Tax Policy Endogeneity: Evidence from R&D Tax Credits

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Abstract

Because policymakers may consider the state of the economy when setting taxes, endogeneity bias can arise in regression models that estimate relationships between economic variables and taxes. This paper quantifies the policy endogeneity bias and estimates the effect of research and development (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 affect state-level R&D tax incentives because of the simultaneity of state and federal corporate taxes. With this exogenous variation, my preferred estimates indicate that a 1% increase in R&D tax incentives leads to a 2.8-3.8% increase in R&D. Alternatively, estimates that ignore endogenously determined policies indicate that a 1% increase in R&D tax incentives leads to a 0.4-0.7% increase in R&D. These results are consistent with tax policies that are implemented before an economic downturn.

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. For example, the United States has repeatedly adjusted its corporate income tax rate and built up corporate income tax credits to attain favorable economic outcomes (Goolsbee, 1998). These tax incentives are a cost for the government. The economic rationale behind tax incentives is that they correct for market failures. For example, in the case of the research and development (R&D) tax credit, because of moral hazard in the financing market for R&D projects and the positive technological spillovers from R&D, the level of R&D in the economy without government intervention is below the efficient level (Arrow, 1962; Griliches, 1992). Therefore, a tax incentive to promote additional spending on R&D would help move the economy toward the efficient level of R&D.

Policymakers and many economists hold a deep-rooted belief about the efficacy of fiscal policy. A necessary condition to evaluate whether tax incentives are an effective use of revenues is to estimate whether tax incentives promote their targeted economic activity. Unfortunately, economic research estimating the real effects of tax incentives must overcome the inherent endogeneity of tax policies.[1] Among other factors, the state of the economy affects tax policies.

Endogeneity bias may lead regression models to either overestimate or underestimate the efficacy of tax policies. For example, suppose that the true effect of tax policies on the economy is zero and that governments change tax incentives while the economy is in a trough. This timing of the tax policies could come about with or without the government actively using taxes to respond to the trough. In this scenario, as the true effect of the tax policies is zero, a revitalized economy after policymakers implement tax incentives could simply be mean reversion, trend reversion, or both. A difference-in-differences approach that compares aggregate activity before and after the tax policy changes and ignores the endogenously determined timing of the policies would attribute mean or trend reversion to an effect of tax policies on the economy. Regression estimates would

[1] Previous studies that investigate the effect of tax policies include 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).

be biased toward finding an effect.

As an alternative scenario, suppose instead that tax incentives affect the economy and that, in terms of timing, tax incentives change just prior to when a downturn would occur without the tax incentives. As in the previous scenario, this timing of tax incentives could be with or without government foresight of the impending downturn. Such a downturn could be a general economic downturn caused by business cycle fluctuations or a large firm that is planning on halting operations to relocate to a different geographic region. If lawmakers change tax policies just prior to when a downturn would occur, and the true effect was that the tax incentives prevented the downturn, then econometricians would observe no effect of the tax policies when the true effect was positive. In this second case, the bias in a regression model would be toward finding no effect (also called attenuation bias).

To quantify the endogeneity bias driven by the timing of tax policies and to evaluate the efficacy of a particular targeted tax incentive traditionally supported by the market failures argument, this paper estimates the elasticity of 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 an exogenous source of variation in state-level R&D tax incentives: variation driven by changes in federal corporate tax laws. State policymakers give special attention to their own state's economic conditions when tailoring their state-level tax policies. However, the federal government arguably pays less attention to state-level conditions when it forms 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 mitigates endogeneity concerns and may generate unbiased estimates.

In addition, when a federal tax law changes, preexisting state tax laws determine the federal law's effect across states. Because these preexisting state laws differ by state, changes in federal corporate tax laws have different effects on state-level R&D tax incentives across states. This feature of state tax codes allows this paper to disentangle the effects of federal tax policies from those of other macroeconomic shocks.

The general identification strategy of using federal laws for policy variation across states has been used in other ways, such as analyzing minimum wages (Card, 1992). I follow the personal income tax literature to isolate the exogenous variation in state-level R&D tax incentives driven by federal corporate tax laws (Gruber and Saez, 2002). In the literature on R&D tax incentives, this paper is closest to Wilson (2009).[2]

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. My preferred estimates indicate that if governments were to increase R&D tax incentives by 1%, then R&D would increase by 2.8-3.8%.

My estimates are large relative to results from the previous literature on R&D tax incentives. Hall and Van Reenen (2000), Table 2, reviews studies of U.S. data and suggests that existing research finds an average elasticity of 1.0 with a range of [0, 1.6]. To be comparable with previous studies, this paper also estimates models using corporate tax variation from both state and federal laws. These models should give biased estimates because states choose their tax incentives. Models with corporate tax variation from both state and federal laws give estimates consistent with existing literature in the range of [0.4, 0.7], a statistically significant difference. A comparison of the estimates using exogenous federal law variation with estimates using endogenous state law variation suggests serious bias toward finding that tax incentives are ineffective when ignoring the endogenous determination of tax policies, which is consistent with Yang (2005); Romer and Romer (2010).[3] This attenuation bias supports the story that tax incentives offset future economic downturns, either because policymakers have foresight about downturns or because of fortunate timing of the taxes.

[2]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). The main contribution over Wilson (2009) is that I abandon the assumption that state-level R&D tax policies are exogenous. I discuss other differences in the results section.

[3]Yang (2005) simulates growth models. The paper shows that calibrated models that omit preemptive tax policies are misspecified. Romer and Romer (2010) use narrative information on federal taxes to separate endogenously determined taxes from exogenously determined taxes. With vector autoregressions, Romer and Romer (2010) find the endogenous tax variation leads to underestimates of the impact of taxes on the economy.

2 Data and Estimation

In order to quantify the effect of R&D tax incentives on R&D expenditures, I estimate the following accelerator-type model that takes into account partial adjustment of R&D expenditures and allows for other macroeconomic shocks:

$$ln(RD_{it}) = \pi ln(RD_{it-l}) + \varphi_i + \lambda_t + \gamma ln(RDTaxIncentiveRate_{it}) + ln(X'_{it})\beta + \varepsilon_{it} \tag{1}$$

where subscript i represents a state, subscript t is time, $ln()$ is the natural log operator, X is a matrix of controls, and the key regressor, $RDTaxIncentiveRate$, is the proportion of R&D that the government pays for through tax incentives. This model is analogous to the panel data models of Bloom, Griffith, and Van Reenen (2002); Wilson (2009). With state fixed-effects φ and time dummies λ, applying ordinary least squares (OLS) to equation (1) amounts to using the standard within estimator.

The primary source of data on state corporate tax policies that I use to construct state-level R&D tax incentive rates consists of the volumes of laws that each state passes in a given year, called state session laws.[4] 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). Because of the detailed nature of the session law data, I am able to construct a more refined measure of $RDTaxIncentiveRate$ than used by existing studies. Appendix B describes the computation and the assumptions behind $RDTaxIncentiveRate$ in detail.

The dependent variable, RD, is state-year company-financed R&D expenditures from 1981-2006. This variable excludes federally-financed R&D, income taxes, and interest on tax. These data come from the Survey of Industrial Research and Development (SIRD), sponsored by the National Science Foundation (NSF).[5] These data are biennial (odd year) observations of company-

[4]Session laws are printed by each state and are accessible digitally through HeinOnline.

[5]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 incentives (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

financed R&D up to 1997 and annual observations from 1997-2006. I focus on spending for four reasons: 1) a tax incentive's first-order effect is on spending, 2) other measures of innovative output are noisy, 3) identification of the causal effect of tax incentives on innovative output is even more problematic given the lags in innovation, and 4) the additional projects that the firm would undertake with more generous tax incentives likely have a different marginal private and social products than projects that would be undertaken without tax incentives.

The NSF censors observations when the disclosure of a state's R&D in a particular year would reveal information about an individual firm's R&D. This censoring tends to eliminate observations from low-R&D states and states where R&D is concentrated among a few firms. Therefore, I analyze the 21 high-R&D states where I observe R&D expenditures consistently without imputation in the 1980s and 1990s. Observing states in the 1980s and 1990s is necessary because federal R&D tax incentive laws were passed in the 1980s and 1990s.[6]

Because I observe states on a yearly basis, 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.[7] 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 the acquired public funds for private funds.[8] I control for federal funding

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.

[6]For the period from 2000-2006 the NSF provides imputed observations of R&D for states that are not in the data for the 1980s and 1990s. For this paper, I cannot use the states that appear in the sample after 2000 due to imputation by the NSF because the variation I use for identification is in the 1980s and 1990s. The states in my sample are the 21 with few or no imputed observations: 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 makes up 80-90% of R&D after 2000. Two percent of data from this sample of states are imputed by the NSF. Dropping the imputed observations has no effect on the results.

[7]See Barlevy (2007), Ouyang (2011), or Chang (2013) for research into macroeconomic determinants of R&D.

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

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.[9] 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 gross domestic product deflator.[10]

I estimate specifications both with and without the lagged dependent variable. The lagged dependent variable captures the adjustment costs of R&D. To incorporate this lag, I impose a biennial structure over the entire sample period and use the first available lag of R&D ($t-2$). Imposing a biennial structure on the data drops observations when R&D data are available on an annual basis, but it has no effect on the results.[11]

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, I have data with a time dimension similar to Bloom, Griffith, and Van Reenen (2002); Wilson (2009) of between 12-19 observations, which should reduce the bias from the within estimator.[12]

3 R&D Tax Incentive Rates

This section describes the calculation of state-level R&D tax incentive rates and shows pre-treatment plots that support this paper's identification strategy.

[9] 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.

[10] 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.

[11] Appendix A conducts a robustness check that uses the annual data from 1997-2006.

[12] As a robustness check, I also attempt to correct for potential Nickell bias with both the one-step and two-step Blundell and Bond (1998) generalized method of moments (GMM) estimators, transforming the instrumenting equation using the orthogonal deviations transformation (Arellano and Bover, 1995) to maximize the sample size, and I also perform the three bias-corrections of the bias-corrected least squares (LSDVC) estimators of Bruno (2005a,b). Unfortunately, both the Blundell and Bond (1998) and Bruno (2005a,b) LSDVC estimators generate imprecise estimates.

3.1 Computation of R&D Tax Incentive 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.[13] The decrease in tax liability from a marginal dollar of R&D is the government's R&D tax incentive 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 tax incentive rate for the representative firm,[14] $RDTaxIncentiveRate$, as:

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

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.[15] I set the discount rate as the dividend-to-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).[16,17] To construct $RDTaxIncentiveRate$, I use only assumptions that are either the same as or weaker than existing studies. Appendix B describes the computation and the assumptions in detail.

Equation (2) incorporates tax variation from both state and federal laws.[18,19] The variation

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

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

[15] 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 an M-year moving-average base of previous R&D expenditures. This calculation implies that taking R&D tax credits in period t can affect the ability of a firm to take a credit in future periods. The model takes into account future changes in taxes only when they would be affected by a moving-average base, which is at most four years into the future.

[16] 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.

[17] 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 that 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.

[18] The tax rates described by tax laws are called statutory rates.

[19] At the end of my sample in 2006, the average effective state R&D tax incentive is worth about one-half of the federal R&D tax incentive. Therefore, firms have a strong incentive to take into account state-level R&D tax incentives.

from state laws is likely endogenous to R&D expenditures at the state level. This endogeneity might arise because state policymakers may set R&D tax incentives as a function of unobserved state economic or political conditions. For example, if a firm threatens the state legislature that it will close down its operations and move to a different state, then the threat of relocation by the firm may cause the legislature to pass a tax incentive policy that benefits the firm.

A large body of research from economists and political scientists finds that observed state characteristics influence tax policy changes: tax policies are not randomly changed. These state characteristics range from business cycle measures, such as the unemployment rate, to political variables, such as balanced budget rules.[20] Specific to R&D tax incentives, the generosity of state-level R&D tax incentives may be affected by politicians' concerns over revenue loss (Kim, 2010). A state's initial adoption of a R&D tax credit is also correlated with observed state-level economic conditions (Miller and Richard, 2010).

