimate to the main results of Table 2. For all specifications subject to sample modifications, federal R&D complements company-financed R&D. Academic R&D and the unemployment rate are insignificant.

4.3.2 Other Dynamic Forms and Alternative R&D Subsidy Rate

Table 5, columns (1) - (2) present robustness checks with alternative formulations of the lagged dependent variable. Following Wilson (2009), in column (1) I continue to make use of the entire R&D sample and instead incorporate the lagged dependent variable as the most recent available lag of R&D: $t-2$ for the biannual period and $t-1$ for the annual period. This specification

[29] Weighting states by average GSP from 1981-2006 also gives similar results.

allows the coefficient on the lagged dependent variable to vary between the biannual and annual periods. Column (1) gives a slightly larger response of R&D to tax incentives, but the results are qualitatively similar to the main results from Table 2.

In Table 5, column (2) I return to the biannual data structure and use RD_{it-4} instead of the most recent available lag, RD_{it-2}. If R&D tax policy is contemporaneously determined with lagged R&D, then including both $RDSubsidyRate^{fed}$ and lagged R&D will lead to inconsistent estimates. Incorporating a deeper lag of R&D in the model instead of the most recent lag ameliorates concerns over contemporaneously determined lagged R&D and R&D tax incentives. Using RD_{it-4} causes the coefficient on $RDSubsidyRate^{fed}$ to increase to 5.71. Since RD_{it-4} has smaller predictive power over current R&D than RD_{it-2}, this result is similar to having a larger downward bias on the lagged dependent variable, such as when using only pre-2000 data in Table 4, column (3). Incidentally, the coefficient on RD_{it-4} is approximately the square of the coefficient from using RD_{it-2} as the lagged dependent variable. This coefficient value is what we would expect given constant predictive power of lagged R&D for current R&D over time.

Table 5, column (3) calculates R&D subsidy rates using only variation from PL 101-239, the largest source of across-state variation in R&D subsidy rates from federal laws. The table denotes this formulation of R&D subsidy rates as $RDSubsidyRate^{PL101-239}$. Replacing $RDSubsidyRate^{fed}$ with $RDSubsidyRate^{PL101-239}$ makes the model directly analogous to a binary treatment/control setup where the treatment law is PL 101-239. Using only variation from PL 101-239 also implies I calculate the treatment variable with only variation from R&D tax credits and not variation from more general income tax deductions. Income tax deductions are applicable to other types of investments available to a firm. Changes in income tax deductions might elicit complementary/substitutable investments for R&D and would imply the response of R&D to changes in these more general tax deductions might be different than the response of R&D to R&D specific changes in the subsidy rate (i.e., R&D tax credits). However, calculating R&D subsidy rates with only variation from PL101-239 continues to suggest an elastic response of R&D to tax incentives (standard error) of 2.43 (1.12).[30] Table 5, column (4) uses $RDSubsidyRate^{PL101-239}$ as the key regressor and drops states that changed their R&D tax credits between 1990-1991 (Illinois and Massachusetts) to avoid confounding the effect of PL 101-239 with changes in state R&D tax credits around the same time period. These states might have endogenously responded to the large change in the federal R&D tax credit by enacting their own R&D tax incentives. However, dropping Illinois and Massachusetts has almost no effect on the estimates.

Finally, I run specifications with the R&D subsidy rate as an extension of the Hall and Jorgenson (1967) user cost of capital. Following Chirinko and Wilson (2008) and Wilson (2009), I form the user cost of R&D capital $RDUserCost$ as the relative R&D subsidy rate $RDSubsidyRate^{fed}$ to the subsidy rate of output $OutputSubsidyRate$, where output is a fully deductible expense that does not have an associated tax credit,[31] adjusted for depreciation δ of R&D and the discount rate r:

$$RDUserCost_{it} = \frac{RDSubsidyRate_{it}^{fed}}{OutputSubsidyRate_{it}}[r_t + \delta_t] \tag{5}$$

Rewriting equation (1) with the natural logarithm of the user cost as the key regressor yields:

$$\begin{aligned} RD_{it} &= RD_{it-l} + \varphi_i + \lambda_t + ln(r_t + \delta_t) + ln(RDSubsidyRate_{it}^{fed}) \\ &\quad - ln(OutputSubsidyRate_{it}) + X_{it}^{'}\beta + \varepsilon_{it} \end{aligned} \tag{6}$$

Under depreciation and discount rates that are uniform across states, the time dummies absorb $ln(r_t + \delta_t)$ so that equation (6) amounts to the original model with a new term for the subsidy rate of output, $ln(OutputSubsidyRate_{it})$. Including $ln(OutputSubsidyRate_{it})$ in the model continues to indicate an elastic response of R&D to tax incentives. For example, the specification in column (5) of Table 2 yields a R&D subsidy elasticity estimate (standard error) of 2.98 (1.17). The control

[30] Researchers may be concerned that firms anticipated PL 101-239, which was effective January 1, 1990 but passed on December 19, 1989. However, anticipation of PL 101-239 would bias the elasticity estimates toward zero. In 1989 the federal R&D tax credit was a credit amount for R&D over a 3-year moving average base of R&D. The moving average base created a disincentive for firms to claim the R&D tax credit as taking a credit in a given year would reduce the allowable credit for the next 3 years. PL 101-239 removed the moving average base amount and the opportunity cost of claiming the R&D tax credit. If firms anticipated this policy change in 1989, then more firms would have claimed the R&D tax credit in 1989, which would bias the estimate of the effect of PL 101-239 in 1990 toward zero.

