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Information Transparency and the Effectiveness of R&D Tax Credits

Abstract

Using staggered changes in state-level R&D Tax Credits (RTC), I investigate the effectiveness of RTCs offered by U.S. states and their dependence on information transparency. The results show that RTCs increase aggregated patenting activities within a state, with more substantial effects observed in states with transparent information environments, as measured by state adoption of the Inevitable Disclosure Doctrine (IDD) and aggregated peer information driven by presence of public firms in the same industry. Additionally, the evidence suggests that the impact of information transparency on individual firms' reaction to RTCs varies depending on the tradeoff between benefits (e.g., reduced cost of capital, increased innovation efficiency, and more patent transactions) and costs (e.g., spillover effects of innovation). These findings have important implications for policymakers aiming to stimulate innovation with a given budget.

Keywords: Information Transparency, R&D Tax Credit, Tax Credit Effectiveness

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1 INTRODUCTION

Governments frequently employ R&D Tax Credits (RTCs) to stimulate innovation, and many countries, states, and industries presently offer innovation incentives to enhance their business competitiveness. When making decisions on R&D tax policies, policymakers and lobbying parties often use R&D tax policies offered by other countries or states as benchmarks. For instance, in October 2022, over four hundred corporations and organizations signed a coalition letter on R&D taxes urging Congress and the House to reverse the tax code on the amortization of R&D expenses. In the letter, they stated, "China currently provides a super deduction for R&D expenses up to an extra 100% of eligible R&D expenses in addition to actual R&D expenses. At a time of increasingly fierce global competition for research dollars, this change will make it harder for the next R&D dollar to be spent in the U.S. which will ultimately hurt future U.S. competitiveness."[1] Despite frequent comparisons between the generosity of one innovation incentive to another, there is a lack of empirical evidence on the comparison of the effectiveness of tax incentives across different regimes. Without considering the effectiveness of the tax incentive, government competition on R&D tax incentives may result in the misallocation of resources and deadweight loss of social welfare.

In this paper, I explore the effectiveness of RTCs offered by U.S. states and investigate whether information transparency impacts their effectiveness. According to OECD R&D Tax Incentives database, the total government support through R&D tax incentives in the U.S. was $25.485 billion in 2019, which was the highest among the expenditures on R&D tax incentives of

[1] The coalition letter is available at https://www.uschamber.com/taxes/coalition-letter-on-research-development-taxes.

all countries[2]. Of this amount, the federal government provided around $11.7 billion while state governments provided the remaining $13.8 billion[3]. While some studies have found positive effects of state RTCs on R&D expenditure, growth in high-tech industries, and employment (Wu 2008; Fazio, Guzman, Stern 2019; Selby 2020), others report mixed results (Schmidt 2021). Given the significant amount of state RTCs and governments' strong motivation to help their domestic businesses stay competitive in technology competition, more evidence is needed on the effectiveness of state RTCs and factors that affect their effectiveness. This will help policymakers evaluate effectiveness of RTCs and improve their real impact.

I expect information asymmetry to be a significant obstacle that impedes the effectiveness of R&D tax incentives to increase innovation. Ideally, policymakers would be able to observe the innovation abilities and real innovation efforts of firms and, consequently, maximize the effectiveness of R&D tax incentives by allocating incentives to firms with potential to generate innovation breakthroughs. However, in reality, information asymmetry exists, and may affect the ability of R&D tax incentives to reach their full potential. The importance of information transparency for the effectiveness of R&D incentives is highlighted by Akcigit, Hanley, and Stantcheva (2022), who consider the existence of asymmetric information and propose an optimal tax and R&D policy model that differs from the policy without information asymmetry. One implication of their theoretical model is consistent with my expectation of a positive impact of information transparency on the effectiveness or R&D tax incentives.

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[2] The total government support through R&D tax incentive in the United States in 2019 was 1.192% of GDP. The data is available at https://stats.oecd.org/Index.aspx?DataSetCode=RDTAX.

[3] According to the Joint Committee on Taxation's (JCT) Estimates of Federal Tax Expenditures for Fiscal Years 2019-2023, the R&D tax credit reduced tax revenue of the federal government by about $11.7 billion in 2019—$10.3 billion for corporations and $1.4 billion for individuals. The report is available at https://www.jct.gov/publications/2019/jcx-55-19/.

To investigate the impact of R&D tax credits (RTCs) on innovation outcomes, I leverage the introduction of state-level RTCs and state-level patent data in the U.S. from 1982 to 2020. Patent application data provides a reliable identification of locations of innovation, enabling me to measure real innovation activities within state borders. By focusing on patenting activities aggregated at the state level, I directly evaluate how effectively RTCs achieve their intended purpose of promoting innovation outcomes. Because RTCs were introduced in different years, I employ a staggered difference-in-differences (DID) approach to assess their impact on innovation. This approach also facilitates a better identification of the causal effects of RTCs.

To capture the information transparency that may be relevant to the allocation of R&D tax incentives within a state, I employ state adoption of the Inevitable Disclosure Doctrine (IDD) and aggregated peer information driven by presence of public firms. IDD blocks employee mobility through which firms can learn about innovation-related information of their peers, reducing information transparency, particularly for non-public and proprietary information (Li, Ma, and Shevlin 2021; Klasa et al. 2018; Chen, Gao, and Ma 2021). In contrast, presence of public firms in an industry increases public information available in that industry, leading to an increase in information transparency. When a state has a large percentage of firms operating in industries with high public firm presence, firms in the state tend to have more relevant industry level information available.

Although public firm presence is less likely to increase proprietary information disclosure, their aggregated disclosure can also provide valuable insights into innovativeness of projects. Firms in an industry are influenced by similar economic forces, so the aggregated information can inform about their industry level supply, demand, and competitive conditions and is a valuable source for decisions of peer firms, stakeholders, and competitors. Several studies have shown that presence of public firms affects private firms' investment and cost of capital, import market competition, and patent sales (Badertscher, Shroff, and White 2013; Shroff, Verdi, and Yost 2017; Glaeser and Omartiam 2021; Kim and Valentine 2023). Literature examining macro effects of accounting information suggests that information transparency can facilitate efficient allocation of resources across firms with different production productivities[4]. Similarly, presence of public firms can also help external market participants (e.g., capital providers, potential acquirers, or potential patent buyers) better evaluate innovation projects and innovation abilities of firms in the industry. As a results, incremental innovation investments stimulated by RTCs with higher return are more likely to be supported by these market participants. Overall, I expect to find a positive impact of information transparency on the effectiveness of RTCs.

The findings of my main tests indicate that the introduction of RTCs leads to increased innovation outcomes in states, especially in states with high information transparency. My results show a significant increase in the number of patents and top cited patents, with a positive but not significant effect on overall citations received. When considering the impact of IDD, I find significant positive main effects of both RTCs and IDD, but a significant negative interaction effect on innovation outcomes. The results suggest that states with IDD experience an attenuated effect of RTCs on innovation outcomes. To test whether aggregated public firms' presence affect RTCs' effectiveness, I conduct the subsample analyses for states with high (top tercile) and low (bottom tercile) information transparency measured by aggregated public firms' presence. The results show that RTCs have a more substantial positive effect on the total citations received in states with high information transparency. Additionally, I use aggregated public firm presence at patent class level

[4] Hann et al. (2020) document that high-quality accounting information at the industry level can inform external market participants about firm productivity, and hence mitigate the effect of information frictions on allocation efficiency and, in turn, reduce productivity dispersion.

to control for variation in patenting patterns. By testing the variation of patenting activities of a particular patent class in a state relative to that of the same patent class in the other states, I can control patent class invariant factors on top of state and time invariant factors. The results document significant positive effects of RTCs on innovation outcomes only when the patent class has transparent information, consistent with my hypothesis.

I then conduct analysis to examine heterogeneous effects of information transparency on RTCs' impact on innovation outcomes generated by public and private firms. While innovation outcomes at the aggregated state level capture an overall impact of RTCs, at individual firm level, the net effect of RTCs and information transparency may be positive or negative depending on the tradeoffs between benefits and costs. I test the impact of IDD on RTCs' effects on innovation generated by public and private firms and document that private firms generate more innovation under RTCs when IDD is present, while public firms experience a reduction in their innovation. This net negative effect of IDD on RTCs' effectiveness is primarily driven by public firms, which cannot easily acquire information and key personnel from private firms after IDD adoption, limiting their ability to realize the full benefits of RTCs. Moreover, I used aggregated public firm presence at the patent class level as a proxy for information asymmetry and find that the positive effect of information transparency on the effectiveness of RTCs is mainly driven by private firms. This suggests that private firms benefit more from aggregated information of public firms, as supported by previous studies (Badertscher, Shroff, and White 2013; Shroff, Verdi, and Yost 2017). Overall, my findings indicate that information transparency affects the allocation of R&D tax credits by altering the costs and benefits for individual firms.

While information transparency increases costs for individual firms due to spillover effects of innovation, the benefits of that on individual firms could be attributed to several factors, including reduced cost of capital, increased innovation outputs for each dollar of R&D investment, and patent-related transactions. To explore how information transparency affects the effectiveness of RTCs at micro-level, I test these mechanisms respectively. I first investigate whether the positive effect of the interaction term of IDD and RTCs on innovation generated by private firms becomes more significant when access to capital is easier and aggregated information of public firms is transparent. Private firms tend to be more financially constrained and are less likely to fully realize the positive benefits of IDD and RTCs if they don't access to capital. Additionally, Shroff, Verdi, and Yost (2017) find that the industry-level presence of public firms is effective in reducing private firms' cost of capital since their firm-specific information is not publicly available. Using the index developed by Rice and Strahan (2010) to capture firms' accessibility to capital[5], I find that the positive effects of the interaction of IDD and RTCs on innovation generated by private firms are significant only when access to capital is easier. Moreover, conditional on the availability of capital, the effects become more substantial when the information transparency of the technology class is high. This evidence suggests that information transparency improves the effectiveness of RTCs by reducing the cost of capital.

Second, I investigate the innovation efficiency of additional R&D stimulated by RTCs for firms in industries with high and low public firm presence. External information, such as that generated by other firms or at the macro level, can impact investment decisions (Shroff, Verdi, and Yu 2014; Badertscher, Shroff, and White 2013). I examine whether additional innovation outcomes generated by one incremental R&D stimulated by RTCs are more substantial for firms

[5] Rice and Strahan (2010) measure the deregulation of interstate bank in a state. Such deregulation permits banks from other states to establish branches with low entry barriers in a state, which results in increased bank competition. Cornaggia et al. (2015) document that high bank competition can reduce the cost of capital of innovation, especially for small firms. Following the evidence, I use interstate banking deregulation index to proxy bank competition in a state, which is associated with the availability to capital.

operating in high information transparency industries. The results suggest that RTCs increase innovation efficiency only for firms operating in high information transparency environments. This suggests that individual firms can generate more innovation outcomes by applying RTCs when information is transparent.

Third, I investigate whether information transparency increases technology-driven acquisitions and patent sales. If firms anticipate that they can efficiently realize the value of innovation by selling patents, they are more likely to respond to innovation incentives and increase their innovation efforts. I use the number of firms being acquired and the number of patents sold in a state as proxies for patent transactions and investigate whether a transparent information environment facilitates patent transactions. The results indicate that private firms with patents in states with high information transparency are more likely to be acquired when RTCs are introduced. Additionally, patents generated in states with high information transparency are more likely to be sold after the introduction of RTCs. This suggests that a transparent information environment supports efficient patent transactions.