Of course, if observable characteristics were all that drive tax policy changes, then a model could control for these observables. The concern is that *unobservable* variables influence tax policies. A direct test for unobservable characteristics that affect tax polices is impossible.[21] However, an abundance of anecdotal evidence documents that state lawmakers respond to state economic conditions when formulating tax policies. Many of these conditions are probably unobservable to econometricians. 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 create jobs, we have to cut taxes... I ask this new legislature to create

[20] Examples of studies that research how state characteristics affect taxes include Berry and Berry (1992, 1994) for electoral cycles, Stratmann (1992, 1995) for strategic coalitions among politicians, Poterba (1994) for balanced budget rules, Crain and Muris (1995); Gilligan and Matsusaka (2001) for legislative structure, Swank and Steinmo (2002) for unemployment and capital mobility, and Aidt and Jensen (2009) for fiscal spending pressure and tax collection costs.

[21] By extension, trying to infer policy endogeneity based on corrections between observable variables and the policy is not a meaningful exercise.

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."

In addition to explicit economic conditions, passing bills through informal political coalitions is another unobserved variable that affects the passage of tax policies.[22] For example, a lawmaker may vote to pass a R&D tax credit tax bill for high-tech companies with the sole purpose of securing another vote for a bill on highway construction. To the extent that firms take into account the state's provision of public goods when making their R&D decisions, this unobserved coalition would be correlated with both R&D expenditures and R&D tax policies, biasing regression estimates. Furthermore, these coalitions between politicians are commonplace (Tullock, 1959).

To get a measure of R&D tax incentive rates free from the bias that arises because states choose their own R&D tax incentives, I isolate the variation in equation (2) from only federal laws. Table 1 lists the laws this paper uses for federally-driven variation in state-level R&D tax incentive 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. However, the federal government sets uniform national R&D tax policies and is less attentive to idiosyncratic state conditions.

Let $\Delta RDTaxIncentiveRate^{fed}$ be changes in the R&D tax incentive rate driven by federal laws. The expression for $\Delta RDTaxIncentiveRate^{fed}$ is as follows:

$$\Delta RDTaxIncentiveRate_{it}^{fed} = RDTaxIncentiveRate(ST_{it-1}, FT_{it}) - RDTaxIncentiveRate(ST_{it-1}, FT_{it-1}) \tag{3}$$

which is the change in the R&D tax incentive 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 tax incentives is analogous to the Gruber and Saez (2002) method of constructing exogenous personal

[22] This practice is also called logrolling.

income tax rates.[23] The R&D tax incentive rate at time t from only federal laws is the sum of all previous changes in R&D tax incentives driven by federal tax laws:

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

A researcher may be concerned that regression models that use $RDTaxIncentiveRate^{fed}$ might still be biased because state tax policies may respond endogenously to federal corporate tax policies. Another worry is that equation (3) may miss the effects of contemporaneous changes in state and federal corporate tax laws. If state laws change contemporaneously with federal laws, then an estimated coefficient on $RDTaxIncentiveRate^{fed}$ may actually be picking up the effects of contemporaneous state and federal tax law changes instead of the variation in only exogenous federal 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.[24]

Additional evidence against the hypothesis that states are responding endogenously to changes in federal tax laws comes from the session law data. The R&D tax credit laws for some states contain a preamble that describes the rationale behind why the law was passed. The preambles champion goals such as job creation, business expansion, and leadership in innovation. None of the preambles mention changes in federal tax laws as motivation.[25]

Figure 1 plots summary statistics of per-dollar state-level R&D tax incentive rates, calculated with both state and federal laws driving the variation (equation 2). Federal laws induce large shifts

[23] 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. Their exogenous changes in personal income tax rates reflect policy decisions at a higher level (federal government) than the unit of observation (individual). I take the analogous approach and create exogenous R&D tax incentives from variation in federal tax laws at time t by conditioning on the previous period's state tax laws. My exogenous changes also reflect law changes at a higher level (country) than the unit of observation (state).

[24] Appendix A presents the results. Appendix A also presents overidentification tests following a format similar to that in Weber (2014). With these overidentification tests, I am unable to reject the validity of my instrument.

[25] Appendix C gives examples of these preambles.

in state-level R&D tax incentive rates. The figure's vertical lines denote the effective dates for the federal tax laws. For example, the phase-in of the federal R&D tax credit caused the large increase in rates from 1981 to 1982. Similarly, a reworking of the federal R&D tax credit caused the second large increase in rates from 1989 to 1990. On net, federal laws place the average R&D tax incentive 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 and became effective in 1982) increased the cross-state variation in state-level R&D tax incentive rates over time.[26] Figure 2 plots rates for a few individual states. Aside from 1999, between zero and two states in my sample pass a R&D tax credit bill that affects the state's R&D tax incentive rate in each year, whereas in 1999 four states passed such a bill.

Figure 3 plots summary statistics of per-dollar state-level R&D tax incentive rates with only federal laws driving the variation (equation 4). Figure 4 plots the same variable for four individual states. Again, vertical lines show the effective dates for the federal tax laws. 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 tax incentive rates, the cross-state variation in rates continues to increase over time.

4 Institutional Details of the Interactions Between Federal and State Tax Law

The computations of federal and state corporate taxes are interdependent. A firm's federal tax liability depends on its 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 tax incentive rates across states. I model the heterogeneous changes in R&D tax incentive rates from federal laws by taking into account two broad classes of incentives: 1) incentives relating to deductions

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

for corporate income taxes paid and 2) incentives relating to R&D tax credits.[27]

The federal government allowed a deduction for state corporate income taxes starting in 1954. At the same time, some states allow deductions for federal corporate income taxes, state corporate income taxes, or both. Other states allow neither type of deduction. This between-state variation in tax policies implies that 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 damped. The value of this deduction is proportional to the state corporate income tax rate. Suppose that the federal government increases the federal corporate income tax rate from 0.4 to 0.5 and that there are no R&D tax credits or state deductions for state corporate income taxes.[28] 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 five percent 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 five percent 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 effects on the value of deductions, and hence R&D tax incentive rates due to 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. Public Law 101-239 increased the effective federal R&D tax credit and reduced allowable deductions for R&D expenditures starting on January 1,

[27] These two classes are themselves interdependent, but I separate them for the sake of exposition. See the model in Appendix B.

[28] 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.

1990. In 1989, the federal R&D tax credit was 20% of qualified research expenditures (QREs) above a three-year moving-average base amount of QREs.[29] In addition, in 1989 firms could deduct 50% of their QREs claimed for computing the federal R&D tax 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.[30]

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

Two common features of state tax policy are: 1) offering a state R&D tax credit computed with the same method as the federal R&D tax credit and 2) having this computation method linked directly to the Internal Revenue Code (IRC), the document that governs U.S. federal tax law. These two combined features of state tax policy are called piggybacking. For example, Oregon Revised Statues § 317.152, which authorizes a R&D tax credit for Oregon QREs, states that "A credit against taxes otherwise due under this chapter shall be allowed to eligible taxpayers for increases in qualified research expenses... the credit shall be determined in accordance with section 41 of the Internal Revenue Code."

Piggybacking implies that any change in the computation of the federal R&D tax credit automatically updates how piggybacking states calculate their R&D tax credits: changes in federal tax law cause 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

[29] See Guenther (2006) for a review of the federal R&D tax credit.
[30] Treating tax credits as taxable income is called credit recapture.

the federal R&D tax credit. All else being 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*. Therefore, for these states PL 101-239 caused a disproportionally large increase in R&D tax incentive rates relative to states without piggybacked R&D tax credits. For states without piggybacked R&D tax credits, PL 101-239 caused an increase in R&D tax incentive rates of between nine and thirteen cents per dollar of R&D. The increase in rates for states with piggybacked R&D tax credits was approximately 50% greater than the increase in rates for states without piggybacked R&D tax credits.

The basis for state taxable income also helped foster heterogeneous effects of PL 101-239 on state-level R&D tax incentive rates. In general, states use either 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. However, states that form state taxable income by starting with income from all sources do not incorporate federal-specific deductions and exemptions, so alterations to the IRC have no effect on their state tax codes. Public Law 101-239 disallowed the 50% QRE deduction allowed prior to 1990 when taking the federal R&D tax credit (IRC § 280C(c)). For states with federal taxable income as a base, PL 101-239 caused an automatic increase in the state income base (that is, 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. This feature of state tax codes also contributes to differential effects of federal laws on state-level R&D tax incentive rates. Appendix D gives a detailed example of how a federal tax law passes through to the construction of equation (4).[31]

[31] In the interest of brevity I simplified this discussion slightly. Some states have specific provisions that override what the base would predict. See Appendix B for details.

5 Pre-treatment Plots

Separating the effect of R&D tax incentives on R&D from other macroeconomic shocks relies on heterogeneous effects of federal tax laws on state-level R&D tax policies. One concern with this strategy is that the effects of federal laws on state-level policies are non-randomly assigned. If states receive disproportionate tax incentives from federal laws because of unobserved state-level factors that also affect R&D, then even federal variation in taxes would give biased estimates.

To check for 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 plots bolster the case for random assignment of the treatment.

A slight complication with the plots arises because the treatment is a series of laws - each of which treats all states - not just a single standard binary treatment and control setup. Federal laws affect some states more than others, but each federal law affects every state. To make results comparable to a standard plot, I divide states into two groups - one with above median R&D tax incentive rates and another with below median R&D tax incentive rates - and plot the average R&D for each of the two groups.

Figure 5 divides states into the two groups based on variation from both state and federal laws (equation 2). The dashed line represents average nominal R&D for the set of states with an above median average value of R&D tax incentives from 1981-2007.[32] The solid line is the set of states with a below median average value of incentives over the same time period. From 1963-1971, the trends look parallel, although the level of R&D for states with above median tax incentives is higher in each year. From 1971-1979, a gap emerges between these two groups of states, with nominal R&D growing faster for states that implement more generous tax incentives from 1981-2007.

Figure 6 instead divides states into the two groups with the rates calculated from only federal

[32]This group consists of: Arizona, California, Connecticut, Indiana, Massachusetts, Minnesota, New Jersey, New York, Pennsylvania, and Wisconsin.

law variation (equation 4). Again, the dashed line represents states above the median.[33] From 1963-1977, the trends and levels of R&D for the two groups are close. A small gap opens up in 1979, with the above median group showing higher R&D. However, the pre-treatment lines match more closely, in both levels and trends, when I group states according to rates calculated from only federal law variation.

6 Results

This section presents my main specifications and a robustness check involving the user cost of capital. Appendix A conducts additional robustness checks.

6.1 Main Specifications

Table 2 presents instrumental variables estimates with $RDTaxIncentiveRate^{fed}$ instrumenting the statutory tax incentive rate $RDTaxIncentiveRate$. The table reports coefficients as elasticities from natural log-natural log specifications. All specifications indicate an elastic response of R&D to tax incentives of at least 2.0. Columns (1) and (2) present results from static specifications that omit the lagged dependent variable. Column (1), a specification that includes only the R&D tax incentive rate with state fixed effects and time dummies, indicates an elasticity (standard error) of 4.51 (1.59). Column (2) adds lagged federal R&D, following Wilson (2009), as well as academic R&D and the unemployment rate as controls. The coefficient (standard error) of the rate term remains elastic at 5.06 (2.02). 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 because of R&D's high adjustment costs. Dynamic specifications also allow me to back out an implied long-run elasticity, $\gamma/(1-\pi)$,

[33]This group consists of: California, Colorado, Connecticut, Indiana, Minnesota, New York, North Carolina, Pennsylvania, Oregon, and Wisconsin.

where γ is the coefficient of the key regressor and π is the coefficient on the lagged dependent variable. Columns (3) - (5) represent my preferred estimates that include the lagged dependent variable.

The lagged dependent variable attenuates the elasticity estimate of R&D to tax incentives, but improves the precision.[34] Furthermore, the results continue to indicate that 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 the instrumented tax rate, the lagged dependent variable, and fixed effects, implies an elasticity estimate (standard error) of 2.89 (1.14). This estimate of 2.89 (1.14) comes without any other macroeconomic controls. The coefficient (standard error) on the lagged dependent variable is 0.46 (0.10), confirming the presence of adjustment costs for R&D and implying a long-run elasticity (standard error) of 5.38 (1.74).