[31] Specifically, I compute $OutputSubsidyRate$ with the model in Appendix A without the terms for R&D specific tax incentives.

variables have similar point estimates and the subsidy rate of output is insignificant at standard levels.[32]

4.3.3 Generalized Method of Moments and Bias-Corrected Least Squares Estimation

I now turn to the bias of the lagged dependent variable arising from the within estimator. When the within estimator is applied to a model with a lagged dependent variable and fixed effects, the coefficient on the lagged dependent variable is consistent but biased downward (Nickell, 1981). The consistency of the within estimator depends on the length of the time dimension. The specifications so far use the within estimator due to its favorable precision. However, to get a handle on the bias from the within estimator, I reestimate column (5) of Table 2 using some alternative unbiased estimators.

One solution to correct the potential bias is to instrument the lagged dependent variable. The dynamic panel data literature suggests instrumenting using lags or transformations of lags with GMM estimators, such as the Arellano and Bond (1991) or Blundell and Bond (1998) GMM estimators. Unfortunately, instrumenting leads to decreased precision. Consistency also depends on a large cross-sectional dimension (Kiviet, 1995). With a small cross-sectional dimension GMM estimators run into substantial finite-sample bias, particularly when more instruments are exploited (Everaert and Pozzi, 2007; Roodman, 2009).

Putting these concerns aside, I estimate specifications with the Blundell and Bond (1998) GMM estimator.[33] Table 6, columns (1) - (4) show the results from GMM estimation. Column (1) instruments the lagged dependent variable using its first two available lagged observations (RD_{it-4} and RD_{it-6}, since the data are biannual). Column (2) extends the instrument set to include up to ten available lagged observations. Columns (3) and (4) use instrument sets beginning with the second

[32]Calculating $OutputSubsidyRate$ by isolating only state-level tax variation from federal laws in the cost of output with the analogous definition from equation (3) gives similar results.

[33]The Blundell and Bond (1998) GMM estimator is designed to overcome the weak instruments problem of the Arellano and Bond (1991) GMM estimator with persistent data. I present results from the one-step estimator because the two-step estimator often generates erroneous results, such as a coefficient on the lagged dependent variable being far below the estimate from the within estimator (which is already downward biased). I transform the instrumenting equation using the orthogonal deviations transformation (Arellano and Bover, 1995) to maximize the sample size.

available lagged observation of the dependent variable to avoid first-order serial correlation of the error term, which would cause inconsistent estimation.[34]

As expected, GMM estimation generates results with less precision compared to the within estimator and are also somewhat sensitive to the choice of instruments. However, the point estimates still indicate an elastic response of R&D to tax incentives: the same story as the results from the within estimator. Among the GMM estimates column (4) generates the smallest response of R&D to tax incentives, but still implies a 1% increase in R&D tax incentives would lead to a 1.76% increase in R&D. In column (1), the coefficient on the lagged dependent variable is negative, suggesting finite-sample bias. However, for columns (2) - (4) the coefficients on the lagged dependent variable are similar to the main results in Table 2, suggesting the results from the within estimator are approximately unbiased.

As an additional check on the bias from the within estimator, I estimate specifications using the bias-corrected least squares estimator (LSDVC) of Bruno (2005a).[35] LSDVC estimators use the results from the within estimator and apply an analytical approximation of the expected bias to arrive at corrected estimates. The goal is to exploit the superior precision of the within estimator over GMM estimators and also derive unbiased estimates. The downsides of LSDVC estimators are the dependence on strict theoretical assumptions and standard errors that may lead to incorrect inference in small samples (Everaert and Pozzi, 2007).

Table 6, column (5) presents the results from this LSDVC estimator. The point estimate of the elasticity is slightly smaller at 1.63, but still larger than the average estimate from the existing literature. In unreported specifications using the endogenous R&D subsidy rate, $RDSubsidyRate$, instead of $RDSubsidyRate^{fed}$ this LSDVC estimator still yields estimates close to zero. Unfortunately, the precision of the LSDVC results is still poor, although the precision is better than the

[34] I present results using instrument sets starting with both the first and the second available lagged observation of the dependent variable because Arellano-Bond serial correlation tests occasionally support first-order serial correlation of the error term, but never second-order serial correlation.

[35] Bruno (2005a) proposes three separate corrections for the bias from the within estimator. I present results from Bruno (2005a)'s highest-order correction. The other two bias corrections give similar results. Simulation evidence from Bruno (2005b) indicates all three corrections usually give similar results, with the highest-order correction giving slightly more accurate estimates.

GMM results.

5 Conclusion

Policymakers form tax policies based on the state of the economy. This selection mechanism leads to endogeneity bias in regression models that attempt to estimate the effect of taxes on economic variables. To determine this endogeneity bias and the real effects of tax incentives, this paper estimates the elasticity of R&D with respect to R&D tax incentives.

This paper improves on previous studies by using identifying tax variation in state-level R&D tax incentives from changes in federal corporate tax laws. Because the federal government sets uniform national tax policies and is less attentive to idiosyncratic state-level economic conditions compared to state governments, this variation reduces concerns over biased estimates stemming from states selecting their own tax polices. This paper finds R&D is sensitive to tax incentives, with the average estimate indicating a 1% increase in R&D tax incentives would lead to a 2% increase in R&D expenditures.

This paper also estimates specifications with R&D subsidy rates calculated using tax variation from both state and federal laws. These models are similar to those from previous studies and should generate biased estimates due to states selecting their own R&D tax incentives. The models with endogenous tax variation in R&D subsidy rates lead to much smaller estimates of the elasticity of R&D with respect to tax incentives, with an average estimate of 0.5. The difference between the estimates from using uncorrected endogenous tax variation and only exogenous federal tax variation indicates serious attenuation bias from the endogenous tax variation. The direction of this bias suggests state lawmakers may be implementing tax incentives to deter economic downturns, which is consistent with Yang (2005); Romer and Romer (2010).