To address concerns about endogeneity, I perform two tests. First, I match technology classes in neighboring states with the same technology class in the focal state and control for the level of innovation in time t. The results generated from this matched sample indicate that the positive effect of RTCs on innovation is only present for technology classes with high information transparency, which is consistent with the main findings. Second, I conduct pre-trend analyses for the period (t-2, 0) before the introduction of state-level RTCs. The results show no significant difference in innovation outcomes and patent transactions, which rejects the argument that the documented results are due to pre-existing trends. These findings provide additional support for my main results.

This study makes several contributions to academic research and policymaking. First, the findings have important policy implications for tax and R&D policymakers globally who aim to help businesses in their domestic market lead in the new technological classes. The evidence shows that the overall transparency of peer information, which is aggregated from publicly available information of individual firms, as well as the transparency of innovation-related information (e.g., adoption of IDD), can improve the effectiveness of innovation tax incentives. The findings also suggest that similar innovation incentives cannot necessarily be expected to produce the similar effects across different regimes as transparency of nonproprietary information and proprietary information vary significantly. Policymakers should consider a possibly reduced effect of an innovation incentive if the overall information is not transparent. Small or private firms are likely to benefit more significantly from transparent information compared to public firms. Given that innovation is key to a country's economy and competitiveness, governments may want to consider enhancing information transparency to further improve the effectiveness of innovation incentives and increase the likelihood of success in the new wave of technological revolution.

This study also makes a contribution to the existing literature on the effectiveness of R&D tax incentives. Previous studies have primarily focused on examining the net effect of RTCs (Wilson 2009; Rao 2016; Thomson 2017). However, since the design of tax incentives may vary, the evidence on the effectiveness of one or a few tax policies may not be generalizable to other tax incentives. By leveraging a setting with controllable variation in the designs of tax policies and identifying clean measures of innovation output, this study provides robust evidence on how information transparency affects the effectiveness of RTCs.

Finally, this study contributes to the literature on the value of public firm presence, the macro effect of financial disclosures, and to information transparency and innovation. Since the findings of Badertscher, Shroff, and White (2013) suggesting that the presence of public firms can facilitate the investment of private firms, many studies have documented the impact of information transparency developed from the presence of public firms in various settings, such as import competition (Glaeser and Omartian 2022) and patent sales (Kim and Valentine 2023). Building on the evidence of Badertscher, Shroff, and White (2013) and Shroff, Verdi, and Yost (2017), this study finds that public firm presence can improve the effectiveness of R&D tax incentives, with the results mainly driven by private firms. This study is also related to the emerging area of accounting research on the macro effect of accounting information. For example, Hann et al. (2020) document that high-quality financial reporting with respect to firm productivity can mitigate information frictions and hence facilitate the efficient allocation of resources across firms. This study adds to this area by documenting that aggregated accounting information can help allocate tax incentives more efficiently. Moreover, this study is in line with studies that document that information transparency improves innovation (Zhong 2018; Brown and Martinsson 2019) by showing that transparent information increases innovation outcomes promoted by RTCs.

I organize the remainder of the dissertation as follows. Section two provides the background and literature revie. I then present the hypothesis development in section three. Section four presents the sample, variable, and research design. Section five presents the results. Finally, section six concludes.

2 BACKGROUND AND LITERATURE REVIEW

2.1 Background of R&D Tax Incentives

2.1.1 R&D Tax Incentives around the World

R&D tax incentives have been used to stimulate innovation for decades and have become increasingly popular globally over time. Since the start of the digital revolution in the 1970s, major technological breakthroughs have not only created new industries but also disrupted existing ones. In order to remain competitive, many countries have implemented various forms of R&D tax incentives to promote innovation and drive economic growth. As the growth of several Asian economics since 1980s, such as South Korea, Singapore, and China, which all successfully utilized R&D tax incentives to promote innovation and technological development in their economic transformation, the use of R&D tax incentives has continued to grow in popularity.

The popularity of R&D incentives is evidenced by the growth in both the number of countries that provide R&D tax incentives and the extent of such incentives. According to the OECD R&D tax incentives report, only 12 OECD countries offered R&D tax incentives in 1996; however, by 2021, 34 of the 38 OECD countries, 22 of 27 EU countries, and a number of partner economies offered tax relief for R&D expenditures at central or subnational government levels. A similar pattern can be observed in the share of tax relief in total government R&D support, which increased from 36% in 2006 to around 57% in 2019 in OECD countries and from 27% in 2006 to 58% in 2019 for European Union countries. Figure 1 shows the trends in business enterprise R&D expenditure (BERD), government tax support, and direct funding support for BERD for OECD and EU countries from 2000-2019. The trend indicates that, during 2000-2019, the average government tax incentives for the ratio of R&D to GDP in OECD countries increased from 0.04% of GDP to 0.12% and from 0.01% to 0.1% for EU countries. In addition, R&D tax incentives overtook government direct support for BERD and became a more commonly used tool in stimulating innovation in 2016. Appendix A lists the most recent records of government R&D tax incentives in OECD and EU countries. The United Kingdom had the highest government-provided R&D tax support to GDP ratio at 0.307% in 2020, while the United States offered the highest dollar amount of such incentives at 23.76 billion dollars in 2019.

Despite the expansion of R&D tax incentives across countries, the design and extent of reliance on these incentives varies. Factors such as the definition of qualified R&D, tax instrument type, provisions for firms with insufficient tax liability, floors and ceilings of R&D tax benefits, and targeted relief measures all play a role in determining how well these incentives work. Appendix B provides an overview of major R&D tax incentives implemented by OECD and EU countries in 2022. The most common R&D tax incentive design is a tax credit with a volume-based scheme. Other designs include tax allowance, accelerated depreciation, and payroll incentives with incremental or hybrid tax bases.

In recent years, the rise of data and connectivity, along with advancements in artificial intelligence and robotics, has led many major economies to anticipate a new wave of industrial revolution. As a result, these countries have invested heavily in key industries through innovation incentives. For example, the semiconductor industry has received significant attention as it is at the core of modern technology, allowing for the development of faster, more powerful, and more efficient devices. Governments in the United States, China, the European Union, Japan, and Korea have all enacted hundreds of billions of dollars in incentives to stay competitive and remain at the forefront of technological progress. However, the level of R&D incentives alone does not guarantee subsequent quantity and quality of innovation, making it difficult to predict which countries will succeed in this wave of technological competition.

2.1.2 RTCs in the U.S.

The RTC was first introduced at the US federal level in 1981 to encourage private businesses to invest in innovation. Any business that attempts to develop new, improved, or technologically advanced products or trade processes can claim the credit. Corporations claim the credits when they file their federal corporate income tax returns. The original federal credit was calculated as either 25 percent of a corporation's qualified research spending over its average in the preceding three years or 50 percent of its current-year spending. The RTC expired at the end of 1985 and was updated as part of the Tax Reform Act of 1986. The PATH Act of 2015 permanently extended the federal RTC and expanded its provisions.

The RTC was initially introduced at the federal level in the U.S. in 1981 with the aim of incentivizing private businesses to invest in innovation. Any business attempting to develop new, improved, or technologically advanced products or trade processes can claim the credit. The original federal credit was calculated as either 25 percent of a corporation's qualified research spending over its average in the preceding three years or 50 percent of its current-year spending. The RTC expired at the end of 1985 and was updated as part of the Tax Reform Act of 1986. The PATH Act of 2015 permanently extended the federal RTC and expanded its provisions.

Apart from the federal level of innovation incentives, many states have introduced R&D tax incentives to encourage investment in innovation, stimulate regional economies, and drive job creation within their borders. The number of states offering RTCs has risen steadily since 1982 when Minnesota became the first state to enact an RTC. Currently, 35 US states offer the RTC to firms, and compared to RTCs worldwide, there are fewer variations in their designs.

Most RTCs implemented by states in the US rely on incremental-based schemes, with several states using a hybrid tax base. Defining the base level is a crucial feature of an RTC, and there are generally three ways in which states define it. The first way is using a zero base, where a credit with a zero base is known as a "flat credit", and these tax credits are defined as volume-based tax credit schemes. The second type of tax base is a moving average of the firm's R&D spending over the past few years, ranging from one to four years. Finally, a state can also use the allocated federal credit as the tax base for state RTCs. For a given credit rate, flat tax credits provide the most benefits to firms, as every dollar of qualified R&D is eligible for the credit. Examples of flat credits include the RTCs for basic research in New Jersey, Massachusetts, and West Virginia. RTCs with a moving-average type of base or the federal credit as a base provide limited benefits because the increased amount of R&D in a given year reduces the amount of creditable R&D in subsequent years. Apart from variations in defining tax bases for RTCs, other design features also impact how much these incentives can reduce the cost of innovation in a state.

Design features of RTCs, such as limits on taxpayer credits, statewide caps, and restrictions on industries and types of firms may limit their impact. For example, some credits have an annual state R&D limit that is below a certain amount or a certain percentage of tax liability. A statewide program cap refers to the total amount of RTCs that can be awarded under the program in a state each year. Once the cap is reached, no additional tax credits will be awarded in that state until the following year. Some states also have additional eligibility requirements, such as restrictions on the industry or type of organization of firms. For instance, the RTC enacted in Florida is limited to C corporations in targeted industries only, including aviation and aerospace, cloud information technology, homeland security and defense, information technology, life sciences, manufacturing, marine sciences, materials science, and non-technology industries.

To mitigate the limitations of standard RTCs in incentivizing firms with low or no profits, some states have implemented carry-over provisions for tax benefits or even tax refunds, which can expand the positive effects of such tax credits. Among states that have introduced R&D credits with carry-over provisions, the period over which unused tax incentive claims can be carried forward varies significantly across states. For example, in 2020, firms can carry forward unused claims for five years in Illinois and New Hampshire, 15 years in Arizona and Connecticut, 99 years in New Mexico, and indefinitely in California, Colorado, and Kansas. Additionally, 11 state RTCs are refundable, with six of them allowing any excess credit on top of the tax liability to be paid in part to the taxpayer or only for small business taxpayers.

Some states offer preferential tax credits for specific industries or types of firms, which may have varying effects on firms depending on their size and industry. For instance, Delaware doubles the RTC rate for qualifying small businesses. In contrast, Arizona, North Dakota, and Rhode Island have a higher tax credit rate for qualified R&D expenditures under a threshold and a lower rate for the amount over the threshold, which can benefit young, innovative firms in the stage of investing in developing and launching their products. California provides a significantly higher RTC rate for basic research than general qualified R&D expenditure, while Maine and Massachusetts offer a preferential tax credit rate for basic research expenditures compared to other types of R&D expenditures.

To be eligible for a state RTC, a taxpayer is generally required to have a physical presence in the state and conduct R&D activities within the state borders, with the exception of Alaska. Eligible R&D costs typically include related labor, the cost of supplies, and the rental or lease cost used to conduct qualified research for in-house research. For contract research, research funded by the taxpayer but not conducted at the taxpayer's business, only a portion of the amounts paid are eligible, with different percentages applying to research performed by non-profit organizations and small firms, universities, or federal laboratories. Costs associated with purchased equipment or buildings, overhead costs, and fringe benefits for employees are examples of non-eligible expenditures.