Column (4) of Table 2 includes a full set of control variables. The coefficient (standard error) of the instrumented $ln(RDTaxIncentiveRate)$ is still large at 3.69 (1.59). 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 tax incentive rate (state and federal laws driving the tax variation) estimated with OLS. The lack of an instrument 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 choosing their R&D tax policies.

With OLS, all specifications in Table 3 indicate a smaller response of R&D to tax incentives than the response from models that instrument the tax rate. Columns (1) and (2) present results

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

from static models, which omit the lagged dependent variable. The specification in column (1) includes only the endogenous tax incentive rate, $ln(RDTaxIncentiveRate)$, and fixed effects. This specification indicates that a 1% increase in the R&D tax incentive rate causes a 1.66% 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 tax rate remains almost unchanged.

Table 3, columns (3) - (5) present results from my preferred dynamic specifications. The estimates from these dynamic specifications indicate an inelastic response of R&D to its tax rate, with a range between 0.37 and 0.65. 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 that of the static specifications, and the control variables have the same interpretation as the controls from Table 2.[35]

These point estimates are smaller than the comparable specification from Wilson (2009) (Table 1, column 1), although they fall within the range of estimates reviewed by Hall and Van Reenen (2000). The difference from Wilson (2009) is primarily due to the fact that this paper uses large R&D states without imputed observations while Wilson (2009) uses all available states and imputed observations. I am restricted to large R&D states because they are the ones I observe during the period when federal tax laws were changing (1980s and 1990s). Observations for smaller R&D states are not available before 2000.[36] See Appendix E for additional details.

6.2 Statistical Significance of IV vs. OLS

The point estimates from all IV specifications in Table 2 are different from zero, while the point estimates from all OLS specifications in Table 3 are not different from zero. In addition, as shown at the bottom of Table 3, the difference between the tax incentive rate terms from IV and OLS in

[35] A possible explanation for why the estimates between endogenous and exogenous variation are different is that treatment effects very across states. Unfortunately, this possibility is not testable. The treatment variable's magnitude is only somewhat related (non-linearly) to the endogenous $RDTaxIncentiveRate$. Two of the five states with the highest average $RDTaxIncentiveRate$ are also among the top five states affected by federal tax laws, while the same is true for seven of the top ten.

[36] After 2000 the NSF imputes many observations for these small states, but I cannot use these states because my instrument does not have any variation after 2000.

my preferred dynamic specifications in Tables 2 and 3 is statistically significant. The Wooldridge (1995) cluster-robust score test rejects the hull hypothesis of equality of coefficients from IV and OLS at the 5% level or lower for each of these dynamic specifications.

6.3 Instrument Relevance

From examining the first-stage F-statistics of Table 2, which are below the Staiger and Stock (1997) rule of thumb of 10, a researcher may be concerned that my large tax elasticity estimates are biased. I highlight four reasons why these concerns should be tempered. First, the estimates of Table 2 are just-identified, and just-identified IV is approximately median unbiased (Angrist and Pischke, 2008). Second, with weak instruments IV estimates are mean-biased towards OLS estimates. Therefore, if the IV estimates of Table 2 are mean biased, then the true tax parameter of interest is greater than the Table 2 IV estimates suggest, which would imply that the Table 2 estimates would actually understate the bias of OLS. Third, I estimate over-identified specifications, using additional lags of the federal tax variable as instruments, with the limited information maximum likelihood (LIML) estimator. The LIML estimator exhibits approximately median unbiased behavior even with weak instruments (Angrist and Pischke, 2008). The LIML specifications give similar results to Table 2.[37] Fourth, I run the reduced form regressions of R&D on the federal tax instrument using the same pattern of controls as in Table 2. Assuming the instrument is valid, the reduced form results are unbiased. The reduced form results all show large effects of the instrument on R&D, with point estimates always in excess of 2.5, and are statistically significant at standard levels.

The results in Tables 2 and 3 suggest that 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 offset the future loss of R&D expenditures. For example, if firms plan to relocate R&D

[37] See Appendix A for these results.

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 endogenously determined 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 toward finding no effect of tax policies on R&D.

6.4 User Cost of Capital Robustness Check

In this subsection, I present results from a robustness check involving the user cost of capital. Appendix A presents a variety of additional robustness checks, which show that this paper's results are insensitive to various model and data specifications.

Following Chirinko and Wilson (2008) and Wilson (2009), I form the user cost of R&D capital, $RDUserCost$, as an extension of Hall and Jorgenson (1967). The user cost is the ratio of the R&D tax incentive rate, $RDTaxIncentiveRate^{fed}$, to the tax incentive rate of output, $OutputTaxIncentiveRate$, where output is a fully deductible expense that does not have an associated tax credit,[38] adjusted for depreciation δ of R&D and the discount rate r:

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

Equation (5) captures the fact that the opportunity cost of investment in R&D is an investment in some other good, such as output. Rewriting equation (1) with the natural logarithm of the user cost as the key regressor yields the following:

$$\begin{aligned} ln(RD_{it}) \quad = \quad & \pi ln(RD_{it-l}) + \varphi_i + \lambda_t + \kappa ln(r_t + \delta_t) + \gamma ln(RDTaxIncentiveRate_{it}^{fed}) \\ & -\upsilon ln(OutputTaxIncentiveRate_{it}) + ln(X_{it}^{'})\beta + \varepsilon_{it} \end{aligned} \tag{6}$$

Under depreciation and discount rates that are uniform across states, the time dummies absorb

[38] Specifically, I compute $OutputTaxIncentiveRate$ with the model in Appendix B without the terms for R&D-specific tax incentives.

$ln(r_t + \delta_t)$ so that equation (6) amounts to the original model with a new term for the tax incentive rate of output, $ln(OutputTaxIncentiveRate_{it})$. Including $ln(OutputTaxIncentiveRate_{it})$ in the model continues to indicate an elastic response of R&D to R&D tax incentives. For example, the specification in column (5) of Table 2 yields a R&D tax incentive rate estimate (standard error) of 3.68 (1.74). The control variables have similar point estimates and the tax incentive rate of output is insignificant at standard levels.[39]

7 Conclusion

Policymakers form tax policies based on the state of the economy. This characteristic leads to endogeneity bias in regression models that 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 than state governments to idiosyncratic state-level economic conditions, using variation from federal tax laws reduces concerns over biased estimates stemming from states choosing their own tax polices. This paper finds that R&D is sensitive to tax incentives, with my preferred estimates indicating that a 1% increase in R&D tax incentives would lead to a 2.8-3.8% increase in R&D expenditures.

This paper also estimates models with R&D tax incentive rates calculated using tax variation from both state and federal laws. These models are similar to those from previous studies and should give biased estimates because states choose their own R&D tax incentives. My models with endogenous tax variation in R&D tax incentive rates produce 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 uncorrected endogenous tax variation and those from only exogenous

[39] Calculating $OutputTaxIncentiveRate$ 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.

federal tax variation is statistically significant and indicates serious attenuation bias from the endogenous tax variation. The direction of this bias suggests that tax incentives may offset future economic downturns, which is consistent with Yang (2005); Romer and Romer (2010).

Could policymakers be purposely designing offsetting tax incentives? If so, then policymakers may see a downturn is beginning, or predict one will happen, and change policies to offset the upcoming downturn. Another story is that policymakers could simply be adopting tax incentives when funds are available, which may be just before a downturn starts.

Several mechanisms may contribute to the elastic response of R&D to tax incentives that my models find. Because of the state fixed effects and time dummies, my models identify coefficients based on 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 my 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 compete strategically with tax incentives. Depending on the slope of state reaction functions, strategic competition can lead to either states with too generous tax incentives (relative to the efficient level) 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).

My elasticity estimates could also be explained by firms raising their total R&D in response to being offered tax incentives. This explanation seems plausible when the firm's general investments have strong complementarities or even when just the firm's R&D-specific projects have strong complementarities. For example, suppose that R&D and non-R&D investment are complements. If a tax incentive lowers the price of R&D, then the firm will respond by undertaking additional non-R&D investment. However, this additional non-R&D investment will also incentivize the firm to take on additional R&D and potentially leads to a large response of R&D to tax incentives.

References

Aidt, Toke S., and Peter S. Jensen, "The Taxman Tools Up: An Event History Study of the Introduction of the Personal Income Tax," *Journal of Public Economics* 93:1-2 (2009), 160-175.

Angrist, Joshua D., and Jörn-Steffen Pischke, *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton: Princeton University Press, 2008)

Arellano, Manuel, and Stephen Bond, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies* 58:2 (1991), 277-297.

Arellano, Manuel, and Olympia Bover, "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics* 68:1 (1995), 29-51.

Arrow, Kenneth J., "Economic Welfare and the Allocation of Resources for Invention" (pp. 609-626), in Richard R. Nelson (Ed.), *The Rate and Direction of Inventive Activity: Economic and Social Factors* (Princeton: Princeton University Press, 1962).

Barlevy, Gadi, "On the Cyclicality of Research and Development," *American Economic Review* 97:4 (2007), 1131-1164.

Berry, Frances Stokes, and William D. Berry, "Tax Innovation in the States: Capitalizing on Political Opportunity," *American Journal of Political Science* 36:3 (1992), 715-742.

Berry, Frances Stokes, and William D. Berry, "The Politics of Tax Increases in the States," *American Journal of Political Science* 38:3 (1994), 855-859.

Bloom, Nick, Rachel Griffith, and John Van Reenen, "Do R&D Tax Credits Work? Evidence from a Panel of Countries 1979-1997," *Journal of Public Economics* 85:1 (2002), 1-31.

Blundell, Richard, and Stephen Bond, "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics* 87:1 (1998), 115-143.

Brown, Lawrence D., Thomas J. Plewes, and Marisa A. Gerstein (Eds.), *Measuring Research and Development Expenditures in the U.S. Economy* (Washington D.C.: National Academies Press, 2005).

Brownstone, David, and Robert Valletta, "The Bootstrap and Multiple Imputations: Harnessing Increased Computing Power for Improved Statistical Tests," *Journal of Economic Perspectives* 15:4 (2001), 129-141.

Brueckner, Jan K., "Strategic Interaction Among Governments: An Overview of Empirical Studies," *International Regional Science Review* 26:2 (2003), 175-188.

Brueckner, Jan K., and Luz A. Saavedra, "Do Local Governments Engage in Strategic Property-Tax Competition?" *National Tax Journal* 54:2 (2001), 203-229.

Bruno, Giovanni S.F., "Approximating the Bias of the LSDV Estimator for Dynamic Unbalanced Panel Data Models," *Economics Letters* 87:3 (2005a), 361-366.

Bruno, Giovanni S.F., "Estimation and Inference in Dynamic Unbalanced Panel-Data Models With a Small Number of Individuals," *Stata Journal* 5:4 (2005b), 473-500.

Burnside, Craig, Martin Eichenbaum, and Jonas Fisher, "Fiscal Shocks and Their Consequences," *Journal of Economic Theory* 115:1 (2004), 89-117.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, "Bootstrap-Based Improvements for Inference With Clustered Errors," *Review of Economics and Statistics* 90:3 (2008), 414-427.

Cameron, A. Colin, and Pravin K. Trivedi, *Microeconometrics: Methods and Applications* (New York: Cambridge University Press, 2005).

Card, David, "Using Regional Variation in Wages to Measure the Effects of the Federal Minimum Wage," *Industrial and Labor Relations Review* 46:1 (1992), 22-37.

Chang, Andrew C., “Inter-Industry Strategic R&D and Supplier-Demander Relationships,” *Review of Economics and Statistics* 95:2 (2013), 491-499.

Chirinko, Robert S., Steven M. Fazzari, and Andrew P. Meyer, “How Responsive is Business Capital Formation to its User Cost? An Exploration With Micro Data,” *Journal of Public Economics* 74:1 (1999), 53-80.

Chirinko, Robert S., and Daniel J. Wilson, “State Investment Tax Incentives: A Zero-Sum Game?” *Journal of Public Economics* 92:12 (2008), 2362-2384.