Several mechanisms may be contributing to the elastic response of R&D to tax incentives. Because of the state fixed effects and time dummies, the regression models identify coefficients based off of deviations from mean levels of R&D and R&D tax incentives. Increases in R&D for states that implement incentives and decreases in R&D for states that do not implement incentives would both contribute to the magnitude of the estimates.

A large elasticity could be due to low adjustment costs of R&D across state borders. There may be low adjustment costs because firms may relocate R&D between their establishments to maximize tax incentives. The presence of mobile R&D could be an incentive for states to engage in strategic competition of tax incentives. Depending on the slope of the reaction functions, strategic competition can lead to either too generous tax incentives (relative to the social optimum) or some states with generous incentives and others with minimal incentives (Brueckner and Saavedra, 2001; Brueckner, 2003; Decker and Wohar, 2007; Chirinko and Wilson, 2008, 2011).

The elasticity estimates could also be explained by firms raising their R&D levels in response to being offered tax incentives. This scenario seems particularly plausible in the presence of strong complementarities between the firm's investments or even strong complementarities between the firm's R&D projects. For example, suppose that R&D and non-R&D investment are complements. If the price of R&D is lowered by a tax incentive, then the firm will undertake additional non-R&D investment in response to the tax incentive. However, this additional non-R&D investment will incentivize the firm to take on additional R&D and potentially leads to a large response of R&D to tax incentives.

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A Appendix: R&D Subsidy Rate Model

This appendix provides details on computing the R&D subsidy rate in equation (2).

Let FTI denote federal taxable income, I indicate income, k be the R&D credit rate, subscript i indicate a state-level variable, subscript f indicate a federal-level variable, subscript t be time, χ be the proportion of the federal R&D credit the IRC disallows as a deduction, RD^{fedCR} symbolize the amount of R&D claimed for the federal R&D credit, and RD^{tot} be total R&D expenditures. Because the federal government allows both state corporate income taxes and R&D expenditures as deductions from FTI,[36] the expression for FTI follows (7):

$$FTI_{it} = I_{it} - ST_{it} - RD_{it}^{tot} + \chi_{ft} k_{ft} RD_{it}^{fedCR} \tag{7}$$

Federal taxes, FT, are simply the corporate income tax rate τ times FTI, less the federal R&D credit. The expression for FT is:

$$FT_{it} = FTI_{it} \tau_{ft} - k_{ft} RD_{it}^{fedCR} \tag{8}$$

[36] The federal government has allowed these deductions since prior to the beginning of the R&D data from the National Science Foundation.

After a transitional period from 1981-1982, the federal R&D credit was a percentage of QREs over the greater of 50% of a firm's QREs or a 3-year moving average of QREs. Assuming firms are not constrained by the base,[37] the 3-year moving average makes $RD_{it}^{fedCR} = RD_{it}^{tot} - \frac{1}{3}\sum_{m=1}^{3} RD_{it-m}^{tot}$ and the expression for FT:

$$FT_{it} = FTI_{it}\tau_{ft} - k_{ft}(RD_{it}^{tot} - \frac{1}{3}\sum_{m=1}^{3} RD_{it-m}^{tot}) \tag{9}$$

Since 1990 the federal R&D credit is a percentage of QREs above a fixed base instead of a 3-year moving average base. With QREs unconstrained by this fixed base, $RD_{it}^{fedCR} = RD_{it}^{tot}$ and:

$$FT_{it} = FTI_{it}\tau_{ft} - k_{ft}RD_{it}^{tot} \tag{10}$$

Comparing equations (9) and (10), the 3-year moving average formulation directly increases federal taxes paid by $k_{ft}\frac{1}{3}\sum_{m=1}^{3} RD_{it-m}^{tot}$. There are also indirect effects on the federal tax burden because federal taxes depend on state taxes and vice versa.

In computing state taxable income STI, states generally start with federal taxable income or income from all sources, then add state-specific modifications to form state taxable income. Let ξ be the proportion of state i's income taxes required to be added back to federal taxable income, ϕ be the proportion of state i's federal taxes deductible from state taxable income, ω indicate the proportion of state i's R&D credit recaptured, α represent the proportion of federal recaptured credit allowed as a state deduction, and $RD^{stateCR}$ be the amount of R&D claimed for state i's R&D credit. The expression for STI is:

$$STI_{it} = FTI_{it} + \xi_{it}ST_{it} - \phi_{it}FT_{it} + \omega_{it}k_{it}RD_{it}^{stateCR} - \alpha_{it}\chi_{ft}k_{ft}RD_{it}^{fedCR} \tag{11}$$

which gives way to a state tax burden ST of:

[37] Hall (1993) notes the majority of R&D firms have R&D levels above their base amounts. Mamuneas and Nadiri (1996) and Wilson (2009) also employ the assumption of R&D levels over the base amount.

$$ST_{it} = STI_{it}\tau_{it} - k_{it}RD_{it}^{stateCR} \tag{12}$$

For the corporate income tax rate τ I follow Shea (1993) and Wilson (2009) and use the top-tier corporate rates. For the states in the R&D sample, 2/3 have a single corporate income tax rate for the entire sample period. The remaining 1/3 levy the highest-tier corporate income tax at very low levels of taxable income. For example, among states with graduated rates, in 2000 the average highest tier was only one hundred and forty six thousand dollars of taxable income.

States generally compute their R&D credits in one of three ways: 1) a non-incremental credit, where the credit is calculated as a percentage of QREs, 2) a credit for QREs above a fixed base (following the federal credit formula in place since 1990), or 3) a credit for QREs above a M-year moving average of QREs.[38] With QREs above the fixed base or for the non-incremental credit case, $RD_{it}^{stateCR} = RD_{it}^{tot}$. For the years a state employed a M-year moving average base, $RD_{it}^{stateCR} = RD_{it}^{tot} - \frac{1}{M}\sum_{m=1}^{M} RD_{it-m}^{tot}$.