Overall, most states in the United States have implemented RTCs that are similar to the federal RTC in terms of the requirements for physical presence and location of R&D activities, the definition of qualified R&D, and the tax base. However, there are variations in credit rates, annual limited benefits, program cap, and overall generosity and generosity for specific types of corporations. States can make changes to their programs over time by expanding, limiting the benefits, or terminating a program. For example, Missouri (2005), Montana (2010), Washington (2014), and West Virginia (2013) have allowed their programs to expire without introducing new credits.

2.2 Literature Review

2.2.1 The Effect of RTCs

As RTCs have become more frequently used, a natural question is whether they are effective in stimulating innovation. The most common way to evaluate the effectiveness of an RTC is to compare the level of R&D investment with and without the credit. If firms fully substitute their private R&D with tax support, the tax credit is considered ineffective due to full crowding out. Conversely, if one dollar of tax incentive leads to an increase in R&D investment of more than one dollar, the tax credit is considered effective. Currently, there are two broad approaches to examining the effectiveness of RTCs: quasi-experiments and structural modeling.

The quasi-experimental approach involves comparing the R&D investment of firms that receive RTCs with that of firms that do not. The difference-in-differences estimator is a common tool used to compare the R&D investment of control and treated groups before and after the implementation of an RTC, providing an estimate of the impact of the tax credit. In the early 1980s, studies of RTC effectiveness suggested that the impact of RTCs on additional R&D was relatively small. For example, Eisner, Albert, and Sullivan (1984) find insignificant results when investigating 592 firms with valid R&D data from Compustat from 1981 to 1982. Mansfield (1986) survey 205 firms from three countries, including the United States, Canada, and Sweden, and find that R&D tax incentives in these countries increased R&D expenditures by approximately one percent, which is about one-third of the foregone government revenue.

As the number of RTCs has increased, studies have found larger effects on R&D investment with expanded data accessibility. For instance, Duguet (2010) evaluates the incremental RTC implemented by France from 1994 to 2003 and finds that it is associated with a growth in private funding of R&D and an increase in the number of researchers, suggesting the tax credit is effective. Dechezleprêtre et al. (2016) exploit a change in the asset-based size thresholds for eligibility for the UK's RTC and document a significantly positive effect on both R&D and patents. Using PSM and difference-in-differences methods, Monteiro (2020) evaluates the impact of the Portuguese tax incentive for R&D (SIFIDE) and find a positive effect on both R&D investment and firms' survival. However, the effectiveness of RTCs can be challenging to evaluate due to variations in design and institutional backgrounds of sample firms. Thus, evidence found on one RTC implemented in a particular country, state, or industry may not be generalizable to RTCs in other settings.

The structural modeling approach involves regression analysis to estimate an R&D demand equation and its typical determinants, including the net cost of R&D. The net cost of R&D is defined as the net cost excluding all tax incentives relative to one dollar of revenue. Hall (1993) uses this method to analyze a large sample of U.S. manufacturing firms from Compustat and finds that a 5 percent increase in the RTC increases R&D spending by 10 to 15 percent in the long run (or by 8 to 13 percent in the short term). Hines (1991) examines how manufacturing multinational firms react to the Tax Reform Act of 1986, which reduced the R&D credit from 25 percent to 20 percent and tightened some of the definitions of R&D eligible for the credit. His findings show that the increased after-tax prices of R&D reduce domestic R&D for domestic markets and indicate that the elasticity of demand for R&D lies between -1.2 and -1.6. Similarly, Bloom, Griffith, and Reenen (2002) and Baghana and Mohnen (2009) apply the structural models to estimate the elasticity of demand for R&D and find similar results. While this method directly connects the marginal cost of R&D with the level of R&D in a model, the pre-structured model may not accurately simulate private R&D investment decisions.

The primary goal of RTCs is to stimulate innovation, improve productivity, and enhance social welfare. Thus, evidence that RTCs can spur additional R&D activities alone may not be enough to support the claim that RTCs effectively achieve these objectives. Some studies have taken a more comprehensive approach by directly examining the impact of RTCs on innovation outcomes such as patents, new product introductions, and the share of innovative products in total sales, as well as employing simultaneous equations to model the interrelatedness of these outcomes. For example, Cappelen et al. (2008) evaluate the Norwegian SkatteFUNN R&D incentives program and find that projects receiving tax credits are associated with the development of new production processes and products. However, they also find that firms collaborating with other firms are more likely to succeed in their innovation activities, and that RTCs do not necessarily lead to improvements in innovations related to new products.

2.2.2 Empirical Challenges in Evaluating the Effectiveness of RTCs

While there is extensive evidence from many studies on the effectiveness of RTCs generated by various methodologies, using this evidence for policymaking is challenging. Becker (2015) highlights common research design features and challenges that studies face when evaluating the fiscal and economic impact of R&D tax credits. The first issue raised is data quality and measurement.

Mohnen and Lokshin (2010) categorize RTC's effects as first-order effects measured by innovation inputs, second-order effects measured by innovation outputs, and third-order effects measured by total social welfare. However, the analysis of RTC effectiveness is limited because only observable measures can be tested, and each measure has inherent deficiencies. For example, a significant portion of increased R&D spending may be driven by the relabeling of existing activity-qualified research expenditures (QRE). This makes it difficult to determine whether the increased R&D spending is due to the tax credit or a strategic R&D classification.

Another challenge is establishing causation. Both quasi-experiment and structural modeling methods have endogeneity concerns because variations in innovation inputs and outputs may be due to business entities that want to increase R&D and lobby policymakers to provide RTCs. Additionally, findings regarding the elasticity of demand for R&D may be sensitive to the sample and setting and subject to alternative explanations.

Finally, several studies also document that firms tend to reallocate their R&D innovation activates to regions with low cost of R&D rather than enhancing the overall level of R&D. Wilson (2009) documents that state RTCs are indeed effective at increasing R&D within the state. However, the increase in in-state R&D is mainly drawing R&D away from other states. Knoll et al. (2021) study unconsolidated R&D activity of multinational firms (MNE) in Europe and show that R&D tax incentives serve as beggar-thy-neighbor instruments. Specifically, they find that more generous tax incentives at one group location increase a MNE'S R&D investments in that location, while lowering R&D investments at other group locations. This raises questions about whether R&D credits simply crowd out private R&D.

Given the empirical challenges in understanding the real effect of RTCs, many studies have focused on exploring the determinants of the effectiveness of RTCs to provide insights on which types of firms benefit more from RTCs, and what factors are relevant to the impact of RTCs, other than their design. Policymakers are more concerned about what they can offer to help businesses stay competitive globally, rather than simply concluding whether a tax credit is effective.

2.2.3 Determinants of Effectiveness of RTCs

Most policymakers acknowledge the significance of advancing technology and providing robust incentives to foster innovation, but they face financial constraints at the state or country level and cannot provide unlimited resources. Therefore, exploring how to improve the effectiveness of a given RTC design is more practical than considering revising the provision of the RTC or raising the level of support. The evidence on the determinants also helps explain why prior studies find stronger effects of some RTCs than the effects of other RTCs.

Several studies have explored the determinants of the effectiveness of RTCs. Klassen et al. (2004) compare R&D spending decisions of companies in Canada and the United States matched on size and industry and find that firms that are more financially constrained increase spending more when tax rates are cut. Hosono (2015) investigates R&D of Japanese manufacturing firms and finds that the effect of the present use of R&D tax credit on R&D investment is smaller for firms that are more likely to depend on external financing than for those that are less likely to depend on external financing, suggesting that higher agency costs associated with the larger use of external finance partially mitigate the effect of R&D tax credits. The results suggest that the effect of R&D tax credits on R&D investment is limited for financially constrained firms. Jia and Ma (2017) examine a sample of Chinese-listed companies during 2007-2013 and analyze how institutional conditions shape the effects of RTCs on R&D. They find that the effects of RTCs on R&D are more pronounced for private firms than state-owned enterprises, with more substantial effects for private firms without political connections.

Besides the direct evidence on the determinants of RTCs' effectiveness, evidence on what institutional characteristics affect R&D decisions also indicate the possible factors related to RTC effectiveness. Using data from a broad sample of OECD economies, Brown, Martinsson, and Petersen (2017) find that countries with policies that encourage arm's-length financing, stronger intellectual property protection, and strong contract enforcement share a significant positive relation with R&D in more innovative industries. In contrast, stronger creditor rights and more generous R&D tax credits have a negative differential relation with R&D in more innovative industries. Using a data set including 32 developed and emerging countries, Hsu, Tian, and Xu (2014) find that industries that are more dependent on external financing and that are more high tech intensive exhibit a disproportionately higher innovation level in countries with better-developed equity markets. Kamguia et al. (2022) investigate data from 82 countries and show that a country's natural resources are negatively associated with the country's R&D, while institutional quality and human capital are mechanisms that attenuate this effect.

In addition to empirical evidence, theoretical studies also provide insights into achieving optimal efficiency for innovation tax incentives. Akcigit, Hanley, and Stantcheva (2022) attempt to derive the optimal design of innovation tax incentives that achieves maximum social welfare by recognizing the asymmetric information that can prevent a tax incentive from reaching its full efficiency. They develop a framework that captures this aspect of asymmetric information in innovation and the allocation of innovation incentives. Asymmetric information distorts the market welfare of an R&D incentive from its optimal level. While Akcigit, Hanley, and Stantcheva (2022) theoretically identify the best tax policy design conditional on asymmetric information, one implication from their study is that simply reducing asymmetric information can improve the efficient allocation of innovation incentives.

2.2.4 Information Transparency and Innovation

Accounting information has been recognized to mitigate information asymmetry, and it plays a critical role in corporate governance, resource allocation, and contracting. Many studies have explored the impact of accounting information transparency on innovation at both the macro and micro levels. Transparent information environments can promote innovative investments by reducing information asymmetries and the cost of external equity finance. However, concerns about proprietary costs may also arise in a transparent information environment. Empirical evidence by Brown and Martinsson (2019) suggests that the transparency of the information environment in which firms operate can affect overall levels of innovative activity.

Prior work also tests firm-level accounting information and public disclosure to gauge how a firm's accounting information disclosure decisions impact its innovation-related decisions. Zhong (2018) documents that a firm's information transparency leads to an increase in innovation outcomes by reducing managerial career concerns and enhancing more efficient allocation of R&D capital. Kim and Valentine (2023) find a positive correlation between the presence of public firm disclosures and future patent sales by other related parties. Their findings suggest a reduction in information friction between buyers and sellers of patents when the number of public firms present is high. These studies indicate accounting information disclosures can enhance both internally generated innovation and externally acquired innovation.

High information transparency may have a negative impact on the effectiveness of RTCs or innovation activities, particularly when managers have strong incentives to meet performance targets. Williams and Williams (2021) employ the issuance of Financial Interpretation No. 48 (FIN48) to investigate managers' decision-making on balancing short-term financial earning performance and exploiting innovation credits. FIN48 requires public companies to accrue additional tax expense and record a contingent liability to account for uncertain tax positions like R&D credits. While this requirement is less likely to reduce cash benefits of R&D credits, it does increase tax expense and, therefore, decreases reported earnings. They find that FIN48 reduces firms' willingness to exploit RTCs. Chy and Hope (2021) show that when states require third-party auditor legal liability, firms within that state have increased financial reporting quality but reduced levels of innovation inputs and outcomes. These studies indicate that high information transparency may have a negative impact on the effectiveness of RTCs or innovation activities.