Chirinko, Robert S., and Daniel J. Wilson, “Tax Competition Among U.S. States: Racing to the Bottom or Riding on a Seesaw?” CESifo Working Paper 3535 (2011).

Commerce Clearing House. *IntelliConnect*. https://intelliconnect.cch.com/. Various Access Dates.

Commerce Clearing House, *State Tax Handbook* (Chicago: CCH Editorial Staff, 1964-present).

Commerce Clearing House, *U.S. Master Multistate Corporate Tax Guide* (Chicago: CCH Editorial Staff, 2000-present).

Crain, W. Mark, and Timothy J. Muris, “Legislative Organization of Fiscal Policy,” *Journal of Law and Economics* 38:2 (1995), 311-333.

Czarnitzki, Dirk, Petr Hanel, and Julio Miguel Rosa, “Evaluating the Impact of R&D Tax Credits on Innovation: A Microeconometric Study on Canadian Firms,” *Research Policy* 40:2 (2011), 217-229.

David, Paul A., Bronwyn H. Hall, and Andrew A. Toole, “Is Public R&D a Complement or Substitute for Private R&D? A Review of the Econometric Evidence,” *Research Policy* 29:4-5 (2000), 497-529.

Davidson, Russell, and James G. MacKinnon, “The Size Distortion of Bootstrap Tests,” *Econometric Theory* 15:3 (1999), 361-376.

de Mooij, Ruud A., and Sjef Ederveen, “Corporate Tax Elasticities: A Reader’s Guide to Empirical Findings,” *Oxford Review of Economic Policy* 24:4 (2008), 680-697.

Decker, Christopher S., and Mark E. Wohar, “Determinants of State Diesel Fuel Excise Tax Rates: The Political Economy of Fuel Taxation in the United States,” *Annals of Regional Science* 41:1 (2007), 171-188.

Easterly, William, and Sergio Rebelo, “Fiscal Policy and Economic Growth: An Empirical Investigation,” *Journal of Monetary Economics* 32:3 (1993), 417-458.

Eisner, Robert, Steven H. Albert, and Martin A. Sullivan, “The New Incremental Tax Credit for R&D: Incentive or Disincentive?” *National Tax Journal* 37:2 (1986), 171-183.

Everaert, Gerdie, and Lorenzo Pozzi, “Bootstrap-Based Bias Correction for Dynamic Panels,” *Journal of Economic Dynamics and Control* 31:4 (2007), 1160-1184.

Gilligan, Thomas W., and John G. Matsusaka, “Fiscal Policy, Legislature Size, and Political Parties: Evidence from State and Local Governments in the First Half of the 20th Century,” *National Tax Journal* 54:1 (2001), 57-82.

Goolsbee, Austan, “Investment Tax Incentives, Prices, and the Supply of Capital Goods,” *Quarterly Journal of Economics* 113:1 (1998), 121-148.

Griliches, Zvi, “The Search for R&D Spillovers,” *Scandinavian Journal of Economics* 94 (1992), S29-S47.

Gruber, Jon, and Emmanuel Saez, “The Elasticity of Taxable Income: Evidence and Implications,” *Journal of Public Economics* 84:1 (2002), 1-32.

Guenther, Gary, “Research Tax Credit: Current Status, Legislative Proposals in the 109^{th} Congress, and Policy Issues,” Congressional Research Service Report for Congress (2006).

Hall, Bronwyn, and John Van Reenen, “How Effective Are Fiscal Incentives for R&D? A Review of the Evidence,” *Research Policy* 29:4-5 (2000), 449-469.

Hall, Bronwyn H., "R&D Tax Policy During the 1980s: Success or Failure?" *Tax Policy and the Economy* 7 (1993), 1-35.

Hall, Robert E., and Dale W. Jorgenson, "Tax Policy and Investment Behavior," *American Economic Review* 57:3 (1967), 391-414.

Kim, Jungbu, "Why Are Some States More Generous in Offering R&D Tax Credits than Others?" *International Journal of Public Administration* 33:7 (2010), 371-378.

Kiviet, Jan F., "On Bias, Inconsistency, and Efficiency of Various Estimators in Dynamic Panel Data Models," *Journal of Econometrics* 68:1 (1995), 53-78.

Leff, Barbara, "Quality Jobs Through Renewable Energy," (2009). Available at http://www.barbaraleff.com/qualityjobs.html.

Levin, Andrew, Chien-Fu Lin, and Chia-Shang James Chu, "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties," *Journal of Econometrics* 108:1 (2002), 1-24.

Lokshin, Boris, and Pierre Mohnen, "How Effective Are Level-Based R&D Tax Credits? Evidence From the Netherlands," *Applied Economics* 44:12 (2012), 1527-1538.

Mamuneas, Theofanis P., and M. Ishaq Nadiri, "Public R&D Policies and Cost Behavior of the U.S. Manufacturing Industries," *Journal of Public Economics* 63:1 (1996), 57-81.

Miller, Chad R., and Brian Richard, "The Policy Diffusion of the State R&D Investment Tax Credit," *State and Local Government Review* 42:1 (2010), 22-35.

Mountford, Andrew, and Harald Uhlig, "What Are the Effects of Fiscal Policy Shocks?" *Journal of Applied Econometrics* 24:6 (2009), 960-992.

Nickell, Stephen, "Biases in Dynamic Models With Fixed Effects," *Econometrica* 49:6 (1981), 1417-1426.

Ouyang, Min, "On the Cyclicality of R&D," *Review of Economics and Statistics* 93:2 (2011), 542-553.

Paff, Lolita A., “State-Level R&D Tax Credits: A Firm-Level Analysis,” *B.E. Journal of Economic Analysis and Policy (Topics)* 5:1 (2005), Article 17.

Poterba, James M., “State Responses to Fiscal Crises: The Effects of Budgetary Institutions and Politics,” *Journal of Political Economy* 102:4 (1994), 799-821.

Ramey, Valerie A., “Identifying Government Spending Shocks: It’s All In the Timing,” *Quarterly Journal of Economics* 126:1 (2011), 1-50.

Ramey, Valerie A., and Matthew D. Shapiro, “Costly Capital Reallocation and the Effects of Government Spending,” *Carnegie-Rochester Conference Series on Public Policy* 48 (1998), 145-194.

Rao, Nirupama, “Do Tax Credits Stimulate R&D Spending? Revisiting the Effect of the R&D Tax Credit in its First Decade,” Working Paper (2010).

Romer, Christina D., and David H. Romer, “The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks,” *American Economic Review* 100:3 (2010), 763-801.

Roodman, David, “How to do xtabond2: An Introduction to Difference and System GMM in Stata,” *Stata Journal* 9:1 (2009), 86-136.

Said, Said E., and David A. Dickey, “Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order,” *Biometrika* 71:3 (1984), 599-607.

Shea, John, “The Input-Output Approach to Instrument Selection,” *Journal of Business & Economic Statistics* 11:2 (1993), 145-155.

Shiller, Robert J., *Irrational Exuberance* (Princeton: Princeton University Press, 2005). Data available at http://www.econ.yale.edu/~shiller/data.htm

Staiger, Douglas, and James H. Stock, “Instrumental Variables Regression with Weak Instruments,” *Econometrica* 65:3 (1997), 557-586.

Stratmann, Thomas, “The Effects of Logrolling on Congressional Voting,” *American Economic Review* 82:5 (1992), 1162-1176.

Stratmann, Thomas, “Logrolling in the U.S. Congress,” *Economic Inquiry* 33:3 (1995), 441-456.

Swank, Duane, and Sven Steinmo, “The New Political Economy of Taxation in Advanced Capitalist Democracies,” *American Journal of Political Science* 46:3 (2002), 642-655.

Tullock, Gordon, “Problems of Majority Voting,” *Journal of Political Economy* 67:6 (1959), 571-579.

Weber, Caroline E., 2014, “Toward Obtaining a Consistent Estimate of the Elasticity of Taxable Income Using Difference-in-Differences,” *Journal of Public Economics* 117 (2014), 90–103

Wilson, Daniel J., “Beggar Thy Neighbor? The In-State, Out-of-State, and Aggregate Effects of R&D Tax Credits,” *Review of Economics and Statistics* 91:2 (2009), 431-436. Also as Federal Reserve Bank of San Francisco Working Paper 2005-8 (2007).

Wooldridge, Jeffrey M., “Selection Corrections for Panel Data Models Under Conditional Mean Independence Assumptions,” *Journal of Econometrics* 68:1 (1995), 115-132.

Wu, Yonghong, “The Effects of State R&D Tax Credits in Stimulating Private R&D Expenditure: A Cross-State Empirical Analysis,” *Journal of Policy Analysis and Management* 24:4 (2005), 785-802.

Yang, Shu-Chun Susan, “Quantifying Tax Effects Under Policy Foresight,” *Journal of Monetary Economics* 52:8 (2005), 1557-1568.

Zodrow, George R., “Capital Mobility and Capital Tax Competition,” *National Tax Journal* 63:4-2 (2010), 865-902.

A Appendix: Robustness Checks

A.1 Additional Controls and Sample Restrictions

A researcher may be concerned that the control variables in Tables 2 and 3 are insufficiently rich. Therefore, I experiment with a more saturated specification of controls that uses contemporaneous, one lag, and two lags of all control variables. The R&D tax incentive rate driven only by federal laws generates an elasticity estimate (standard error) of 4.60 (1.82). 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 0.53 (0.77) for the endogenous R&D tax incentive rate driven by both state and federal laws, which is in line with the parsimonious specifications in Table 3.[40,41]

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.[42] I conduct this robustness check to see if the results are driven by only a few observations that the model does not explain well. 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 tax incentive rates from 1981-1982 in Figures 1 and 3. In column (3), I estimate the model only with data up to 1999 because the variation in R&D tax incentive 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 biennial structure used so far. This strategy changes the model from biennial to annual observations from 1997-2006 and addresses concerns over potential loss of precision from dropping observations in the latter part of the sample.[43]

The models subject to these sample modifications continue to suggest an elastic response of

[40]The results are also robust to adding state-specific linear time trends, the rate of growth of GSP, and the first lag of the rate of growth of GSP as controls.

[41]The endogenous R&D tax incentive rate driven by both state and federal laws gives inelastic to approximately unit elastic point estimates for all robustness checks.

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

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

R&D to tax incentives. The smallest estimate comes from removing outliers in column (1), which indicates that if governments were to increase R&D tax incentives by 1%, then R&D would increase by 2.9%.

Estimating the model with data starting in 1985 yields an estimate similar to the main result in Table 2. Therefore, the main result is not driven by the phase-in of the federal R&D tax credit that causes the large increase in R&D tax incentive rates from 1981 to 1982 shown by Figures 1 and 3.

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 6.29 (1.74). 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 0.09 from 0.39 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 biennial 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.[44,45]

[44]The clustered standard errors imply rejection at the 5% level or lower for the key coefficient in the preferred models. I also check the rejection rates, following the recommendation of Cameron, Gelbach, and Miller (2008), by bootstrapping the t-statistic using the wild cluster bootstrap-t procedure (Brownstone and Valletta, 2001). I use Rademacher weights with 1000 replications for each test and impose the null hypothesis that the tax policy variable is zero, as advocated by Davidson and MacKinnon (1999); Cameron, Gelbach, and Miller (2008). The bootstrap blocks are states. The hypothesis test of $H_0 : \gamma = 0$ vs. $H_A : \gamma > 0$ yields p-values between 0.03 and 0.09 for the preferred model's key regressors.

[45]One control I do not consider is some type of geographically-weighted or proximity measure of an out-of-state subsidy rate. For example, adding the weighted R&D tax credit subsidies of Arizona, Nevada, and Oregon as a control observation for California. Geographically-weighted measures most likely ignore or mis-attribute R&D reallocation, particularly within firms situated in multiple states, which would lead to measurement error in a right-hand side variable. For example, the aircraft producer Boeing has manufacturing plants in Washington state and South Carolina. These states are on opposite sides of the U.S., but for purposes of R&D allocation Boeing may want to conduct R&D between these states due to existing infrastructure and human capital while also taking into account R&D tax incentives. However, geographic proximity measures will miss this link. My future work will consider modeling R&D mobility across states. This paper focuses on the within-state response.