The federal R&D credit and approximately 2/3 of states use a single R&D credit rate k for all applicable R&D expenditures (i.e., no credit tiers). The remaining 1/3 of states have tiered credit amounts and are divided between offering higher credit amounts for higher tiers of R&D expenditures and offering lower credit amounts for higher tiers of R&D expenditures. I report results using the highest tier of R&D expenditures as large corporations, which constitute the bulk of R&D spending, are likely to be in the top tier. I also check the results with the median tier, which gives similar results.

These formulations can accompany both states that base STI on FTI and those that start with income from all sources in calculating STI. To see this point, substituting the expression for FTI

[38] In the R&D sample, Connecticut and Maryland are exceptions. Connecticut has had two R&D credits since 1993: a 20% credit for QREs over a 1-year moving average (Connecticut General Statutes § 12-217j) and a level credit for QREs below the moving average (Connecticut General Statutes § 12-217n). The level credit is tiered at 1%, 2%, 4%, and 6% based on the firm's level of QREs. In addition, the firm may only take 1/3 of the level credit in the tax year that it incurs the R&D expenditures. The remainder must be deferred until the next tax period. Transitional provisions were in place from 1993-1994. Like Connecticut, Maryland has two R&D credits that work in tandem and have been in place since 2000 (Maryland Tax-General Code § 10-721). The first component is a 10% credit for QREs above a 4-year moving average of QREs. The second component is a 3% credit for QREs that do not qualify for the 10% credit component.

in equation (7) into equation (11) and setting $\alpha_{it} = 1$ (since states that base STI on income from all sources do not consider the recapture provisions of the federal R&D credit) yields:

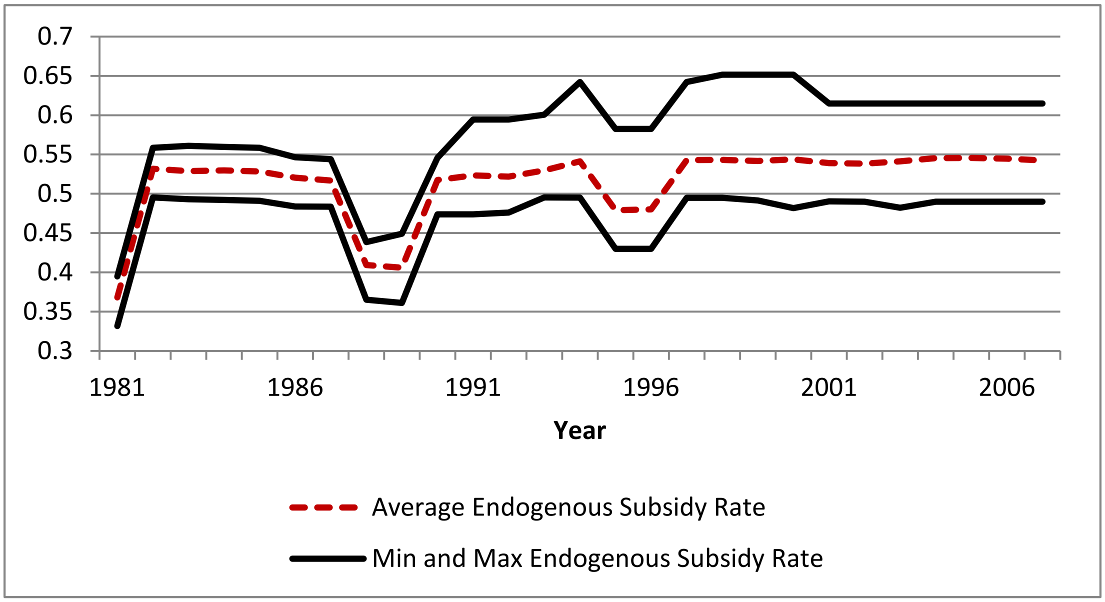
$$\begin{aligned}
STI_{it} &= I_{it} - ST_{it} - RD_{it}^{tot} + \chi_{ft} k_{ft} RD_{it}^{fedCR} + \xi_{it} ST_{it} - \phi_{it} FT_{it} \\
&\quad + \omega_{it} k_{it} RD_{it}^{stateCR} - \alpha_{it} \chi_{ft} k_{ft} RD_{it}^{fedCR} \qquad (13) \\
&= I_{it} + ST_{it}(\xi_{it} - 1) - RD_{it}^{tot} + \chi_{ft} k_{ft} RD_{it}^{fedCR}(1 - \alpha_{it}) - \phi_{it} FT_{it} + \omega_{it} k_{it} RD_{it}^{stateCR} \\
&= I_{it} + ST_{it}(\xi_{it} - 1) - RD_{it}^{tot} - \phi_{it} FT_{it} + \omega_{it} k_{it} RD_{it}^{stateCR}
\end{aligned}$$

which is a sufficiently generic expression for STI for states that use income from all sources as a starting point in their STI computation. For positive taxable income, solving the system of equations depicting FTI, FT, STI, ST, and differentiating with respect to total R&D expenditures RD_{it}^{tot} (the choice variable) yields the expression for the R&D subsidy rate in equation (2).

Computing the discounted changes in taxes for all future periods requires assumptions about how firms form expectations about future tax law. Because the tax data are available at a higher frequency (annually) than the R&D data are (biannually), minor changes to the timing of forming expectations in the tax data still give similar results. Following Romer and Romer (2010), I treat simple extensions of R&D credits as anticipated. I also treat state IRC conformity updates as anticipated. Extensions to R&D credits, which are almost universally enacted on a temporary basis with built-in expiration dates (sunset provisions), are extremely common. In the R&D sample, only one state (Illinois) allowed its R&D credit to lapse for a year before reactivating its R&D credit. Similarly, most state legislatures tend to enact IRC conformity updates during each legislative session.