2.2.5 The Effect of R&D Credits in the U.S.

Many studies take advantage of program changes to Federal R&D tax credits and analyze the economic impact of the credit. While studies often find a positive effect on research conducted by firms due to the credit, the magnitude of the estimate varies significantly across studies and generally is low, ranging from 1.3 to 3.9 percent of the increase in R&D (Hemphill 2009). Three studies utilize policy changes to the credit to the credit's potential effect and find larger effects. Gupta et al. (2011) utilized the 1989 redefinition of base amount to analyze the credit and find that every dollar claimed induced over two dollars of additional R&D expenditure. Using IRS corporate return data from 1981 to 1991, Rao (2016) estimates a ten percent reduction in the user cost of R&D leads an average firm to increase its research intensity by approximately twenty percent. Finley, Lusch, and Cook (2015) find a similar effect—two dollars induced per one dollar claimed—for the Alternative Simplified Credit, which was adopted in 2010 as an alternative means to calculate the federal credit.

Several studies leverage the introduction of state R&D tax credits in the U.S. to explore how tax incentives impact innovation activities and economics at the state level. Focusing on the number of high-technology establishments, Wu (2008) finds that state RTCs lead to the growth of the high-technology sector in the states, indicating more well-paid technical positions in the short term and new or enhanced product competitiveness, and other economic benefits in the state in the long term due to the expanded high-technology sector. Fazio, Guzman, and Stern (2019) implement a DID analysis on the introduction of RTCs at the state level and find that RTCs lead to a significant long-term impact on both the overall quantity and quality-adjusted quantity of entrepreneurship. Selby (2020) finds that state RTCs have a small but statistically significant impact on the number of people with PhDs moving to states and increased innovation activities that have the tax credit. The study further indicates that RTCs are associated with a decrease in the states' fiscal health. Schmidt (2021) thoroughly investigates the impact of RTCs in Iowa and other states and finds mixed evidence depending on whether fixed effects are included in the models. Overall, most of studies supports the positive effect of state RTCs on innovation, employment, and growth of businesses in states, with some evidence suggesting insignificant results.

Some researchers are interested in the characteristics of states that introduce RTCs and the impacts of a state's RTC on innovation in other states. Hearn, Lacy, Warshaw (2014) explore specific socioeconomic, political, and structural conditions that drive state-level adoptions of RTCs. Their evidence suggests that adoption of RTCs is associated with higher state unemployment levels, higher patenting activity, a governorship with constitutionally strong budgetary power, and having a centralized governing board. By employing state-level panel data from 1981 to 2004 and an R&D demand equation, Wilson (2009) finds that almost all of the increased research is relocated from neighboring states, suggesting a zero-sum game among states. The evidence from these studies demonstrates similar empirical challenges as the research focusing on the real effect of RTCs using other settings. With these empirical challenges, evidence showing what makes a state's RTC more effective than another can provide valuable implications for policymakers. However, there is a lack of thorough analysis of the overall effectiveness of RTCs and a lack of understanding of whether the information transparency in a state affects its tax policies and the effectiveness of those policies.

3 HYPOTHESIS DEVELOPMENT

In order to understand how information transparency affects the effectiveness of RTCs the R&D investment decision of individual firms, I start by analyzing the conditions under which firms decide to invest in innovation. Using parameters and simple models, I demonstrate how information transparency affects individual firms' behavior by influencing the related factors. Equation (1) demonstrates that firms invest in R&D only when the expected marginal cost (M_c) of R&D investment is greater than or equal to the expected marginal return of R&D investment (M_r).

$$E(M_{c)} <= E(M_r) \tag{1}$$

However, companies generally underinvest in R&D far below the level where $E(M_c) = E(M_r)$. The main reason for this underinvestment is the reduced net marginal return of R&D for the inventor, which decreases when considering spillover effects *(M_s)*. With technology spillover, the expected marginal return of R&D is diluted by M_s, and firms' R&D investment levels meet the conditions stated in equation (2). The maximum level of R&D is determined by when $E(M_c) = E(M_r) - E(M_s)$.

$$E(M_c) <= E(M_r) - E(M_s) \tag{2}$$

The marginal loss $E(M_s)$ due to technology spillover represents a welfare loss for the individual inventor, but a positive effect on total social welfare. The rationale of R&D tax incentives is to offer tax incentives to compensate inventors for the loss of marginal benefits arising from the technology spillover so that a more socially optimal level of R&D can be achieved. With

RTCs, a firm's net marginal cost of R&D is reduced to the after-tax cost. Therefore, the level of R&D investment will increase to a maximum where the after-credit marginal R&D cost is equal to the net marginal R&D return. Firms can increase their R&D expenditures until they reach the level shown below:

$$E(M_c) \; - Tax\_RD <= E(M_r) - E(M_s) \tag{3}$$

According to model (3), the introduction of R&D tax credits (RTCs) leads to a reduction in the cost of R&D for firms, which is likely to encourage them to increase their innovation activities. Therefore, I state my first hypothesis as:

H1a: The introduction of RTCs improve innovation activities.

The specifications of this model are subject to the assumption that firms have all information available to estimate the best $E(M_r)$, $E(M_c)$, and $E(M_s)$ and that tax authorities are able to observe the $E(M_r)$ of all firms and offer the right amount of tax credit (Tax_RD) for each additional dollar of R&D. These assumptions are unrealistic as and tax authorities cannot observe the innovation return of innovation projects and thus are likely to misallocate tax incentives among firms.

Information transparency can reduce asymmetric information and affect the effectiveness of RTCs for individual firms in multiple ways. First, a transparent information environment can reduce the net cost related to the additional R&D investment incentivized by the RTC by reducing adverse selection problems. To increase R&D investment and claim R&D tax benefits, firms have to incur the related financing cost. When the information environment is less transparent, firms are likely to pay a higher cost of capital to fund R&D, which can offset their incentive to invest. While it is difficult for tax authorities to allocate tax incentives to innovative firms, external and internal governance mechanisms can monitor firms and ensure they neither over- nor underinvest in R&D with the RTCs. A transparent information environment can help maintain efficient external and internal governance (Zhong 2018), which could help achieve an efficient allocation of tax incentives among firms with varying innovation abilities.

Second, a more transparent information environment enables firms to identify valuable innovation projects so that an additional R&D investment project can achieve a higher return. Misreported information can generate unrealistic expectations about future growth and distort firms' real decisions (McNichols and Stubben 2008). A high level of information transparency enables firms to access more reliable information; as a result, firms are more likely to identify profitable investment projects (Badertscher, Shroff, and White 2013; Shroff, Verdi, and Yu 2014; Shroff, Verdi, and Yost 2017; Zhong 2018) and increase their investment in profitable R&D projects when RTCs are available.

Three, a transparent information environment can also facilitate secondary patent market transactions and support efficiently relocating patents from the entities that develop patents to those who can efficiently commercialize innovation. While an RTC may promote R&D investments in the short term, its long-term effect can be limited when its net marginal return and net marginal cost reach a new equilibrium. For firms to keep investing in innovation, the ability to realize a high marginal return by commercializing their innovation is critical. However, firms that are innovative do not necessarily have the ability to commercialize it. Kim and Valentine (2023) document the presence of public firms in a technology class is positively associated with patent sales in that technology class. Based on their findings, innovative firms can gradually increase their R&D investment level and keep exploiting R&D tax credits as they can realize the commercial value of patents themselves or sell them in the patent market.

However, a transparent information environment can also enable competitors to gain easier access to a firm's innovation information, which may discourage the firm from innovating even with the benefits of R&D tax credits (RTCs). Kim and Valentine (2021) examine the impact of accelerated patent application disclosure, driven by the passage of the American Inventor Protection Act (AIPA), and document that this improved information transparency improves both innovation spill-in and spill-out effects. However, the net effect depends on the tradeoff between these effects. transparency may significantly increase the spill-out costs for a group of firms, which may offset the benefits of RTCs and information transparency.

For these reasons, it is unclear whether information transparency affect the effectiveness of RTC for individual firms. However, once innovation outcomes are aggregated at state level, innovation spillover effects of individual firms cancel out each other, resulting a net positive impact of information asymmetry on the effectiveness of RTCs. Combined with the implication of the theory suggested by Akcigit, Hanley, and Stantcheva (2022), I expect that a transparent information environment improves RTC effectiveness. My next hypothesis is:

H1b: A more transparent information environment positively influences the effectiveness of R&D tax credits.

4 DATA, SAMPLE, AND RESEARCH DESIGN

This study intends to answer the research question that when an RTC is introduced in a country, state, or for a specific industry, does its impact vary with the information asymmetry within the country, state, or industry. To better empirically test the role of information in influencing the effectiveness of RTCs, several major empirical challenges need to be considered. These challenges include the heterogeneity of different RTCs, the correct measurement of total

RTC effects, and establishing causality. Leveraging on the introduction of RTCs in the United States, this study can effectively address these empirical concerns.

Using state-level data on innovation activities and institutional characteristics in the U.S., this study can control for the heterogeneity of different RTCs, which remains highly similar across states. Since the level of information transparency can vary across states, testing the effect of RTCs across states can provide insights into whether the impact of an RTC varies with the level of information transparency.

Moreover, I use patent application records to identify states where innovation is taking place, providing a more accurate measure of overall RTC impact. This approach differs from prior studies that focused on specific types of organizations and can better mitigate concerns regarding substitution effects between different types of organizations' innovation activities. By incorporating all innovation activities in the empirical tests, this study can provide a more comprehensive analysis of the effectiveness of RTCs in promoting innovation.

Finally, state RTCs have been introduced in different years, permitting the utilization of a staggered difference-in-differences (DID) approach to identify causal effects more effectively. By employing multiple shocks that influence innovation activities, I can better control for potential biases and noise coinciding with the introduction of state RTCs that affect innovation activities.

4.1 Sample Selection and Data

To investigate the impact of information transparency on the effectiveness of RTCs and the mechanisms involved, I employ state-year, state-patent-class-year, and firm-year level data for conducting analyses. The patent data and information on patenting activities are obtained from publicly available resources at the USPTO. I use patent data from Arora, Belenzon, and Sheer (2021) to identify the first owner of a patent and classify it as applied by a public or private firm, while patent data from Kogan et al. (2017) provides information on the most recent owner of a patent and its value measured by a market method. The state R&D tax credit data is collected from Falato and Sim (2014) and Schmidt (2021), which compile state-level RTCs and updates from 1982-2000. The data is verified by comparing it with other publicly available information and correcting discrepancies.

The state-year, state-patent-class-year, and firm-year level observations samples begin in 1976 and extend to 2020, coinciding with the availability of patent data. For the firm-level observations, additional cleaning steps are taken, including dropping observations with missing NAICs codes, excluding firms in highly regulated industries, and requiring each firm to have at least three observations in the sample period. Firms with missing state data and those whose primary innovation activities are not conducted in their headquarters state are also dropped. The final firm-year sample consists of 33,925 observations.