A.2 Other Dynamic Forms and Alternative R&D Tax Incentive Rates

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 biennial period (1981-1995) and $t-1$ for the annual period (1997-2006). This specification allows the coefficient on the lagged dependent variable to vary between the biennial and annual periods. Column (1) gives a 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 biennial data structure and use $ln(RD_{it-4})$ instead of the most recent available lag, $ln(RD_{it-2})$. If R&D tax policy is contemporaneously determined with lagged R&D, then instrumenting with $ln(RDTaxIncentiveRate^{fed})$ and including lagged R&D in the model 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 $ln(RD_{it-4})$ instead of $ln(RD_{it-2})$ causes the coefficient on $ln(RDTaxIncentiveRate^{fed})$ to increase to 7.11. The estimate on $ln(RD_{it-4})$ decreases to 0.10. These results are similar to the static specifications that omit the lagged dependent variable in Table 4, column (3).

Table 5, column (3) calculates the instrument using only the single law that generates the largest source of variation across states: PL 101-239, which was passed on December 19, 1989 and became effective in 1990. The table denotes this instrument as $ln(RDTaxIncentiveRate^{PL101-239})$. Instrumenting $RDTaxIncentiveRate$ with $ln(RDTaxIncentiveRate^{PL101-239})$ makes the model analogous to a binary treatment and control setup in which the treatment law is PL 101-239 and the pre-treatment period is before 1990. The cost of this setup is removing potentially exogenous variation and increasing measurement error in the key right-hand side variable. A benefit is that this formulation uses 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 or substitutable investments for R&D and would imply that 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 tax incentive rate (for example, R&D tax credits). However, calculating R&D tax incentive rates with only variation from PL 101-239 continues to suggest an elastic response of R&D to tax incentives (standard error) of 3.14 (1.39).[46] The estimates with $ln(RDTaxIncentiveRate^{PL101-239})$ are smaller than those that use all available variation, suggesting some attenuation bias.

Table 5, column (4) uses $ln(RDTaxIncentiveRate^{PL101-239})$ 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.

A researcher may be concerned about selection between states that chose to have laws that bound themselves to PL 101-239 and those that did not enact such laws. Therefore, I estimate models with separate policy variables for states that had and did not have R&D tax credits piggybacked to PL 101-239, which give similar results. The coefficients (standard errors) on $ln(RDTaxIncentiveRate^{fed})$ for the specification in column (5) of Table 2 are 4.15 (2.07) for piggybacked states and 4.35 (2.23) for non-piggybacked states.

Another selection concern is that certain geographic regions might choose to implement certain policies. However, estimating models with separate policy variables by census region (West, South, Midwest, and Northeast) also gives similar results. The coefficients (standard errors) on $ln(RDTaxIncentiveRate^{fed})$ for the specification in column (5) of Table 2 are 3.73 (1.77) for West,

[46]Researchers may be concerned that firms anticipated PL 101-239. 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 three-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 three 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, perhaps at the expense of R&D they would have claimed in 1990, which would bias the estimate of the effect of PL 101-239 in 1990 toward zero.

3.74 (1.82) for South, 3.02 (1.92) for Midwest, and 3.28 (2.04) for Northeast.[47]

A.3 Difference-in-Sargan Overidentification Tests and Limited Information Maximum Likelihood Estimation

As an additional robustness check, I estimate specifications with an overidentified first-stage and run Difference-in-Sargan tests to check for instrument validity. Table 6 runs Difference-in-Sargan overidentification tests following a format similar to that in Weber (2014), Table 2, using the 2SLS estimator. I construct the changes in my instrument by conditioning on different lags of state tax policy:

$$\Delta RDTaxIncentiveRate_{it}^{fed,l} = RDTaxIncentiveRate(ST_{it-l},\, FT_{it}) - RDTaxIncentiveRate(ST_{it-l},\, FT_{it-1}) \tag{7}$$

for $l = 1, 2, 3, 4$. I then test the validity of my instrument by running the Difference-in-Sargan test by excluding the instrument constructed by conditioning on the shortest lag length of state tax policy, which presumably would be most susceptible to endogeneity bias. Column (1) displays the baseline specification from the paper (one instrument, constructed by conditioning on $l = 1$), while columns (2) - (5) display results using an overidentified first stage and corresponding Difference-in-Sargan overidentification test p-values. For all overidentified specifications, I am unable to reject the validity of the baseline instrument from the paper at standard significance levels. The elasticity estimates of the tax incentive rate using multiple instruments are a bit smaller than when using a single instrument but are still in excess of 2.5.

Finally, because the first-stage F-statistics of some columns of Table 6 are below the Staiger and Stock (1997) rule-of-thumb of 10, I re-estimate the specifications of Table 6 with the limited information maximum likelihood (LIML) estimator, which generally has better small-sample properties (i.e., less bias) than 2SLS (Angrist and Pischke, 2008). The estimates from LIML are

[47] Estimating separate policy variables and separate controls for each census region gives imprecise estimates.

very close to the 2SLS estimates.

B Appendix: R&D Tax Incentive Rate Model

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

Let FTI denote federal taxable income, I indicate income, k be the R&D credit rate for established firms, 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 Internal Revenue Code (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,[48] the expression for FTI follows (8):

$$FTI_{it} = I_{it} - ST_{it} - RD_{it}^{tot} + \chi_{ft} k_{ft} RD_{it}^{fedCR} \tag{8}$$

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

$$FT_{it} = FTI_{it}\tau_{ft} - k_{ft} RD_{it}^{fedCR} \tag{9}$$

After a transitional period from 1981-1982, the federal R&D credit was a percentage of qualified research expenditures (QREs) over the greater of 50% of a firm's QREs or a three-year moving average of QREs. Assuming firms are not constrained by the base,[49] the three-year moving average makes $RD_{it}^{fedCR} = RD_{it}^{tot} - \frac{1}{3}\sum_{m=1}^{3} RD_{it-m}^{tot}$ and makes the expression for FT as follows:

$$FT_{it} = FTI_{it}\tau_{ft} - k_{ft}(RD_{it}^{tot} - \frac{1}{3}\sum_{m=1}^{3} RD_{it-m}^{tot}) \tag{10}$$

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

[49] Hall (1993) notes that 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 amounts.

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

$$FT_{it} = FTI_{it}\tau_{ft} - k_{ft}RD_{it}^{tot} \tag{11}$$

Comparing equations (10) and (11), the three-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 and 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 that is 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 as follows:

$$STI_{it} = FTI_{it} + \xi_{it}ST_{it} - \phi_{it}FT_{it} + \omega_{it}k_{it}RD_{it}^{stateCR} - \alpha_{it}\chi_{ft}k_{ft}RD_{it}^{fedCR} \tag{12}$$

which gives way to a state tax burden ST of:

$$ST_{it} = STI_{it}\tau_{it} - k_{it}RD_{it}^{stateCR} \tag{13}$$

For the corporate income tax rate τ I follow Shea (1993) and Wilson (2009) and use the top-tier corporate rates without alternative minimum tax. For states with only a tax on gross income or stated capital instead of net income, I set τ_{it} as the rate on gross income or stated capital. I account for temporary taxes and surcharges in τ_{it}. In the R&D sample, two-thirds of the states have a single corporate income tax rate for the entire sample period. The remaining one-third of the states 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 $146,000 of taxable income.

I model firms as filing based on the calendar year to keep the timing consistent with the other annual variables. If states change a law midway through the year and specify an explicit proration for a calendar year, then I prorate accordingly. For example, if a state has $\tau = 0.1$ for six months of 1990 and then implements an increase to $\tau = 0.2$ for 1990, I code 1990 as $\tau = 0.2$ if no proration clause exists and as $\tau = 0.15$ if a proration clause does exist.

States generally compute their R&D credits in one of three ways: 1) a non-incremental credit, in which 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.[50] 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, $RD_{it}^{stateCR} = RD_{it}^{tot} - \frac{1}{M}\sum_{m=1}^{M} RD_{it-m}^{tot}$. Following Wilson (2009), I do not consider state R&D tax credits specific to a given industry, for a given area within a state, or for a specific firm size because the NSF R&D data are at the state level.

The federal R&D credit and approximately two-thirds of states use a single R&D credit rate k for all applicable R&D expenditures (i.e., no credit tiers). The remaining one-third 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.[51] I also check the results with the median

[50] 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 one-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 take only one-third 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 four-year moving average of QREs. The second component is a 3% credit for QREs that do not qualify for the 10% credit component. I model both of these alternative mechanisms.

[51] Some states impose a maximum credit amount a firm can claim that is not dependent on the firm's taxable income, a statewide limit on the amount of R&D tax credit that can be claimed by all firms in the state each year, or both a firm-specific maximum and a statewide maximum. The firm-specific limit on R&D tax credits is equivalent to a marginal rate of zero for the top tier. I assume that the statewide limit provision is not binding, following Wu (2005); Wilson (2009).

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 in equation (8) into equation (12) 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 the following:

$$\begin{aligned} STI_{it} &= I_{it} - ST_{it} - RD_{it}^{tot} + \chi_{ft} k_{ft} RD_{it}^{fedCR} + \xi_{it} ST_{it} - \phi_{it} FT_{it} \\ &\quad + \omega_{it} k_{it} RD_{it}^{stateCR} - \alpha_{it} \chi_{ft} k_{ft} RD_{it}^{fedCR} \qquad (14) \\ &= I_{it} + ST_{it}(\xi_{it} - 1) - RD_{it}^{tot} + \chi_{ft} k_{ft} RD_{it}^{fedCR}(1 - \alpha_{it}) - \phi_{it} FT_{it} + \omega_{it} k_{it} RD_{it}^{stateCR} \\ &= I_{it} + ST_{it}(\xi_{it} - 1) - RD_{it}^{tot} - \phi_{it} FT_{it} + \omega_{it} k_{it} RD_{it}^{stateCR} \end{aligned}$$

which is a sufficiently generic expression for STI for states that use income from all sources as a starting point in their STI computation. 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 tax incentive rate in equation (2).[52] The system of equations for FTI, FT, STI, and ST takes into account a broader range of deductions than is found in the previous literature and models the simultaneity of state and federal taxes, allowing this paper to compute state-level R&D tax incentive rates with weaker assumptions than in previous studies (Paff, 2005; Wu, 2005; Wilson, 2009). In addition, because of the large number of tax parameters captured by the model and because the effective R&D tax incentive rate is a continuous variable, each state in my sample has a different effective R&D tax incentive rate.

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 (biennially), minor changes to the timing of forming

[52] Equation (2) assumes firms have sufficient taxable income to claim R&D tax incentives, consistent with previous studies of R&D tax incentives. A dummy variable for whether a state has a refundable R&D tax credit (tax credits that can be claimed for any level of taxable income) or allows firms to sell tax credits to other firms has no effect on the results.

expectations in the tax data give the same 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 through November of year t, form expectations based on these laws, 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 firms' expectations of future taxes. However, large corporations with dedicated accounting resources should be anticipating future tax changes that will occur because of laws on the books. I confirmed this assumption through correspondence with a tax lawyer who worked for a large corporation. The session law data allow me to pinpoint how laws will change taxes in future periods, which allows this paper to calculate $RDTaxIncentiveRate$ with a weaker assumption than in previous studies.

C Appendix: R&D Tax Credit Law Preambles

This appendix gives examples of preambles from state R&D tax credit laws. The texts are all from session laws accessible from HeinOnline. The portion in italics motivates the law.

Michigan Public Acts 2007 No. 145: "*An act to meet deficiencies in state funds* by providing for the imposition, levy, computation, collection, assessment, reporting, payment, and enforcement of taxes on certain commercial, business, and financial activities; to prescribe the powers and duties of public officers and state departments; to provide for the inspection of certain taxpayer records; to provide for interest and penalties; to provide exemptions, credits, and refunds; to provide for the disposition of funds; to provide for the interrelation of this act with other acts; and to make appropriations."