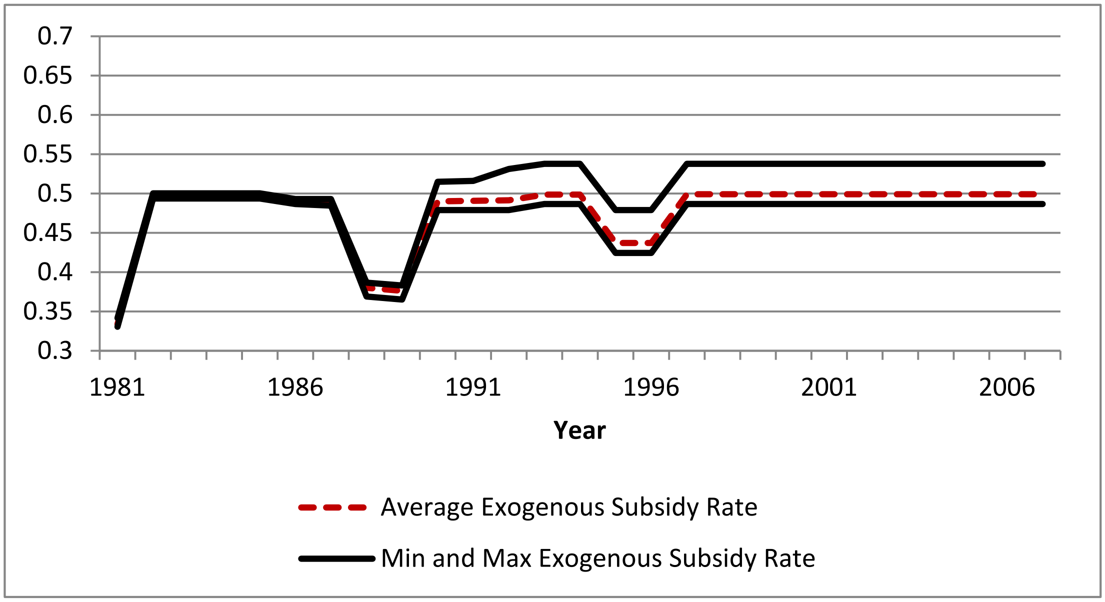
For other tax laws, I assume firms in year t have access to laws in effect in year t, form expectations based on laws in effect in year t, and take into account the laws that will change taxes in future periods. To my knowledge, no hard data exist on the precise timing of firm's expectations of future taxes. However, large corporations with dedicated accounting resources should be anticipating future tax changes that will occur due to laws on the books.

Figure 1: R&D Subsidy Rate - State and Federal Variation



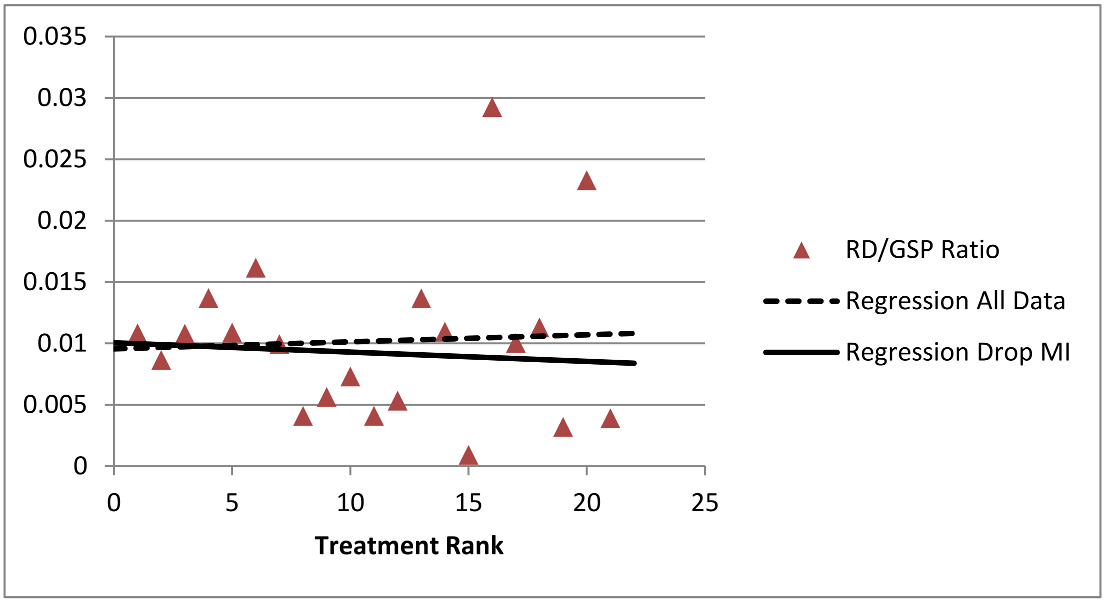
This figure plots summary statistics of state-level R&D subsidy rates, calculated using variation from both state and federal laws, over time.