To obtain state-level innovation measurements, I start with assignee data from the USPTO and identify 3,799,670 patents with the U.S. as the country, an organization type of 2, and non-missing state information. Of these, 1,772,281 patents have matched firm Compustat identifiers (GVKEY), which I define as patents owned by public firms. Patents without matched GVKEYs are considered patents owned by private firms. After aggregating patents and citations by year and state, my state-level sample includes 2,294 observations.

4.2 Variable Measurement

4.2.1 Key Dependent Variable – Innovation Activities

Following prior literature on innovation (Cornaggia et al. 2015; Li, Ma, and Shevlin 2021), I measure innovation using a three-year lag of the natural logarithm of one plus the number of patents applied and granted for by all firms in a state (L3Pat), firms in a state-patent class

(L3CpcTPat), and by a firm (TPat) in year t+3. This three-year lag captures the current year treatment effect, as the innovation investment cycle typically takes three years (Mukherjee, Singh, and Žaldokas 2017; Atanassov and Liu 2020).

Alternatively, the number of citations received by all patents and the number of top-cited patents (above the 90th percentile of the citation distribution for patents applied in a specific year and patent class) are used to proxy for innovation outcomes. L3Cite and L3CpcTCite measure the citations received by all patents applied and granted in a state and state-patent class in year t+3, respectively. L3Top and L3CpcTop proxy for the top-cited patents applied and granted in a state and state-patent class in year t+3, respectively.

I also use TRvalue and TNvalue as alternative measures of innovation activities at the firm level. TRvalue (TNvalue) is the nominal value (real value) of each patent is derived from Kogan et al. (2017), which measures a firm's idiosyncratic stock market return on the day of the patent grant (deflated to 1982 dollars). These variables are measured as the natural logarithm of one plus the total value (total relative value) of all patents applied for and granted during year t+3.

In addition to internally conducted innovation activities, I also assess externally generated innovation activities by examining technology acquisitions and patent sales. I measure the number of M&A deals in a state by counting the number of targets acquired in that state within a year. Moreover, I differentiate the types of firms being acquired by specifically investigating the number of public firms (TPubM&A), public firms with patents (TPubTechM&A), public firms without patents (TPubOperM&A), private firms (TPriM&A), private firms with patents (TPriTechM&A), and private firms without patents (TPriOperM&A) acquired in the state within a year. Firms can also acquire patents by directly purchasing them from other parties. I use two proxies for patent sales: LPatSale and LPriPubPsale. LPatSale measures the natural logarithm of one plus the number of patents that are applied for (ultimately granted) in a state and a year and are sold at least once. LPriPubPsale measures the natural logarithm of one plus the number of patents that are applied for (ultimately granted) by private firms in a state and a year and are sold to public firms at least once.

4.2.2 Key Independent Variable – Credit

Appendix C displays the introduction and major changes of state RTCs between 1982 and 2020. The treatment variable Credit is an indicator variable with a value of 1 after an RTC is enacted in a state, 0 otherwise. I identify the location of innovation activities by examining assignee location and inventor location data from the USPTO. When a patent lists a state in its application, it is counted as a patent applied for in that state in its application year.

4.2.2 Information Transparency

Information Transparency in this study refers to the quantity and quality of external information about business and innovation activities that could affect the net cost or return of the innovation activities performed by individual organizations. I focus on external information transparency rather than internal information transparency because I am interested in the macro-level association between the overall information transparency within an environment and the effectiveness of RTCs introduced for business sectors in that environment. While an individual firm's disclosure decision might affect its net cost and return of conducting innovation, evidence on individual firms' voluntary disclosure and the effectiveness of RTCs cannot be generalized to the macro level due to potential substitution effects.

4.2.2.1 Using Inevitable Disclosure Doctrine (IDD) to Proxy for the State Information Asymmetry

Innovation often involves high proprietary costs and is typically not subject to mandatory disclosure. However, innovation-related proprietary information can still be transferred through other channels, such as employee turnover. To protect this kind of trade secret, many states have adopted legal trade secrecy protections. In recent years, several studies have examined the impact of such trade secrecy protections. Glaeser (2018) finds that firms reduce proprietary disclosure following the state-level adoption of the Uniform Trade Secrets Act (UTSA) IDD. Li, Lin, and Zhang (2018) document a reduction in the disclosure of customer identity following IDD adoption. Chen, Gao, and Ma (2021) report an increased propensity for firms in a state to be acquired after the state's adoption of IDD, suggesting human capital and reduced employee mobility are drivers of acquisitions. The evidence provided by these studies confirms that the quantity of innovation-related information decreases when a state has adopted legal protections related to trade secrecy.

I use IDD as a proxy for the information asymmetry associated with the ease of learning innovation information through employee mobility, following Li, Lin, and Zhang (2018), Klasa, Ortiz-Molina, and Srinivasan (2018), and Chen, Gao, and Ma (2021). IDD mandates that if new employment would inevitably lead to the disclosure of a firm's trade secrets to competitors and cause the firm irreparable harm, then state courts can prevent the employee from working for the firm's competitor or limit the worker's responsibilities in the new firm. When a state adopts the IDD, all firms in the state face a reduced likelihood of learning information about their peers through recruiting their employees and a reduced likelihood of having their proprietary information leaked to peer firms through employee turnover. For individual firms, the effect of the IDD on their innovation and the benefits they can generate from RTCs depends on the trade-offs between the advantages of reduced proprietary cost concerns and the costs of increased information asymmetry. However, at the state level, the IDD imposes high information asymmetry, which may prevent tax incentive resources from being allocated to the most efficient projects.

4.2.2.1 Aggregated Peer Information from Public Firm Disclosure

Besides the unavoidable information leakage through employee channels, external information about the industry, related parties, and peer firms can also be informative for a firm's innovation-related decisions. Firms in an industry are affected by similar economic forces (e.g., common demand/supply shocks). Thus, the information disclosure of other firms in the same industry may have externalities on the decisions of a given firm. Badertscher, Shroff, and White (2013) find that private firms are more responsive to investment opportunities when the level of the industry information transparency is high. Shroff, Verdi, and Yost (2017) find that the information transparency of peer firms in an industry affects the cost of capital for other firms in the industry, especially when there is less publicly available firm-specific information.

Several recent studies directly examine peer information environment driven by public firms' presence on innovation-related activities. Kim and Valentine (2023) find a positive link between public firm presence in an industry and other parties' patent sales, indicating that the public firms' information environment plays an important role in facilitating the trading of innovation assets between firms and helping new buyers and sellers enter the market. Glaeser and Omartian (2022) find that public firm presence within an industry is positively associated with subsequent import competition in that industry, suggesting that foreign competitors use the information created by public firm presence, including what public firms disclose in financial reports, to compete with domestic firms. According to these findings on the peer firm's information environment, if firms in a state are all from industries with a transparent information environment, those firms are more likely to respond to innovation investment opportunities with RTC incentives and generate better innovation outcomes.

Following Badertscher, Shroff, and White (2013) and Shroff, Verdi, and Yost (2017), I use the ratio of the number of public firms to the total number of firms in an industry to proxy for the information environment in that industry, and I further measure a state's information transparency as a weighted average of industry-level public firm presence, with weight of each industry being the ratio of firms in that industry of that state to the total number of firms in that state.

The rationale for using the measure aggregated from the industry level is based on two assumptions: (1) firms in the same industry and different states have similar investment opportunities; therefore, firms with access to state RTCs are more likely to invest in R&D and generate innovation. (2) For firms in the same industry across states, the distribution of the number of public firms is similar to the distribution of the number of private firms. Thus, a high level of state information transparency suggests that there is a high percentage of both public and private firms from industries with a significant presence of public firms. See equations (4) and (5) for the definitions of industry-level information environment and state aggregated information transparency.

$$IndustryInfo_{i,t} = \frac{Total\ number\ of\ public\ firms\ in\ industry_i\ in\ year\ t}{Total\ number\ of\ firms\ in\ industry_i\ in\ year\ t} \tag{4}$$

$$StateInfo_{s,t} = \Sigma_{i=1}^{n}\ \lambda_{i,s,t} \times IndustryInfo_{i,t} \tag{5}$$

The $industry_i$ refers to a 3-digit NACIS industry. $\lambda_{i,s,t}$measures the number of firms in $Industry_i$ and $state_s$, divided by the total number of firms in $state_s$. n represents the total number of industries in state s in year t. The total number of firms in a 3-digit NACIS industry, in a state, and in a 3-digit NACIS industry of a state are obtained from U.S. Census data Business Dynamics Statistics (BDS). The BDS data provides information on the number of firms in each sector at the state-level from 1978 to 2020. Using the crosswalk between the economy sector code and the 3-digit NACIS industry, I identify the 3-digit NACIS industries that can be mapped to an economy sector and the valid data in those industries at the state-level. It is important to note that one economy sector may be composed of several 3-digit NACIS industries. Therefore, not all industries have available information environment data.

There are concerns about the aggregated state-level information transparency used in this study. First, it may capture the industry structure of a state, which is potentially associated with the propensity of enacting RTCs and innovation investment activities. Second, patenting activities vary significantly depending on the main technology generated in different industries and patenting activities in each technology class. These differences may be attributed to the fundamental differences in the technology used in different industries. To mitigate these concerns, I aggregated the peer information environment at the technology class level, ensuring that the industry structure and patenting patterns were appropriately controlled. To measure the information transparency of a patent class, I followed the method used by Kim and Valentine (2023) and based it on the presence of public firms of industries mapped to that class.

$$CPCInfo_{p,t} = \Sigma_{i=1}^{m} \beta_{p,i,t} \times IndustryInfo_{i,t} \tag{6}$$

The $industry_i$ represents a 3-digit NACIS industry. $\beta_{p,i,t}$ measures the number of patents generated by public firms in $Industry_i$ in technology class p in year t, divided by the total number of patents generated in class p by all public firms. The total number of patents is obtained from USPTO, while the patents generated by public firms are from Arora et al. (2021). To map a patent technology class to industries, I use a firm's primary 3-digit NAICS industry code and follow the patent crosswalk used by Lybbert and Zolas (2014), Goldschlag, Lybbert, and Zolas (2016), and Kim and Valentine (2023). A technology class can be mapped to multiple industries, and the information transparency is the weighted average of public firm presence of all industries mapped to this technology class. The Cooperative Patent Classification (CPC) system, jointly developed by the European Patent Office (EPO) and the United States Patent and Trademark

Office (USPTO), is used to classify patents in this paper. The CPC system has nine sections, A-H and Y, which are further divided into classes, sub-classes, groups, and sub-groups. This paper uses the sub-class level of CPC classification, and there are a total of 678 sub-classes based on the most recent version of CPC.

Kim and Valentine (2023) measure the presence of public firms in an industry as the ratio of the total sales of public firms with patents to the total production in that industry, as their variable of interest is patent sales. However, this paper investigates n both internally generated innovation and external patent transactions. Consequently, I use all public firms in an industry as the numerator, as this could provide relevant information. Badertscher, Shroff, and White (2013) use both sales and count-based methods to measure the presence of public firms in an industry. The measure of public firm presence as total sales by public firms scaled by total sales by all firms in the industry gives a higher weight to big firms in the industry, while measuring public firm presence as the number of public firms scaled by the total number of firms in the industry gives equal weight to all firms. Both measures provide different perspectives on the information available in a particular industry. Shroff, Verdi, and Yost (2017) introduce another measure, average analyst forecasts, to proxy for the availability of peer information. In additional analysis, I use sales- and analyst forecast-based measures as alternative measures of the information environment to partition my sample and investigate the robustness of my results.