New York, 2010 Regular Session, Chapter 55, Part MM, § 1: “It is here-by found and declared that New York state needs, as a matter of public policy, to create competitive financial incentives for *businesses to create jobs and invest in the new economy*. The excelsior jobs program act is created to support the growth of the state’s traditional economic pillars including the manufacturing and financial industries and to ensure that New York emerges as the leader in the knowledge, technology and innovation based economy. The program will encourage the expansion in and relocation to New York of businesses in growth industries such as clean-tech, broadband, information systems, renewable energy and biotechnology.”

North Carolina, 1996 Second Extra Session, Chapter 13, House Bill 18: “An act to reduce taxes for the citizens of North Carolina and to *provide incentives for high quality jobs and business expansion* in North Carolina.”

D Appendix: Sample Effect of Federal Tax Law on Treatment Variable

This appendix details how the treatment variable, equation (4), is affected by PL 101-239 for the state of Wisconsin.

In 1989, the year prior to the passage of PL 101-239, the federal R&D tax credit was a 20% incremental credit for R&D expenditures over a three-year moving average base and 50% of the granted credit was treated as federal taxable income for the firm. Wisconsin had a 5% state R&D tax credit that was computed in the same manner as the federal credit. In addition, the computation method for the Wisconsin R&D tax credit was linked to federal tax law. Therefore, any change in the computation method for the federal R&D tax credit would pass through automatically to the state R&D tax credit. Wisconsin also treated half of state tax credits as state income for the firm, disallowed the federal deduction for state taxes paid when computing state taxable income, and did not allow a state income deduction for federal taxes paid. Using the notation from Appendix B, these tax features correspond to state parameters of $\xi_{it} = 1$, $\phi_{it} = 0$, $\alpha_{it} = 0.5$, $k_{it} = 0.05$, $M = 3$, and $\tau_{it} = 0.079$. PL 101-239 removed the moving-average base computation and started to treat the entire federal R&D tax credit as income, thereby changing M to zero and α for Wisconsin to one in 1990. Wisconsin did not change any of its R&D tax credit laws from 1989 to 1990.

To compute the change in the treatment variable from 1989 to 1990, I take the difference between what the R&D tax incentive rate would be post-federal law change conditioned on 1989's state tax laws, less what the state R&D tax incentive rate was in 1989. Because in 1989 Wisconsin's R&D tax credit law was linked to the federal tax law, I compute the former piece as if firms in Wisconsin were subject to both state and federal R&D tax credits that did not use a moving-average base and as if both the state and federal tax credits were treated as ordinary income.

E Appendix: Wilson (2009) Replication and Comparison

This appendix compares the results from Wilson (2009) with a replication and highlights key differences between Wilson (2009) and this paper, particularly the comparable specifications using state-level tax variation in Table 3.

For the replication exercise, Dan Wilson provided me with the tax data for his user cost. However, in replicating his results I do not have the non-tax variables or the code.

Table 7, column (1) reports the results from Table 1, column (1) of Wilson (2009). The key regressor, $ln(RDTaxRate_{it}^{Wilson})$, is the tax user cost from Dan Wilson's data.[53] To compare results with this paper, I switch the sign of $ln(RDTaxRate_{it}^{Wilson})$, as Wilson (2009) reports the key coefficient as the negative of the tax incentive rate, while this paper reports the tax incentive rate. Column (2) of Table 7 is my replication of Table 1, column (1) of Wilson (2009). I report replication results using the credit rate for the highest tier of R&D expenditures and the generalized least squares (GLS) estimator.[54] Although it is unclear from Wilson (2009) which credit tier his results are based on, the 2007 working paper version (pg. 37) specifies that results are for the highest tier of R&D expenditures. In addition, the 2007 working paper version (pg. 19) adds that his results

[53]This coefficient is ρ_{it}^{in} in Wilson (2009).

[54]See Appendix B for additional details on R&D tax credit tiers.

are obtained with the GLS estimator, although the 2007 working paper contradicts the published paper's account of estimation with OLS (pg. 433). However, the results from the 2007 working paper, Table 2, column (2) match the results from Table 1, column (1) of the published version exactly. I also find that replication with the GLS estimator more closely matches the published paper's results.

From Table 7, column (2) we can see that my replication results are close to Dan Wilson's published estimates. The coefficient (standard error) of $ln(RDTaxRate_{it}^{Wilson})$ from the replication is 1.13 (0.43) vs. 1.21 (0.44) as the published estimate in column (1). Replication with the credit rate for the lowest tier of R&D expenditures gives results closer to Wilson (2009), with the key coefficient (standard error) as 1.23 (0.42). The other replication coefficients are similar to those in Wilson (2009). Since I do not have the original data from Wilson (2009) (other than the tax user cost), the non-tax variables that undergo data revision (for example, gross state product) will be different in my replication dataset so some difference in results is expected.

Column (3) restricts Wilson's specification, which uses all 50 states plus the District of Columbia, to include only the sample of 21 high-R&D states from this paper.[55] These 21 states are those where I observe R&D in the 1980s and 1990s, as the NSF does not report R&D during the 1980s and 1990s for the smaller R&D states due to disclosure concerns. For my IV analysis, observing states in the 1980s and 1990s is necessary because that is when the variation in federal tax laws takes place, so my IV specifications cannot use the data from the imputed smaller states. The estimate of $ln(RDTaxRate_{it}^{Wilson})$ drops from slightly above unit elastic to an inelastic 0.20 and is insignificant from zero. In column (4), I replace Wilson's key coefficient with my measured tax rate, $ln(RDTaxIncentiveRate_{it})$, which also gives an inelastic estimate of 0.15.[56] Therefore, the difference in estimates between Table 3 and Table 1, column (1) of Wilson (2009) is not due to my data or my calculation of $ln(RDTaxIncentiveRate_{it})$, although $ln(RDTaxIncentiveRate_{it})$ tends to

[55]These states 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.

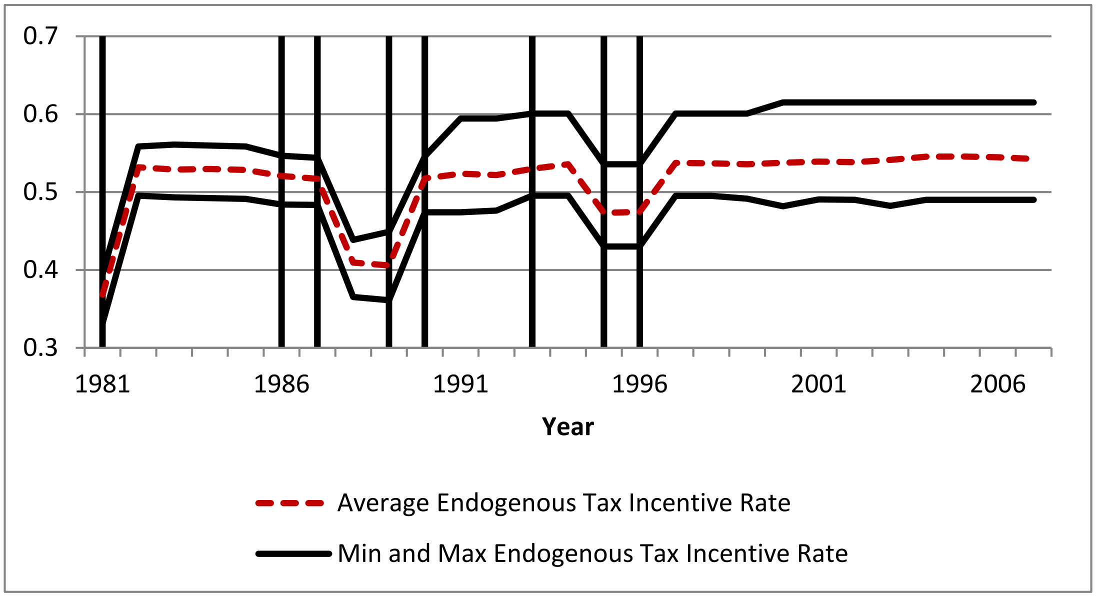
[56]Changing the estimator from GLS to OLS gives an estimate (clustered standard error by state) for $ln(RDTaxIncentiveRate_{it})$ of 0.48 (0.64).

give more precise estimates than the user cost from Wilson (2009).[57]

After 2000, the NSF began additional reporting of imputed R&D observations for smaller R&D states. Wilson (2009) includes these imputed observations, although my IV analysis cannot include these observations because my instrument does not vary after 2000. Wilson (2009)'s use of imputed observations drives some of the difference in estimates between columns (3) - (4) and column (2). In Table 7, column (5) I again use Wilson (2009)'s sample and key coefficient but drop imputed observations. The estimate of $ln(RDTaxRate_{it}^{Wilson})$ drops from 1.13 to 0.79, suggesting that about one-third of the difference in our OLS estimates comes from imputation, while the remaining two-thirds comes from sample state composition. A researcher may be concerned that the composition of my sample may be driving some of the difference between my estimates using exogenous variation, $ln(RDTaxIncentiveRate_{it}^{fed})$ (for example, in Table 2) and those in previous literature. While I cannot rule out this possibility, my estimates with comparable specifications and variation in Table 3 using $ln(RDTaxIncentiveRate_{it})$ still produce similar results to those from previous studies. Also, my sample of states is arguably the relevant sample to use as these states are doing most of the actual innovating.

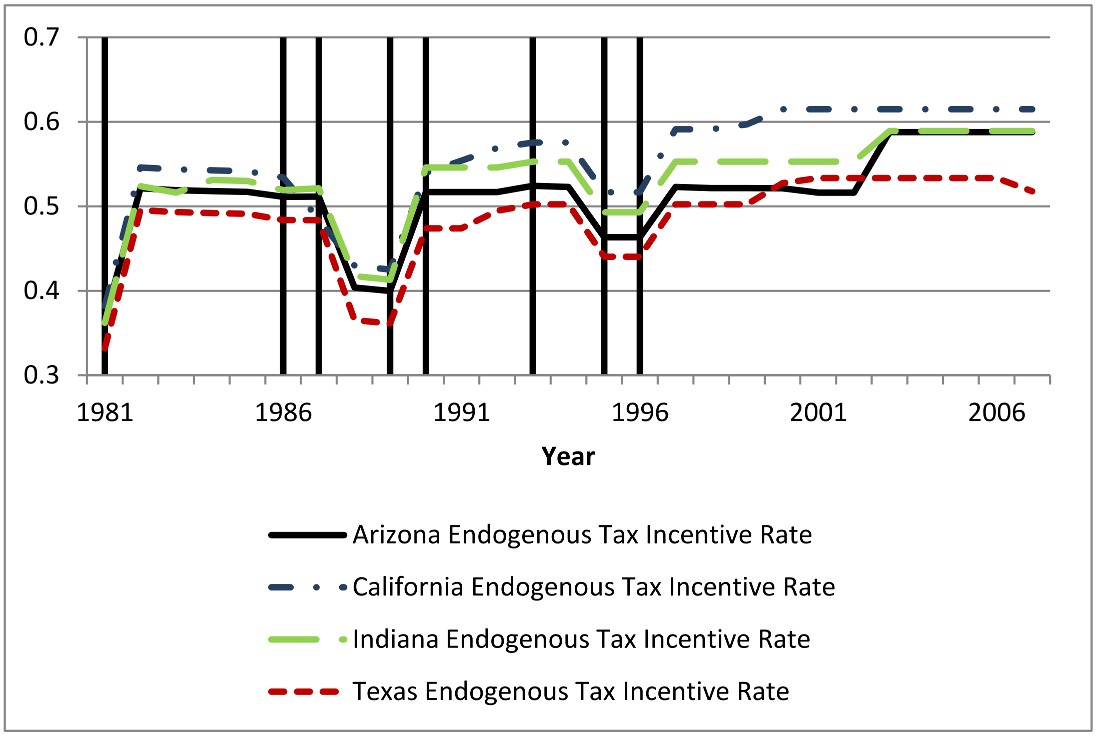
[57] Better precision is due to more detailed modeling and high-quality data. See Appendix B.