Figure 2: R&D Subsidy Rate - Only Federal Variation



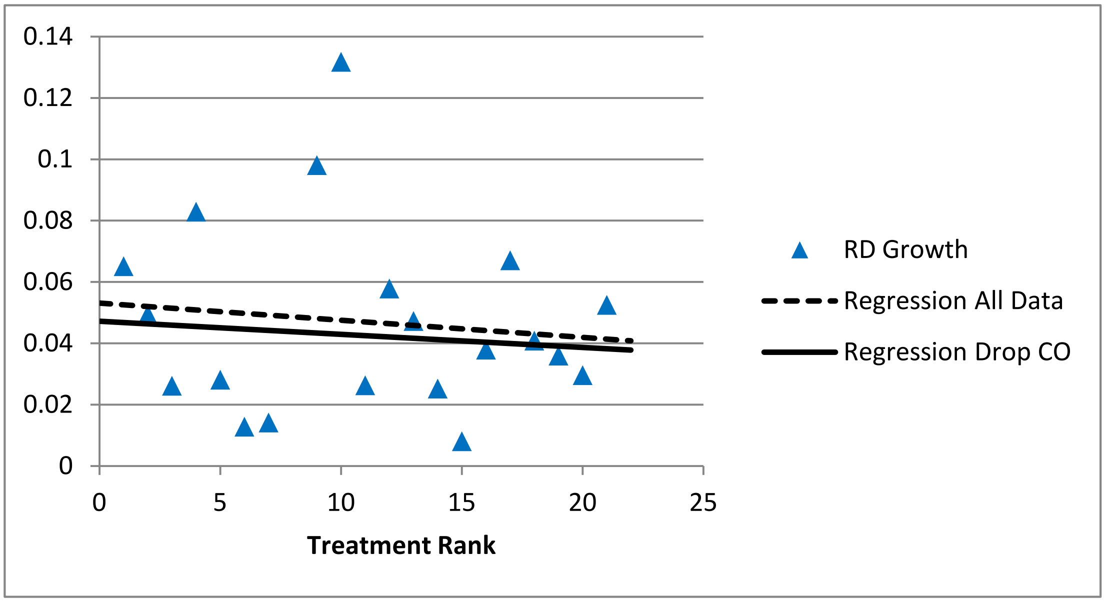
This figure plots summary statistics of state-level R&D subsidy rates, calculated using variation from only federal laws, over time.

Figure 3: R&D Intensity Prior to Federal R&D Credit - Exogenous R&D Subsidy Rate



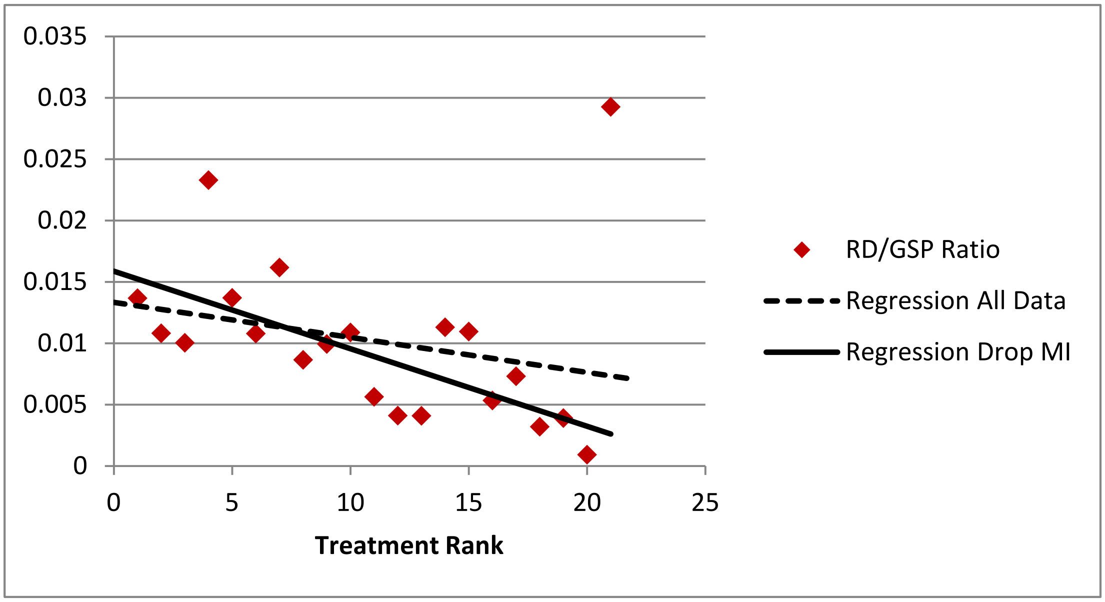
This figure plots pre-treatment state R&D intensity, measured as state R&D/GSP ratio, vs. state treatment rank. This figure ranks states based on the average value of R&D tax incentives over 1981-2007 using only variation from federal laws in state-level R&D tax incentives. Higher ranks indicate more generous incentives. The dashed line is a regression of R&D/GSP on treatment rank using all data. The solid line is the same regression dropping Michigan. The correlation between R&D intensity and rank is -0.05 (0.09 excluding the outlier Michigan).

Figure 4: Mean R&D Growth Prior to Federal R&D Credit - Exogenous R&D Subsidy Rate