In summary, I measure state-level information transparency in two ways: through the restriction of transferring innovation-related information via employee mobility, and by assessing the aggregated peer information environment. Using IDD as a proxy captures reduced information transparency related to information with high proprietary cost, providing insight into the overall impact of increased information asymmetry on the effectiveness of RTCs, as well as its asymmetrical impact on public and private firms. Additionally, peer information environment-based measures capture the availability of information related to public disclosures, which typically possess low proprietary cost. This enables me to assess how general information transparency impacts the effectiveness of RTCs. These two measures complement each other, providing a more comprehensive understanding of how information transparency affects the effectiveness of RTCs.

4.3 Research Design

States have introduced RTCs in different years. Thus, I can compare the before–after patenting activities conditional on the existence of IDD of the RTC in affected states (the treatment group) to the before–after effect conditional on the existence of IDD in states without the RTC (the control group). To test my hypothesis that IDD impacts the effectiveness of state RTCs, I estimate the following models (7) and (8).

$$\begin{aligned} Ln3PatMeasure_{s,t} = {} & \alpha + \beta_1 CREDIT_{s,t} + \beta_2 CREDIT_{s,t} \times IDD_{s,t} + \beta_3 IDD_{s,t} + \\ & \beta_4 LnPatMeasure_{s,t} + \beta_m CONTROLS_{s,t} + \epsilon_{s,t} + \\ & StateFE + YearFE \end{aligned} \tag{7}$$

$$\begin{aligned} Ln3PatMeasure_{s,p,t} = {} & \alpha + \beta_1 CREDIT_{s,p,t} + \beta_2 CREDIT_{s,p,t} \times IDD_{s,p,t} + \beta_3 IDD_{s,p,t} + \\ & \beta_4 LnPatMeasure_{s,p,t} + \beta_m CONTROLS_{s,p,t} + \epsilon_{s,t} + \\ & StateFE + CpcFE + YearFE \end{aligned} \tag{8}$$

The unit of observation in model (7) is at the state s and year t. $Ln3PatMeasure_{s,t}$ is measured by the natural logarithm of the 1) total number of patents 2) citation, and 3) top cited (90 percentile) patents in state s and year $t+3$. The innovation measure in state s and year t is controlled for since the current innovation ability is highly associated with innovation ability in year $t + 3$. State and year fixed effects are added to control for any time-invariant, state-specific effects, or factors specific to a given year. Standard errors are clustered by year. A positive coefficient on β_3 suggests that states with IDD generate more innovation when RTC is introduced in that state compared to states with RTC but not IDD.

I control for a vector of factors that may be related to the introduction of RTCs and innovation outcomes. State GDP level (GSP), GDP growth (GSPGrowth), and unemployment rate (GSPGrowth) are indicators of a state's economy and are controlled for in all regressions. The total available labor resources (StateEMP) are related to the labor inputs in the innovation investments and are also controlled in my analyses. High labor market concentration is negatively associate with labor supply elasticity (Marinescu and Steinbaum 2019), and the overall labor market concentration can be an indicator of a state's economy structure. Therefore, I control for the labor market concentration (LaborC). Corporate tax rates directly relate to the cost of innovation and can impact innovation (Mukherjee, Singh, and Žaldokas 2017; Atanassov and Liu 2020). Akcigit, Hanley, and Stantcheva (2022) document that corporate taxes and personal income taxes can impact innovation production and mobility of inventors. I control for the corporate tax and individual tax of a state to its total GDP ratio to capture the overall level of corporate tax and individual tax rate (CorpTaxR and IndTaxR). The number of innovation incentives offered to business sectors by a state is associated with its revenue, so I control for the revenue of a state generated from all tax resources.

The unit of observation in model (8) is at the patent class p, state s, and year t. The variable $Ln3PatMeasure_{s,p,t}$ is measured by taking the natural logarithm of one plus the 1) total number of patents 2) citations, and 3) top cited (90 percentile) patents in patent class p, state s, and year $t + 3$. Additionally, the innovation measure in the same patent class and state in year t is controlled for to capture variation in innovation performance in year $t+3$ that are explained by prior innovation outcomes. Patent class, state, and year fixed effects are added to control for any time-invariant technology class-specific effects, state factors, or factors specific to a given year. Standard errors are clustered by patent class, state, and year. Similarly, state-level controls are implemented in model (8).

$$Ln3PatMeasure_{s,t} = \alpha + \beta_1 CREDIT_{s,t} + \beta_2 LnPatMeasure_{s,t} + \beta_m CONTROLS_{s,t} + \epsilon_{s,t} + StateFE + YearFE \quad (9)$$

$$Ln3PatMeasure_{s,p,t} = \alpha + \beta_1 CREDIT_{s,p,t} + \beta_2 LnPatMeasure_{s,p,t} + \beta_m CONTROLS_{s,p,t} + \epsilon_{s,t} + StateFE + CpcFE + YearFE \quad (10)$$

To test the impact of information transparency at the state or state-patent-class level on the effectiveness of RTCs, I divide the sample into subsamples based on high and low levels of information transparency. High information transparency refers to years where the transparency is in the top tercile, while low information transparency refers to years where the transparency is in the bottom tercile. The study then examines the effect of RTCs on innovation for each subsample. If the coefficient on β_2 for the high information transparency subsample is higher than the coefficient for the low information transparency subsample, the results suggest that states or patent-classes with high information transparency generate more innovation when RTCs are introduced, compared to states or patent-classes with low information transparency.

5 RESULTS

5.1 Descriptive Statistics

The descriptive statistics of state and state-patent-class level variables are presented in Table 1, Panel A and C respectively. Thirty-eight percent of the sample are firms with state RTCs.

Panel B and Panel D show that the treated sample has more innovation than the control sample. One reason is that the observations after the introduction of tax credits are all grouped in the treatment sample, which tend to have more patenting activities as they are in recent year. The reason also explains correlation matrix for state-level sample in Table 2. According to the correlations, state introduction of RTCs is positively correlated with level of patenting activities, GSP level, unemployment growth, total employment, and individual tax rate, and total tax revenue.

5.2 IDD and the Effectiveness of RTCs

To test H1b, I run model (9) using state-year level data to test the overall effect of RTCs on innovation without differentiating the level of information transparency. The results in Table 3 indicate that the number of patents and top cited patents in a state significantly increase after the introduction of RTCs, while the total number of citations is not significantly enhanced. Overall, the innovation outcomes are positively associated with the total employees and the total tax revenue in a state. Intuitively, the labor concentration ratio, corporate tax, and individual tax are negatively related to a state's innovation outcomes.

When a state is perceived as one entity with no information asymmetry and no restrictions on employment mobility, the RTC introduced by this state would lead to all profitable innovation projects within this state being executed by innovators with the highest ability and stimulate maximum innovations. However, when there are legal restrictions on the flow of human capital and information, inefficiencies might be created, and deadweight loss may occur in total welfare. Using the innovation generated at the state level, I explore whether the presence of IDD in a state impacts the state RTCs' effect on innovation. Table 4 presents the results with the interaction between IDD and Credit and the main effect of IDD added to the model. Overall, the main effect of IDD on innovation is positive, consistent with the findings from Chen, Gao, and Ma (2020).

However, the presence of IDD attenuates the effect of R&D tax credits on innovation, demonstrated by the negative coefficients on the interaction terms in all three regressions. The coefficients on other control variables are similar to the analyses without considering the effects of IDD. The evidence suggests that IDD can reduce the number of patents, citations, and top-cited patents stimulated by state R&D tax credits.

5.3 IDD and the Effectiveness of RTCs for Private vs Public Firms

Although the restrictions brought by IDD on information transparency and labor mobility can reduce the effectiveness of RTCs for a state as a whole, how IDD impacts the effect of RTCs on innovation for specific types of organizations depends on the tradeoff between the benefits from protecting their trade secrets from leaking through employee turnover and the cost of reduced information inflow from recruiting employees associated with other organizations. I split the innovation generated in a state and a year into the innovation generated by public firms and innovation generated by private firms. Public firms are subject to extensive disclosure requirements and can also voluntarily disclose extra information. The amount of publicly available information indicates a relatively low marginal return from increased protection of proprietary information. Generally, public firms are more competitive in providing compensation and can easily attract employees, who can bring new ideas and skills from their previous employers to their new positions. With IDD, public firms cannot easily acquire innovation-related information and employees and experience a significant reduction in benefit. Conversely, private firms tend to benefit more from IDD because they can retain personnel and protect their proprietary information, enabling them to exploit RTC more efficiently.

Table 5 presents the heterogeneous effects of IDD on the effectiveness of RTCs for private and public firms, respectively. Columns (1), (3), and (5) demonstrate that public firms in a state with IDD experience a reduction in their innovation performance when RTC is introduced in this state, which could be attributed to a stronger ability for private firms to retain employees when both RTC and IDD are in place. Columns (2) and (4) show more positive innovation performance measured by the number of patents and citations generated by private firms, which have access to RTCs and IDD. Together with the findings on the overall state-level innovation conditional on the availability of RTC and IDD, the evidence suggests that higher information asymmetry induced by more stringent intellectual property protection reallocates innovation resources and generates a potentially suboptimal innovation outcome.

The benefits of using IDD as a proxy for information asymmetry are that IDD, measured at the state level, applies to all organizations within a state and we can draw a conclusion on its association with the overall effect of RTC, which is also a state-level measure. However, one challenge of this measure lies in the fact that employee mobility and information transfer cannot be disentangled. The purpose of IDD is to protect trade secrets and proprietary information, and the way to achieve its purpose is through limiting the mobility of employees. It is possible that some innovation-related information can still be transferred among firms without employee mobility. Such cases could potentially attenuate my findings in Tables 4 and 5, but the main findings should remain, as most proprietary information is expected to be well-protected given the high litigation liability for employees if they leak proprietary information.

5.4 Information Transparency and the Effectiveness of RTCs

To explore the evidence that can be applied to a more generalized setting regarding information asymmetry and the effectiveness of RTCs, this study uses a measure of information transparency aggregated from industry-level presence of public firms. The extent of public firm presence can positively correlate with both the quantity and quality of available information in an industry for several reasons. First, mandatory SEC filings and voluntary disclosures of public firms can contain technology-relevant information. Second, stakeholders, such as partners from the supply chain, institutional investors, creditors, and information intermediaries, including the business press, financial analysts, and media, can increase the amount of information and enhance its quality. Collectively, the information from all sources can improve the information transparency for firms within the same industry by reducing uncertainty about demand, supply, investment, cost, and competitive conditions, as these factors are interrelated within an industry (Badertscher, Shroff, and White 2013; Glaeser and Omartian 2022; Kim and Valentine 2023). Therefore, this study expects the presence of public firm disclosures to be helpful in assisting firms to identify innovative ideas, evaluate the uncertainty and return of innovation projects, and gain access to capital for innovation projects when RTCs are available.