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



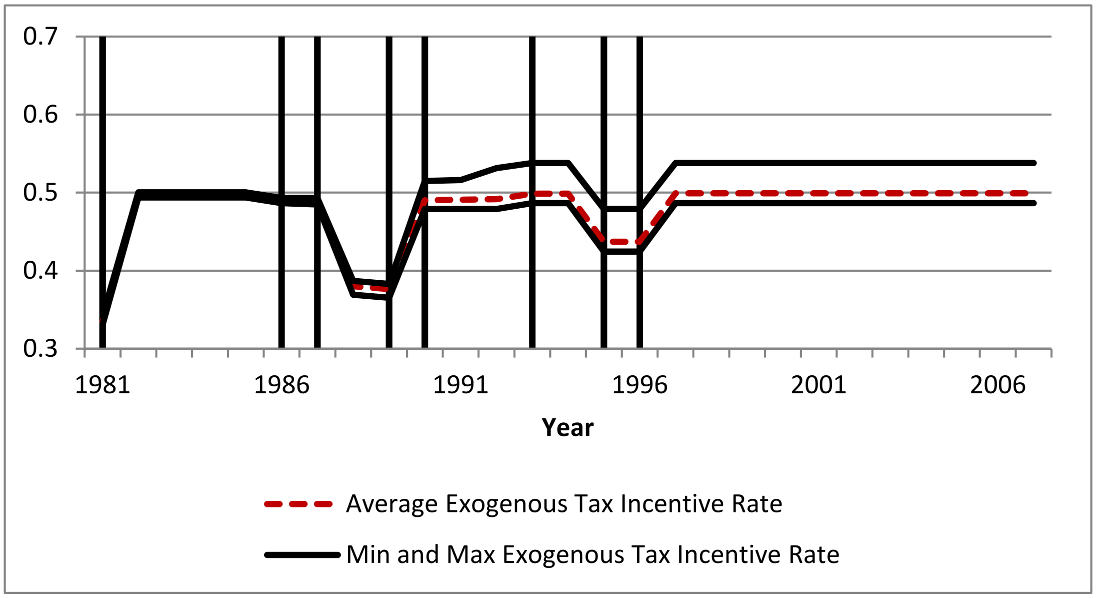
This figure plots summary statistics of state-level R&D tax incentive rates, calculated using variation from both state and federal laws, over time. Vertical lines indicate the dates that federal tax laws were effective. Sources: State session laws, Internal Revenue Code.

Figure 2: R&D Tax Incentive Rate - State and Federal Variation (Selected States)



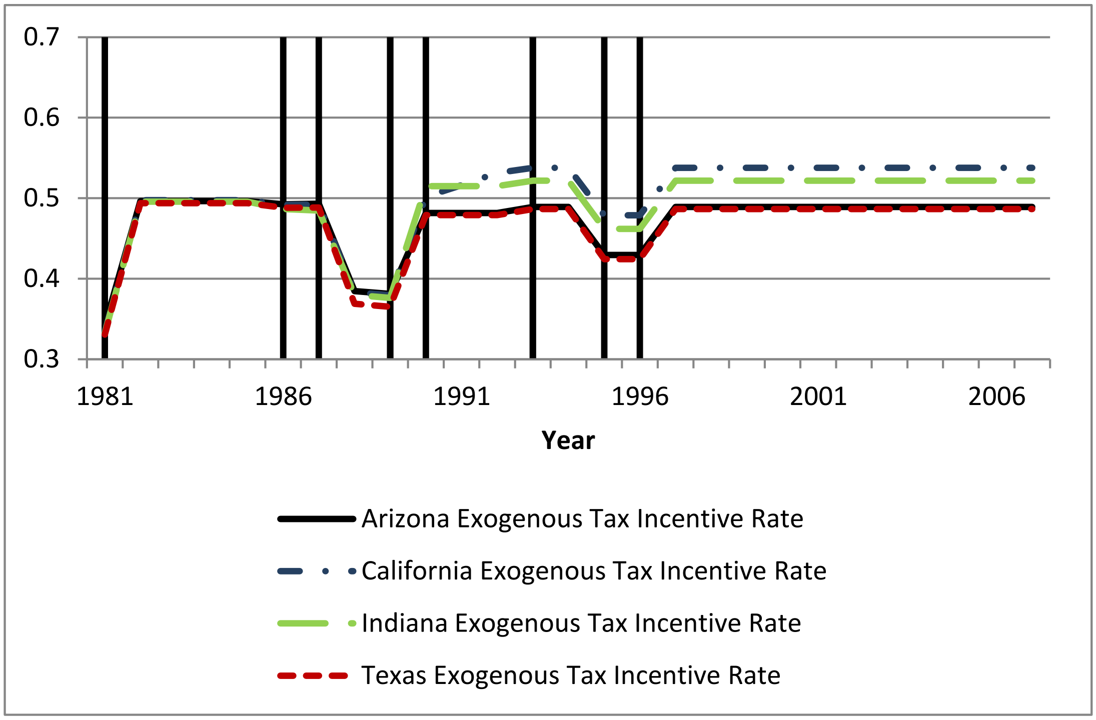
This figure plots state-level R&D tax incentive rates, calculated using variation from both state and federal laws, for Arizona (solid line), California (dashed dotted line), Indiana (long dashed line), and Texas (short dashed line). Vertical lines indicate the dates that federal tax laws were effective. Sources: State session laws, Internal Revenue Code.

Figure 3: R&D Tax Incentive Rate - Only Federal Variation



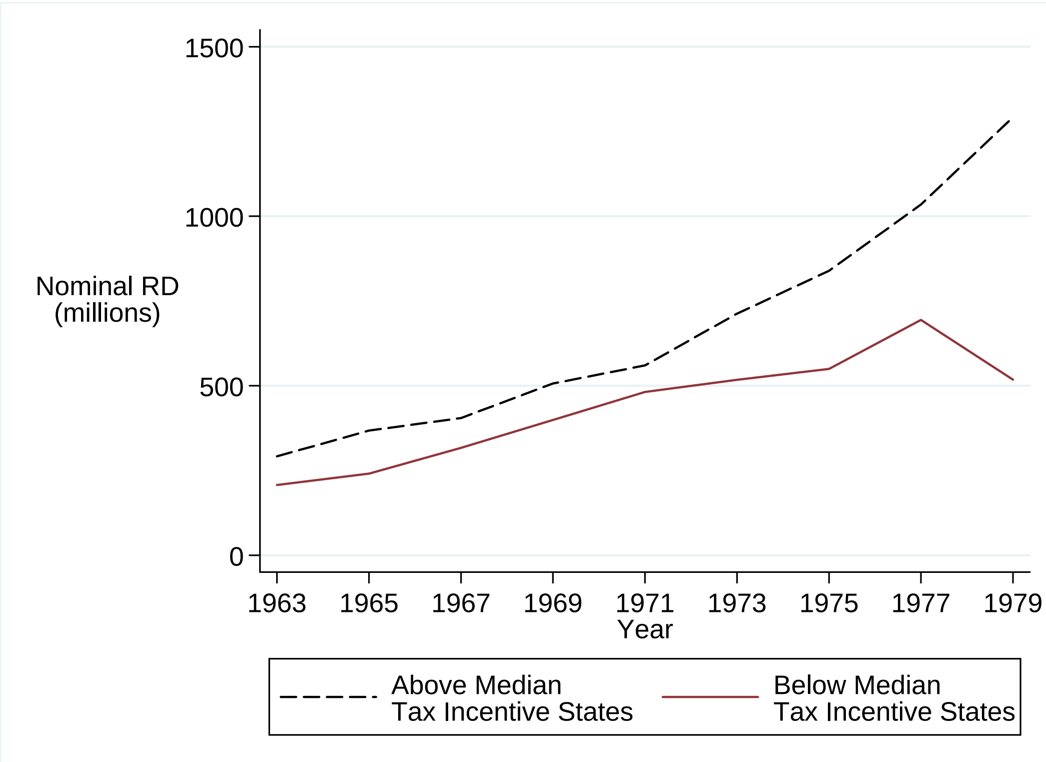
This figure plots summary statistics of state-level R&D tax incentive rates, calculated using variation from only federal laws, over time. Vertical lines indicate the dates that federal tax laws were effective. Sources: State session laws, Internal Revenue Code.

Figure 4: R&D Tax Incentive Rate - Only Federal Variation (Selected States)



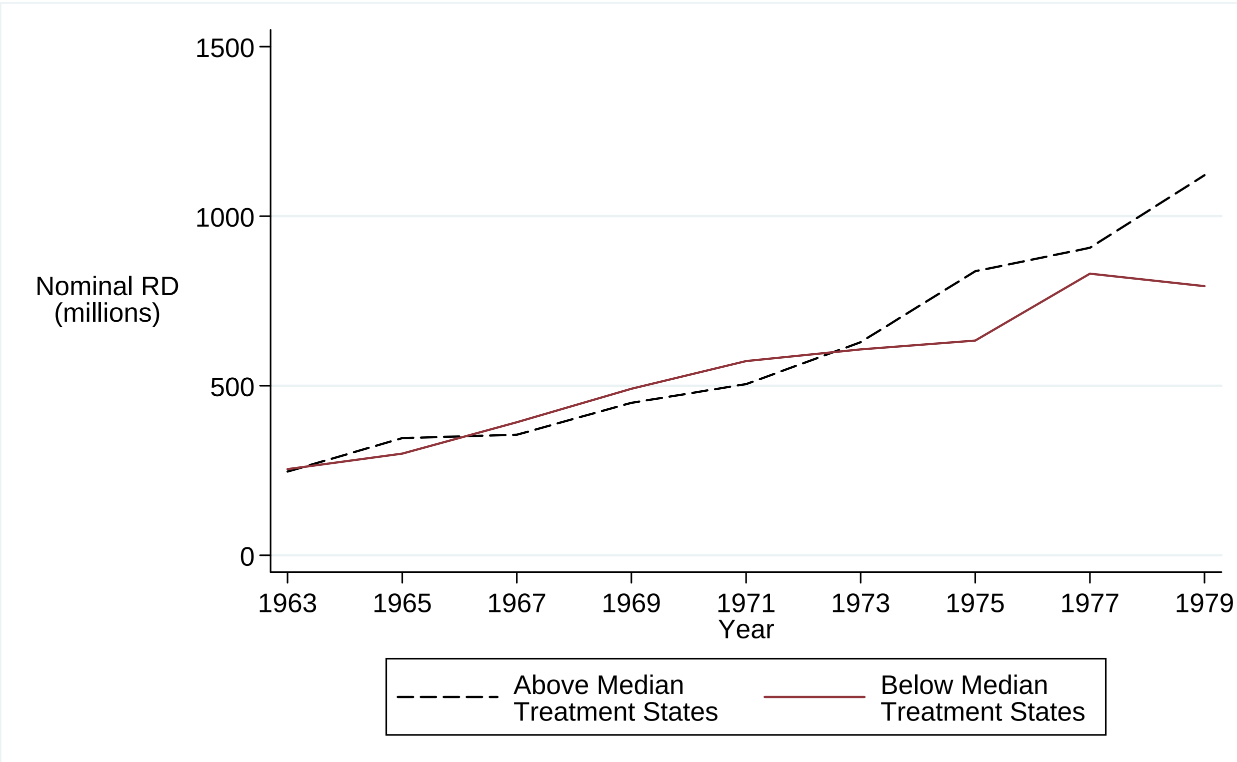
This figure plots state-level R&D tax incentive rates, calculated using variation from only federal laws, for Arizona (solid line), California (dashed dotted line), Indiana (long dashed line), and Texas (short dashed line). Vertical lines indicate the dates that federal tax laws were effective. Sources: State session laws, Internal Revenue Code.

Figure 5: Nominal R&D Prior to Federal R&D Credit - Endogenous R&D Tax Incentive Rate Grouping



This figure divides states into two groups - one with above median average R&D tax incentives from 1981-2007 and another with below-median incentives - using variation from both state and federal laws in state-level R&D tax incentives. The dashed line represents average nominal R&D for states with higher than the median average value of R&D tax incentives. The solid line is for states with lower than median average value of R&D tax incentives. Sources: National Science Foundation's Survey of Industrial Research and Development; State session laws.

Figure 6: Nominal R&D Prior to Federal R&D Credit - Exogenous R&D Tax Incentive Rate Grouping



This figure divides states into two groups - one group with above median average R&D tax incentives from 1981-2007 and another group with below-median incentives - using tax variation from only federal laws. The dashed line represents average nominal R&D for states with higher than the median average value of incentives from federal tax laws. The solid line is for states with lower than the median average value of incentives from federal tax laws. Sources: National Science Foundation's Survey of Industrial Research and Development; State session laws.