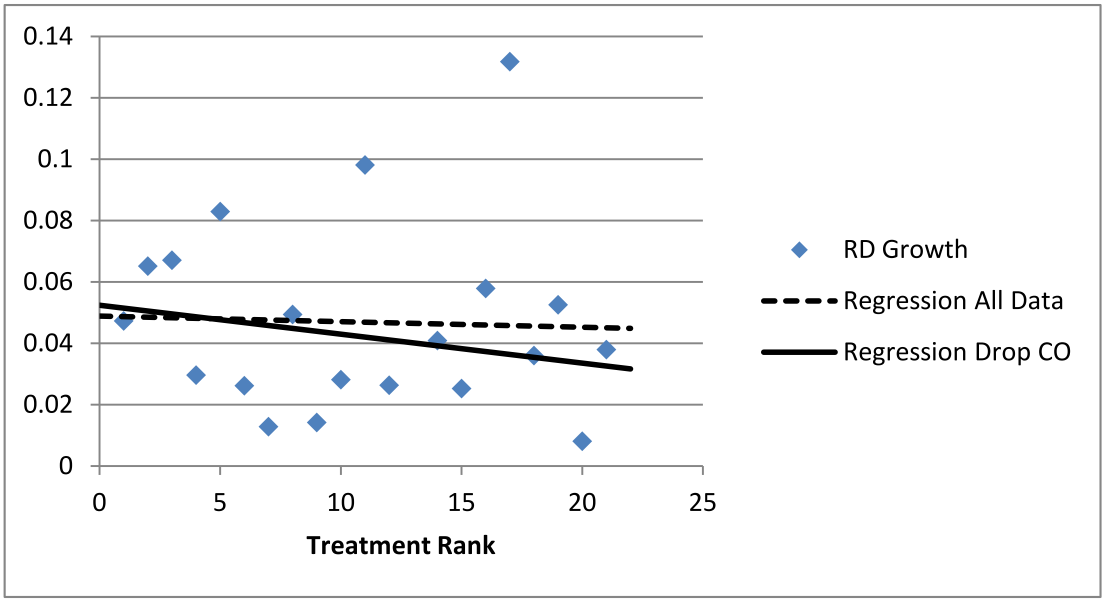
This figure plots average pre-treatment state R&D growth vs. state treatment rank. This figure ranks states based on the average value of R&D tax incentives over 1981-2007 using only variation from federal laws in state-level R&D tax incentives. Higher ranks indicate more generous incentives. The dashed line is a regression of R&D growth on treatment rank using all data. The solid line is the same regression dropping Colorado. The correlation between R&D growth and rank is 0.12 (0.11 excluding the outlier Colorado).

Figure 5: R&D Intensity Prior to Federal R&D Credit - Endogenous R&D Subsidy Rate



This figure plots pre-treatment state R&D intensity, measured as state R&D/GSP ratio, vs. state treatment rank. This figure ranks states based on the average value of R&D tax incentives over 1981-2007 using variation from both state and federal laws in state-level R&D tax incentives. Higher ranks indicate more generous incentives. The dashed line is a regression of R&D/GSP on treatment rank using all data. The solid line is the same regression dropping Michigan. The correlation between R&D intensity and rank is 0.27 (0.71 excluding the outlier Michigan).

Figure 6: Mean R&D Growth Prior to Federal R&D Credit - Endogenous R&D Subsidy Rate



This figure plots average pre-treatment state R&D growth vs. state treatment rank. This figure ranks states based on the average value of R&D tax incentives over 1981-2007 using variation from both state and federal laws in state-level R&D tax incentives. Higher ranks indicate more generous incentives. The dashed line is a regression of R&D growth on treatment rank using all data. The solid line is the same regression dropping Colorado. The correlation between R&D growth and rank is 0.04 (0.25 excluding the outlier Colorado).

Table 1: Federal Laws Affecting R&D Subsidy Rates

Public Law	Tax Code Change	Effective Year
97-34	R&D Credit Implemented at 25%	1981
99-514	R&D Credit Reduced to 20%	1986
	Corporate Income Tax Reduced to 34%	1987/1988
100-647	R&D Credit Recapture Increased to 50%	1989
101-239	R&D Credit Recapture Increased to 100%	1990
	R&D Credit Base Computation Changed	1990
103-66	Corporate Income Tax Increased to 35%	1993
104-188	R&D Credit Renewed After Expiration	1996

Table 2: Exogenous R&D Subsidy Rate From Federal Laws Indicates Elastic Response

Dependent Variable: Company-Financed R&D					
	(1)	(2)	(3)	(4)	(5)
$RDSubsidyRate_{it}^{fed}$	4.07	4.37	2.63	2.85	2.96
	(2.33)*	(2.66)*	(1.00)***	(1.02)***	(1.11)***
RD_{it-2}			0.52	0.46	0.48
			(0.11)***	(0.08)***	(0.10)***
GSP_{it}				0.91	
				(0.18)***	
$Federal\ RD_{it-2}$		0.36		0.14	0.18
		(0.11)***		(0.06)**	(0.06)***
$Academic\ RD_{it}$		0.16		-0.39	-0.13
		(0.32)		(0.22)*	(0.21)
$Unemployment\ Rate_{it}$		2.84		0.62	0.89
		(2.69)		(1.81)	(1.74)
State Fixed Effects	X	X	X	X	X
Time Dummies	X	X	X	X	X
Observations	226	226	206	206	206

The key regressor $RDSubsidyRate^{fed}$ is the R&D subsidy rate calculated using only changes from federal laws. This table reports coefficients as elasticities except for the unemployment rate, which is a semielasticity. Clustered standard errors by state in parentheses. *, **, ***: significant at 10%, 5%, 1%.

Table 3: R&D Subsidy Rate Comparable to Previous Studies Indicates Inelastic Response

Dependent Variable: Company-Financed R&D					
	(1)	(2)	(3)	(4)	(5)
$RDSubsidyRate_{it}$	0.84	0.95	0.46	0.24	0.55
	(1.00)	(1.11)	(0.49)	(0.53)	(0.52)
RD_{it-2}			0.53	0.49	0.50
			(0.11)***	(0.08)***	(0.10)***
GSP_{it}				0.89	
				(0.20)***	
$Federal\ RD_{it-2}$		0.37		0.12	0.16
		(0.11)***		(0.07)*	(0.06)***
$Academic\ RD_{it}$		0.08		-0.44	-0.20
		(0.30)		(0.21)**	(0.20)
$Unemployment\ Rate_{it}$		2.31		0.01	0.93
		(2.87)		(1.76)	(1.72)
State Fixed Effects	X	X	X	X	X
Time Dummies	X	X	X	X	X
Observations	226	226	206	206	206

The key regressor $RDSubsidyRate^{fed}$ is the R&D subsidy rate calculated using changes in both state and federal laws. This table reports coefficients as elasticities except for the unemployment rate, which is a semielasticity. Clustered standard errors by state in parentheses. *, **, ***: significant at 10%, 5%, 1%.