5.4.1 State Information Transparency and the Effectiveness of RTCs

I first aggregate the state-level information transparency as the weighted average of industry-level public firm presence in a state and investigate whether innovation performance with RTCs varies in states with high and low information transparency. Table 6 shows that states with high information transparency generate a greater number of patents and citations following the introduction of RTCs. However, there are no significant differences in the number of top-cited patents. The evidence is generally consistent with the hypothesis. One assumption of this state-level information transparency is that firms in the same industry and different states have similar investment opportunities, and their different innovation outcomes are due to RTCs. However, once the information transparency in a state is aggregated, it is challenging to determine whether the aggregated industry shares similar investment opportunities. Moreover, it cannot be verified whether the distribution of the number of public and private firms of an industry in a state is similar.

Additionally, the findings on the innovation measured by patent-based measures could be attributed to the different patenting patterns in various technology classes. To mitigate these concerns, I rerun the analyses by using the patent-class level information transparency.

5.4.2 Patent-class Information Transparency and the Effectiveness of RTCs

To better capture innovation opportunities and patenting patterns, I next aggregate the information transparency at the patent-class level and test whether a technology class has better innovation outcomes in states with RTCs than in states without. Table 7 shows the effect of RTCs on the total number of patents, citations, and top cited patents generated in a technology class of a state. Columns (1), (3), and (5) show the insignificant effect of RTCs for technology classes with low information transparency, while columns (2) and (6) document the positive effect of RTCs on innovation for technology classes with high information transparency. The evidence suggests that RTCs are only effective in stimulating innovation when a given technology class has high information transparency.

If the findings in Table 7 correctly capture the positive impact of information transparency on the effectiveness of the R&D environment, I should observe stronger effects for innovation generated by private firms, as the peer information environment matters more for private firms (Shroff, Verdi, and Yost 2017). Therefore, I divide the number of patents, citations, and top-cited patents generated in a technology class, state, and a year into innovations generated by private firms and public firms and repeat the tests. The regression analyses are listed in Table 8. Technology class, state, and year fixed effects are controlled for in all regressions. Although I do not have extra technology class controls, the innovation performance corresponding to the dependent variable in year t is controlled for in every regression and should capture most of the variation related to the past performance of a technology class in a state.

Table 8, Panel A presents the effect of RTCs on innovation outcomes for technology classes with low information transparency. Regardless of the innovation generated by public firms or private firms, the RTCs have no impact on innovation when information transparency is low. Table 8, Panel B presents the impact of RTCs on innovation for technology classes with high information transparency. Consistent with the expectation, the positive effect of RTCs shown in Panel B suggests that only private firms benefit from RTCs hen the information transparency is high, which supports my hypothesis.

5.5 The Mechanisms

The results presented in Table 5 suggest that information transparency affects the effectiveness of RTCs differently for private and public firms. This heterogeneity is due to the fact that after IDD adoption, public firms are unable to acquire information and key personnel from private firms as easily, and consequently, experience a reduced effect of RTCs on improving innovation activities. In contrast, private firms benefit from the reduced spillover effect due to improved protection of their proprietary information. These findings provide evidence of how information asymmetry can increase costs to the effectiveness of RTCs for firms. Next, I will explore the mechanism through which information transparency improves the effectiveness of RTCs for individual firms by analyzing the innovation activities of different types of firms (private vs public). Specifically, I will test whether the effectiveness of RTCs varies with the cost of capital, innovation efficiency, and innovation trading through technology acquisitions and patent sales.

5.5.1 Cost of Capital

Despite the fact that RTCs can reduce the cost of R&D, firms may not be able to fully take advantage of them due to the high uncertainty of R&D and difficulty in raising capital. Shroff, Verdi, and Yost (2017) document that the peer information environment can reduce the cost of capital for firms in the same industry, especially for those without public information available. Based on this evidence, I expect that private firms, which tend to be financially constrained, would benefit more from RTCs if they have access to capital. The positive effects should be more significant If the information transparency is high. In contrast, public firms with RTCs, which may not be financially constrained, are less likely to benefit from access to capital.

To proxy for the availability of capital, I use the index developed by Rice and Strahan (2010) to measure the deregulation of interstate banking in a state. Such deregulation permits banks from other states to establish branches with low entry barriers in a state, which results in increased bank competition. Cornaggia et al. (2015) document that high bank competition can reduce the cost of capital of innovation, especially for small firms. By employing the deregulation of interstate banking index, I partition the patent-class-state-year observations into subsamples with high and low bank competition, and subsequently examine whether firms with RTC and IDD generate more innovation when they are more likely to raise capital at a low cost, for private firms and public firms, respectively.

Table 9, Panel A presents how innovation generated by private firms in a technology class of a state varies with the bank competition in that state and the level of information transparency in that state. Column (1) and (2) report the regression results when the bank competition is low. The coefficient on the interaction of IDD and Credit suggests the effect of Credit with the presence of IDD. The results in Tables 5 and 6 suggest that private firms can generate more positive innovation outcomes when IDD and RTCs are both available. However, the effect is not significant when the bank competition is low, indicating that private firms have more difficulties in funding their innovative ideas, even though the R&D tax incentives and protection of proprietary information are available. Columns (3) and (4) document positive coefficients on the interaction term when bank competition is high, indicating that the access to capital is essential for firms to exploit R&D tax benefits. Additionally, information transparency strengthens the positive effect of access to capital on the effectiveness of RTCs.

As a comparison, Table 9, Panel B presents the results on innovation generated by public firms. Generally, the IDD has a negative impact on the effectiveness of RTCs for public firms, regardless of the degree of bank competition and the level of information transparency, which is consistent with the evidence shown in Table 5 and Table 6. However, when access to capital is more available (bank competition is high), the effects become even more negative, indicating that public firms may incur a high cost to retain employees when private peers have access to capital. The best scenario for public firms is when both capital is scarce for small firms (bank competition is low) and the information environment is not transparent, and in that case, the negative impact of the interaction between IDD and Credit on their innovation outcomes would become insignificant.

To address concerns that the results in Table 9 may be influenced by differences in covariates, I construct a matched sample and repeat the analyses. Specifically, I match state-patent-class-year observations in the treated sample with observations in the control sample based on patent class, the number of patents in year t, and state GDP level. Table 10 presents the results of the matched sample analyses, which are consistent with those in Table 9. Overall, the results in Tables 9 and 10 provide evidence that information transparency has a significant impact on the effectiveness of RTCs by reducing the cost of capital for funding innovation projects.

5.5.2 Innovation Efficiency

According to the findings of Badertscher, Shroff, and White (2013) and Glaeser and Omartian (2022), a transparent information environment enables private firms in the same industry and competitors in import market to better identify investment opportunities and respond efficiently to these investment opportunities. In the context of innovation, firms that invest in the same technology class share a similar technology knowledge base. Information about peer firms' innovation projects, employee recruitment, and product development can help the focal firm to better evaluate factors such as inputs in R&D, timeline of innovation projects, technology feasibility, expected innovation outcomes, and more. As more peer information is accumulated, firms are more likely to identify profitable investment projects, increase R&D expenditure with RTCs, and generate more innovation outcomes with one unit investment of R&D.

To evaluate whether information transparency affects innovation efficiency for firms with access to RTCs, I use firm-year level observations as reported R&D and other detailed financial information from public firms can assist in exploring innovation efficiency. Similarly, investments of public firms are less likely to benefit from the peer information environment as public firms have alternative sources of information, including connected firms from the supply chain, institutional investors, board of directors, etc. If there is empirical evidence showing that information transparency can improve the effectiveness of public firms by increasing the innovation output of each unit of R&D investment, the innovation efficiency mechanism will work for private firms.

As the incremental return on R&D depends on the level of R&D, the conclusion on the innovation efficiency is sensitive to the level of R&D. I compose a sample where treatment firms are matched with firms at the level of R&D, the number of patents, and size. Matching on the level of R&D also confirms that the cost reduction effect of RTCs for treated firms in high and low information transparency industries are similar. Table 11 presents the regression using the matched sample, with firm, state, and year fixed effects. The variable of interest is the interaction of R&D

and Credit, indicating the incremental innovation generated by one dollar of R&D after the introduction of RTCs. The results suggest that firms in industries with high information transparency generate more innovation measured by the number of patents, citations, and high-cited patents compared to firms in low transparency environments.

5.5.3 Trading of Patents

The value of a patent to a firm depends on the net value of the patent and the commercialized value that the firm can generate using the patent. Innovative firms can generate influential patents but may not be able to realize their commercialized value. If innovative firms specialize in inventing and selling their innovations to firms that specialize in commercializing them, the overall social welfare will be improved. However, patent trading poses challenges such as valuing innovations and information asymmetry. Kim and Valentine (2023) find that the presence of public firms in a technology class is positively associated with patent sales in that technology class. Based on their evidence, I expect that transparent information can enable more efficient trading of patents so that innovative inventors can sell their patents and reinvest the proceeds from patent sales in more R&D projects.

I use technology acquisitions and patent sales to measure patent trading, as the purpose of both types of transactions is to generate high returns from externally acquired patents. Chen, Gao, and Ma (2021) document that state adoption of IDD increases the propensity of firms to be acquired in that state, especially for firms with high human capital, such as firms with patents. Based on their evidence, I expect that firms are more likely to be acquired when RTCs and IDD are available in a state, as the decreased R&D marginal cost after the benefits from RTCs can make human capital-driven M&A more cost-efficient. In Table 12, Panel A, I examine whether firms in states with RTCs and IDD are more likely to be acquired. The results confirm this expectation.

Specifically, only public firms with patents are not significant in the likelihood of being acquired. Panel B presents the results of IDD and RTCs on the number of firms being acquired when the state-level information transparency is low. Specifically, only the acquisition of private firms without patents is significant at 10%. Panel C documents that private firms with patents are more likely to be acquired under IDD and RTCs when information transparency is high. Regardless of the level of information environment transparency, public firms are less likely to be acquired when a state has both IDD and RTC in place. This finding on public firms is consistent with how the measure is generated. Public firms have firm-specific information available, and acquiring public firms is less likely to be affected by industry-level information. This evidence supports the argument that firms with low ability to commercialize their innovations (most likely private firms) are more likely to be acquired when information transparency is high.

Following Kim and Valentine (2023), I examine how the presence of public firms affects patent sales when RTCs are available in states. Table 13 shows the results of RTCs on patent sales using the state-level information transparency to partition the sample. The results in columns (1) and (2) suggest a positive effect of RTCs on the patent sales from private firms to public firms, but insignificant effects for the total patent sale. The results of the subsample analyses presented in columns (3)-(6) suggest that there are more patent sales after the introduction of RTCs in states with a high average presence of public firms (information transparency).

In an alternative analysis, I examine the association between patent sales and RTCs using state-patent-class level observations to further control for variations in different industries and technology classes. The results shown in Table 14 do not report significance on the full sample, indicating that RTCs do not increase patent trading. However, in columns (5) and (6), I find increased patent sales, including all patent sales and patent sales from a private firm to a public firm, when RTCs are available for patents in technology classes with a high information transparency. Columns (3) and (4) report a non-significant effect of RTCs on all patent sales and a weak effect on patent sales from a private firm to a public firm when the information transparency of a technology class is low. These findings suggest that information transparency can improve the effectiveness of RTCs by stimulating patent trading and technology acquisition, especially patent sales from the private patent owners and technology acquisition of private firms.