Table 1: Federal Laws Affecting R&D Tax Incentive 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

Source: Internal Revenue Code (Lexis annotations).

Table 2: Instrumental Variables Estimates Indicate Elastic Response

Dependent Variable: $ln(RD_{it})$					
	(1)	(2)	(3)	(4)	(5)
$ln(RDTaxIncentiveRate_{it}^{fed})$	4.51	5.06	2.89	3.69	3.78
	(1.59)***	(2.02)**	(1.14)***	(1.59)**	(1.69)**
$ln(RD_{it-2})$			0.46	0.38	0.39
			(0.10)***	(0.10)***	(0.11)***
$ln(GSP_{it})$				0.58	
				(0.31)*	
$ln(Federal\ RD_{it-2})$		0.39		0.20	0.22
		(0.12)***		(0.07)***	(0.07)***
$ln(Academic\ RD_{it})$		0.07		-0.31	-0.15
		(0.29)		(0.24)	(0.21)
$Unemployment\ Rate_{it}$		-0.69		-1.27	-1.14
		(3.27)		(2.67)	(2.69)
Implied Long-Run			5.38	6.00	6.23
Tax Incentive Elasticity			(1.74)***	(2.00)***	(2.09)***
First-stage F-statistic	2.28	2.50	2.14	1.78	1.84
State Fixed Effects	X	X	X	X	X
Time Dummies	X	X	X	X	X
Observations	226	226	206	206	206

The key regressor *RDTaxIncentiveRate* is instrumented with $RDTaxIncentiveRate^{fed}$. The estimator is two-stage least squares. First-stage F-statistic is for the excluded instrument. This table reports coefficients as elasticities except for the unemployment rate, which is a semielasticity. Clustered standard errors by state in parentheses. The implied long-run elasticity is the coefficient of the tax rate divided by one minus the coefficient on the lagged dependent variable with the standard errors calculated with the delta method. *, **, ***: significant at 10%, 5%, 1%.

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

Dependent Variable: $ln(RD_{it})$					
	(1)	(2)	(3)	(4)	(5)
$ln(RDTaxIncentiveRate_{it})$	1.66	1.74	0.58	0.37	0.65
	(1.00)	(1.11)	(0.73)	(0.73)	(0.76)
$ln(RD_{it-2})$			0.53	0.49	0.49
			(0.11)***	(0.09)***	(0.11)***
$ln(GSP_{it})$				0.89	
				(0.20)***	
$ln(Federal\ RD_{it-2})$		0.37		0.13	0.16
		(0.11)***		(0.07)*	(0.06)***
$ln(Academic\ RD_{it})$		0.08		-0.44	-0.18
		(0.30)		(0.22)*	(0.20)
$Unemployment\ Rate_{it}$		2.31		0.85	0.94
		(2.87)		(1.84)	(1.78)
Implied Long-Run Tax Incentive Elasticity			1.21	0.72	1.29
			(1.40)	(1.37)	(1.38)
p-value of IV-OLS Estimates	0.23	0.22	0.04**	0.01***	0.01***
State Fixed Effects	X	X	X	X	X
Time Dummies	X	X	X	X	X
Observations	226	226	206	206	206

The key regressor $ln(RDTaxIncentiveRate)$ is the R&D tax incentive rate calculated using changes in both state and federal laws (the statutory rate). The estimator is ordinary least squares. This table reports coefficients as elasticities except for the unemployment rate, which is a semielasticity. Clustered standard errors by state in parentheses. The implied long-run elasticity is the coefficient of the tax rate divided by one minus the coefficient on the lagged dependent variable with the standard errors calculated with the delta method. For each column, the p-value of IV-OLS estimates row uses the Wooldridge (1995) cluster-robust score test for the difference between the IV estimate of $ln(RDTaxIncentiveRate_{it}^{fed})$ in Table 2 and the OLS estimate of $ln(RDTaxIncentiveRate_{it})$ from this Table, with the null hypothesis of no difference. *, **, ***: significant at 10%, 5%, 1%.

Table 4: Sample Modifications

Dependent Variable: $ln(RD_{it})$	(1)	(2)	(3)	(4)
$ln(RDTaxIncentiveRate_{it}^{fed})$	2.96	3.21	6.29	3.41
	(1.25)**	(1.82)*	(1.74)***	(1.66)**
$ln(RD_{it-2})$	0.48	0.31	0.09	0.44
	(0.11)***	(0.15)**	(0.10)	(0.11)***
$ln(Federal\ RD_{it-2})$	0.24	0.24	0.36	0.20
	(0.06)***	(0.07)***	(0.12)***	(0.06)***
$ln(Academic\ RD_{it})$	-0.22	-0.25	0.15	-0.20
	(0.17)	(0.20)	(0.27)	(0.19)
$Unemployment\ Rate_{it}$	-1.68	1.59	-5.18	-0.62
	(2.31)	(2.85)	(2.99)*	(2.46)
Implied Long-Run	5.69	4.70	6.88	6.14
Tax Incentive Elasticity	(1.62)***	(1.97)***	(1.45)***	(2.29)***
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

This table reports coefficients as elasticities except for the unemployment rate, which is a semielasticity. Clustered standard errors by state in parentheses. The implied long-run elasticity is the coefficient of the tax incentive rate divided by one minus the coefficient on the lagged dependent variable with the standard errors calculated with the delta method. *, **, ***: significant at 10%, 5%, 1%.

Table 5: Alternative Specifications

Dependent Variable: $ln(RD_{it})$				
	(1)	(2)	(3)	(4)
$ln(RDTaxIncentiveRate_{it}^{fed})$	5.25	7.11		
	(2.75)**	(2.84)***		
$ln(RDTaxIncentiveRate_{it}^{PL101-239})$			3.14	2.89
			(1.39)**	(0.91)***
$ln(RD(Biennial)_{t-2})$	0.42			
	(0.11)***			
$ln(RD(Annual)_{it-1})$	0.31			
	(0.15)**			
$ln(RD_{it-2})$			0.41	0.44
			(0.10)***	(0.10)***
$ln(RD_{it-4})$		0.10		
		(0.13)		
$ln(Federal\ RD_{it-2})$	0.13	0.34	0.21	0.17
	(0.09)	(0.11)***	(0.06)***	(0.05)***
$ln(Academic\ RD_{it})$	-0.23	-0.03	-0.15	-0.24
	(0.20)	(0.35)	(0.19)	(0.21)
$Unemployment\ Rate_{it}$	-1.87	-2.99	-0.71	-0.15
	(3.12)	(4.22)	(2.40)	(2.11)
Implied Long-Run	7.58	7.90	5.35	5.15
Tax Incentive Elasticity	(2.49)***	(2.42)***	(1.82)***	(1.14)***
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

Column (1) uses all available data and divides the coefficient on the lagged dependent variable into separate coefficients for the biennial (1981-1996) and annual (1997-2006) R&D data periods. Columns (2) - (4) use the default biennial data structure over the entire sample. In columns (3) and (4), $ln(RDTaxIncentiveRate^{PL101-239})$, uses only variation from Public Law 101-239 in R&D tax incentive rates. Column (4) drops Illinois and Massachusetts because of changes in state R&D credits that are contemporaneous 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. The implied long-run elasticity is the coefficient of the tax incentive rate divided by one minus the coefficient of the dependent variable (annual lag for column 1) with the standard errors calculated with the delta method. *, **, ***: significant at 10%, 5%, 1%.

Table 6: Difference-in-Sargan Overidentification Tests

Dependent Variable: $ln(RD_{it})$					
	(1)	(2)	(3)	(4)	(5)
$ln(RDTaxIncentiveRate_{it})$	3.78	3.13	3.55	2.59	2.55
	(1.69)***	(1.44)**	(1.70)**	(0.84)***	(0.85)***
$ln(RD_{it-2})$	0.39	0.42	0.40	0.43	0.43
	(0.11)***	(0.11)***	(0.11)***	(0.10)***	(0.10)***
$ln(Federal\ RD_{it-2})$	0.22	0.21	0.22	0.20	0.19
	(0.07)***	(0.06)***	(0.07)***	(0.05)***	(0.05)***
$ln(Academic\ RD_{it})$	-0.15	-0.16	-0.15	-0.16	-0.16
	(0.21)	(0.20)	(0.21)	(0.19)	(0.19)
$Unemployment\ Rate_{it}$	-1.14	-0.71	-0.99	-0.34	-0.32
	(2.69)	(2.43)	(2.73)	(2.04)	(2.00)
Implied Long-Run	6.23	5.35	5.92	4.55	4.50
Tax Incentive Elasticity	(2.10)***	(1.75)***	(2.14)***	(0.94)***	(0.98)***
Instrument Lags	1	1,2	1,2,4	1,3,4	3,4
Difference-in-Sargan p-value		0.26	0.25	0.54	0.19
First-stage F-Statistic	1.84	2.11	3.51	12.94	19.1
Observations	206	206	206	206	206

Each column estimated with two-stage least squares. First-stage F-statistic tests the excluded instruments. All columns include state fixed effects and time dummies. Clustered standard errors by state in parentheses. "Instrument Lags" refers to instruments constructed with the referenced lags of state tax policy. For example, in column (2) I instrument the endogenous *RDTaxIncentiveRate* with $RDTaxIncentiveRate^{fed}$, which I construct by conditioning on the first lag of state tax policy, and $RDTaxIncentiveRate^{fed}$ which I create by conditioning on the second lag of state tax policy. The table calculates the Difference-in-Sargan test by excluding the instrument computed with the shortest listed lag length. The implied long-run elasticity is the coefficient of the tax incentive rate divided by one minus the coefficient on the lagged dependent variable with the standard errors calculated with the delta method. *, **, ***: significant at 10%, 5%, 1%.

Table 7: Wilson (2009) Comparison

Dependent Variable: $ln(RD_{it})$					
	Wilson (2009) Reported	Wilson (2009) Replication			
	(1)	(2)	(3)	(4)	(5)
$ln(RDTaxRate_{it}^{Wilson})$	1.21	1.13	0.20		0.79
	(0.44)***	(0.43)***	(0.43)		(0.40)**
$ln(RDTaxIncentiveRate_{it})$				0.15	
				(0.30)	
$ln(RD(Biennial)_{t-2})$	0.49	0.43	0.56	0.56	0.49
	(0.04)***	(0.04)***	(0.05)***	(0.05)***	(0.04)***
$ln(RD(Annual)_{it-1})$	0.45	0.39	0.48	0.48	0.43
	(0.05)***	(0.04)***	(0.05)***	(0.06)***	(0.04)***
$ln(GSP_{it})$	0.73	0.67	0.73	0.75	0.55
	(0.18)***	(0.18)***	(0.20)***	(0.19)	(0.17)***
$ln(Federal\ RD_{it-2})$	-0.05	-0.01	-0.02	-0.02	-0.01
	(0.01)***	(0.01)	(0.01)	(0.01)	(0.01)
Implied Long-Run	2.18	1.83	0.38	0.28	1.37
Tax Incentive Elasticity	(0.81)***	(0.69)***	(0.83)	(0.55)	(0.70)*
State Fixed Effects	X	X	X	X	X
Time Dummies	X	X	X	X	X
Only Largest R&D States			X	X	
Drop Imputed Observations			X	X	X
Observations	365	366	232	232	336

Column (1) contains the reported values of Table 1, column (1) of Wilson (2009). Column (2) is my replication of Table 1, column (1) of Wilson (2009). Columns (3) and (4) restrict the sample to 21 high R&D states used in this paper. Column (5) uses all states, including the District of Columbia, and drops observations where $ln(RD_{it})$ is imputed. For all columns, the estimator is generalized least squares with standard errors that allow for first-order autoregressive serial correlation and within-state heteroskedasticity, following Wilson (2009). The implied long-run elasticity is the coefficient of the tax incentive rate divided by one minus the coefficient on the annual period's lagged dependent variable with the standard errors calculated with the delta method. *, **, ***: significant at 10%, 5%, 1%.