Table 4: Sample Modifications

Dependent Variable: Company-Financed R&D				
	(1)	(2)	(3)	(4)
$RDSubsidyRate_{it}^{fed}$	2.20	2.62	4.70	2.76
	(0.97)**	(1.33)**	(1.31)***	(1.01)***
RD_{it-2}	0.56	0.40	0.21	0.53
	(0.08)***	(0.15)**	(0.05)***	(0.09)***
$Federal\ RD_{it-2}$	0.20	0.21	0.22	0.16
	(0.06)***	(0.07)***	(0.08)***	(0.06)***
$Academic\ RD_{it}$	-0.20	-0.25	0.21	-0.18
	(0.18)	(0.19)	(0.28)	(0.19)
$Unemployment\ Rate_{it}$	-0.06	2.98	-0.73	0.93
	(1.65)	(2.42)	(2.24)	(1.62)
State Fixed Effects	X	X	X	X
Time Dummies	X	X	X	X
Observations	202	199	143	287
Sample Modification	Trim Outliers	Post-1984	Pre-2000	Annual Data Post-1997

The key regressor $RDSubsidyRate^{fed}$ is the R&D subsidy rate calculated using only changes from federal laws. This table reports coefficients as elasticities except for the unemployment rate, which is a semielasticity. Clustered standard errors by state in parentheses. *, **, ***: significant at 10%, 5%, 1%.

Table 5: Alternative Specifications

Dependent Variable: Company-Financed R&D				
	(1)	(2)	(3)	(4)
$RDSubsidyRate_{it}^{fed}$	3.36	5.71		
	(0.93)***	(1.52)***		
$RDSubsidyRate_{it}^{PL101-239}$			2.43	2.29
			(1.12)**	(1.16)*
$RD(Biannual)_{it-2}$	0.56			
	(0.08)***			
$RD(Annual)_{it-1}$	0.50			
	(0.07)***			
RD_{it-2}			0.48	0.49
			(0.10)***	(0.10)***
RD_{it-4}		0.25		
		(0.11)**		
$Federal\ RD_{it-2}$	0.11	0.28	0.17	0.16
	(0.05)*	(0.07)***	(0.06)***	(0.07)**
$Academic\ RD_{it}$	-0.15	0.02	-0.15	-0.18
	(0.15)	(0.34)	(0.21)	(0.25)
$Unemployment\ Rate_{it}$	0.49	2.18	1.15	1.28
	(1.60)	(1.77)	(1.71)	(1.84)
State Fixed Effects	X	X	X	X
Time Dummies	X	X	X	X
Observations	306	202	206	188
Sample Modification	Annual Data Post-1997	None	None	Drop IL, MA

The key regressor in columns (1) and (2), $RDSubsidyRate^{fed}$, is the R&D subsidy rate calculated using only changes from federal laws. Column (1) uses all available data and divides the coefficient on the lagged dependent variable into separate coefficients for the biannual (1981-1996) and annual (1997-2006) R&D data periods. Columns (2) - (4) use the default biannual data structure over the entire sample. The key regressor in columns (3) and (4), $RDSubsidyRate^{PL101-239}$, only uses variation from Public Law 101-239 in R&D subsidy rates. Column (4) drops Illinois and Massachusetts due to contemporaneous changes in state R&D credits with Public Law 101-239. This table reports coefficients as elasticities except for the unemployment rate, which is a semielasticity. Clustered standard errors by state in parentheses. *, **, ***: significant at 10%, 5%, 1%.

Table 6: Alternative Estimators

Dependent Variable: Company-Financed R&D					
	(1)	(2)	(3)	(4)	(5)
$RDSubsidyRate_{it}^{fed}$	3.93	1.87	2.07	1.76	1.63
	(7.15)	(2.68)	(3.77)	(2.75)	(2.13)
RD_{it-2}	-0.31	0.54	0.46	0.58	0.71
	(2.62)	(0.27)*	(0.73)	(0.34)*	(0.08)***
$Federal\ RD_{it-2}$	-0.33	-0.10	-0.12	-0.09	0.14
	(0.75)	(0.15)	(0.20)	(0.14)	(0.08)*
$Academic\ RD_{it}$	1.58	0.51	0.61	0.45	-0.26
	(3.42)	(0.43)	(0.90)	(0.42)	(0.27)
$Unemployment\ Rate_{it}$	12.73	5.42	6.10	5.07	0.97
	(18.78)	(4.95)	(8.60)	(6.11)	(2.55)
State Fixed Effects	X	X	X	X	X
Time Dummies	X	X	X	X	X
Observations	206	206	206	206	206
Estimator	GMM	GMM	GMM	GMM	LSDVC
Instrument Lags	4-6	4-20	6-8	6-20	N/A
Instrument Count	2	9	2	8	N/A

The key regressor $RDSubsidyRate^{fed}$ is the R&D subsidy rate calculated using only changes from federal laws. This table reports coefficients as elasticities except for the unemployment rate, which is a semielasticity. GMM columns use the one-step Blundell and Bond (1998) generalized method of moments estimator to instrument RD_{it-2} and apply the forward orthogonal deviations transformation (Arellano and Bover, 1995) to the instrumenting equation. Clustered standard errors by state in parentheses. The LSDVC column uses the highest-order bias-corrected least squares estimator of Bruno (2005a). Bootstrapped standard errors following Bruno (2005a,b) with 1000 replications in parentheses. *, **, ***: significant at 10%, 5%, 1%.