5.6 Causal Inference

5.6.1 Comparisons with Neighboring States

Although the findings have documented how information transparency affects the effectiveness of RTCs after controlling for observable state-level variables in the regression, it is possible that some unobservable factors associated with state economy, innovation, or information transparency could bias my results. To support a causal inference of my findings, I focus on treated technology classes in a state and the corresponding technology classes in neighboring states. States that share borders are more likely to share similar economic conditions. I then match the level of patenting activities in year t to generate a matched sample. This enables me to limit the sample to observations in the same technology class located in two states sharing a border and having similar levels of activities. The analyses using this matched sample are more likely to reflect a causal effect of an RTC under different levels of information transparency.

Table 15, Columns (1), (2), and (3), show that when the information transparency of a technology class is low, RTCs do not impact the innovation performance in that technology class. As the results presented in columns (4) and (6), the RTC in a state does increase the number of patents and the top-cited patents for technology classes with a high information transparency compared with the innovation outcome in the same technology class from a neighboring state.

5.6.2 Pre-trend Test of Introduction of RTCs

The conclusion on the effect of information transparency on the effectiveness of RTCs relies on the assumption that the introduction of RTCs is exogenous. However, an alternative explanation of the results found above is that pressure from a decline in innovation motivates state governments to introduce an RTC. In order to support the causal inference of this study, I examine whether innovation activities differ before the RTCs. Following Atanassov and Liu (2020), I run model (11) as presented below.

$$Ln3PatMeasure_{s,p,t} = \alpha + \beta_1 Credit_{t-2} + \beta_2 Credit_{t-1} + \beta_3 Credit_t + \beta_4 Credit_{t+1} + \beta_5 Credit_{t+2} + \beta_6 Credit_{t+3} + \beta_7 Credit_{t4+} + \beta_m CONTROLS_{i,t} + \epsilon_{s,p,t} + StateFE + CpcFE + YearFE \quad (11)$$

In Model (11), s indexes the state, p indexes the technology class, and t indexes the year. The dependent variables include patent-based measures at the state-year level and patent trading related measures. $Credit_{t-2}$, $Credit_{t-1}$, $Credit_{t+1}$, $Credit_{t+2}$, and $Credit_{t+3}$ are indicator variables, defining two years before, one year before, one year after, two years after, and three years after introducing RTC for treatment firms. $Credit_{t4+}$ is set to one four and more years after the introduction of RTC for treatment firms.

The results in Table 16 Panel A show that the coefficients on $Credit_{t-2}$ and $Credit_{t-1}$ are insignificant in all columns, indicating that there is no significant difference in innovation quantity and quality generated by all firms, public firms, or private firms in states with RTCs and control groups in the years before the introduction of state RTCs. In Panel B, there is also no evidence of a pre-trend in the number of deals and patent sales.

5.7 The Variation in Design of RTCs

Although the design of RTCs across states is similar in terms of the definition of qualified R&D and tax base, there are variations in the design of state RTCs. To address concerns that the results I have documented are driven by generous tax credits, I reran the analyses by focusing on the least generous tax credits. Using four dimensions (limit tax benefits, program cap, refundability, and carryovers), I defined each dimension as 1 if a state RTC has no limited tax benefits each year, no program cap, has refundability, or carryovers. I then aggregated the indicators and focused on the RTCs with the least generosity score. The least generosity score of an RTC is 1, and approximately 10% of patent-class-state-year observations have a score of 1. The regression results are reported in Table 17, with only technology class and year fixed effects controlled. There are significant effects of the least generous RTCs on innovations for technology classes with high information transparency only, although the effects are significant at the 10% level.

Some states offer small firms a preferential RTC in order to support those firms with limited resources to invest sufficiently in R&D. I test whether these incentives successfully enhance the innovation of small firms and whether information transparency matters for the effectiveness of RTCs. Table 18 reports the patents-related measures generated by private firms. All the coefficients on credit are significant, with the coefficients for technology classes with high information transparency being slightly greater. The findings confirm that more preferential state tax credits for small firms can have a more significant impact on innovations generated by private firms.

5.8 Alternative Measures of Industry Information Environment

I use sales and analysts' forecasts-based measures as alternative measures of information transparency to partition my sample and investigate the robustness of the results (Shroff, Verdi, and Yost 2017). Table 19, Panel A reports regression results using the sales-based industry information transparency measure to partition the sample, while Panel B reports regression results using the average analysts' forecasts per firm in an industry as the measure of information transparency. Using the average forecasts per firm to proxy industry information transparency to partition the sample generates a similar result as using the ratio of the number of public firms. Using the sales-based measures, the results show a significant impact of RTCs on innovation for technology classes with low information transparency as well, although the effect is not as strong as the effect for technology classes with high information transparency. Collectively, the alternative measures of information transparency generate consistent results.

6 CONCLUSIONS

This dissertation investigates the effectiveness of RTCs offered by U.S. states and how state information transparency influences their effectiveness. I document that the introduction of state RTCs increases state level innovation outcomes measured by the amount of patenting activities. I employ Two types of measures to proxy for information transparency: the adoption of Inevitable Disclosure Doctrine (IDD) and aggregated publicly available information from public firms. I find a positive impact of state information transparency on the effectiveness of the RTCs.

Aggregated state innovation data provides an overall picture of the impact of R&D tax credits (RTCs) on all firms within a state's border, as intra-firm resource reallocation and innovation spillover effects tend to cancel each other out. However, by separately testing the innovation of public and private firms, this study finds that information transparency has heterogeneous effects on the effectiveness of RTCs for private and public firms. The net effect depends on the trade-off between the benefits and costs of improving information transparency on how RTCs incentivize individual firms' innovation. Notably, this study finds that public firms experience a reduction in the effectiveness of their RTCs when Innovation Disclosure Doctrine (IDD) is present in a state, suggesting that the main cost is due to the innovation spillover effect.

The study further explores the mechanisms through which information transparency can benefit individual firms. First, the study finds that private firms achieve better innovation outcomes with both R&D tax credits (RTCs) and Innovation Disclosure Doctrine (IDD) available in the state, particularly when there is easier access to capital and a more transparent information environment. This suggests that one way in which information transparency improves the effectiveness of RTCs is through a reduced cost of capital. Second, by examining a sample of public firms, the study finds that firms headquartered in states with R&D tax credits (RTCs) and operating in industries with high information transparency generate significantly more innovation for each additional dollar of R&D than firms with RTCs available but operating in industries with low information transparency, indicating improved innovation efficiency under RTCs. Moreover, I test how RTCs affect technology acquisitions and patent sales and how the results differ with the level of information transparency. Focusing on both technology-driven acquisitions and patent sales, I document a more substantial effect of RTCs on the number of private firms with patents being acquired and the number of patents sold when information transparency is high. These findings confirm that information transparency can increase positive return of incremental innovation investment through more efficient patent-related transactions.

This dissertation makes three primary contributions to the literature. First, the findings of this dissertation suggest that improving the transparency of the information environment where RTCs are introduced can lead to a more positive effect on innovation. Second, this study identifies information transparency as a determinant that impacts the effectiveness of RTCs, adding to the existing literature on the effectiveness of R&D tax incentives. Finally, this study extends the literature on the economic value of public firm presence, the macro effect of financial disclosures, and information transparency and innovation by documenting that public firm presence can improve the effectiveness of R&D tax incentives, and that aggregated accounting information can help allocate tax incentives more efficiently.

However, there are several limitations to this dissertation. First, the availability of industry-level public firm presence measures is limited, and state-level measures may not fully capture the overall information available. Second, the use of a staggered DID model has received criticisms in recent years, and it is necessary to conduct further tests to address these concerns. Finally, the test on increased innovation efficiency faces an empirical challenge. As RTCs aim to reduce the marginal cost of R&D, treated firms are expected to generate more innovation for each additional dollar of R&D investment. Therefore, the increase in innovation outcomes observed in this study for each additional dollar of R&D investment may be due to the cost reduction effect of RTCs rather than improved innovation efficiency.

One argument put forward in this dissertation is that information transparency could enhance the effectiveness of RTCs by enabling more efficient patent transactions. Such transactions can benefit innovative firms with limited commercialization abilities by allowing them to sell their patents to firms that specialize in commercialization. This, in turn, can provide them with proceeds that can be reinvested in innovation. Further research could investigate the actual effects of patent transactions by examining whether patent sellers experience stronger and sustained innovation performance and whether patent buyers generate high commercial value from purchased patents.

Another possible direction for future research is to explore variation in innovation inputs. The analyses in this study are based on innovation outcomes, which have limitations in explaining how RTCs affect the decisions of individual firms. For instance, the evidence suggests that when a state with IDD introduces RTCs, the innovation outcomes of private firms become more significant, while the innovation outcomes of public firms experience an attenuated effect, leading to an overall negative effect at the state level. It would be worthwhile to examine whether the total deadweight loss is attributable to the reduced overall innovation inputs or the loss of efficiency.

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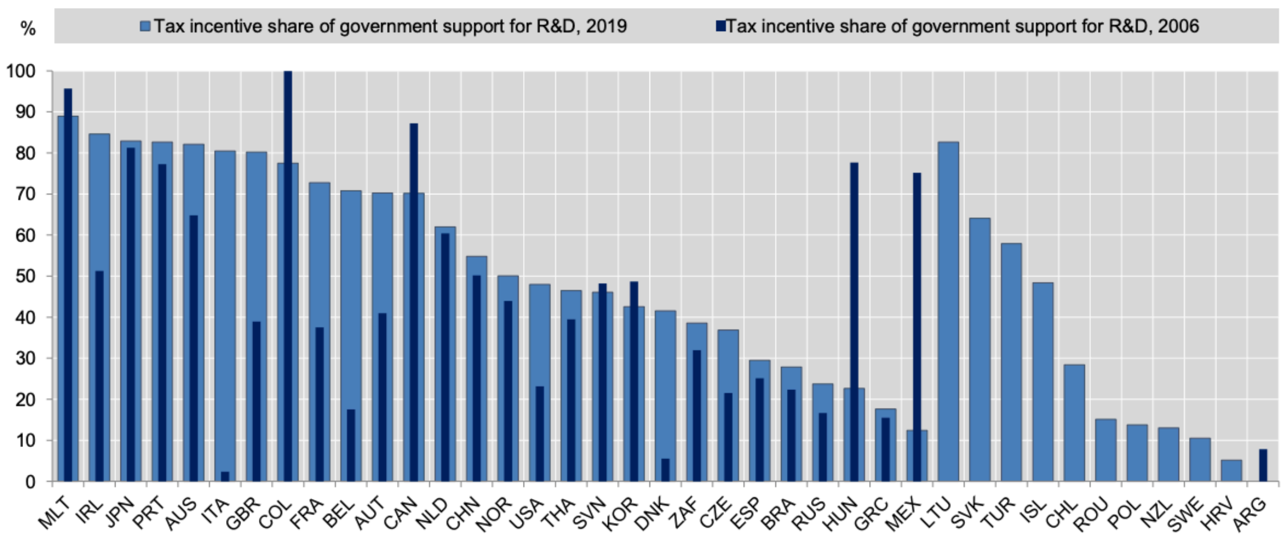
Figure 1. R&D Tax Incentive Support as a Percentage of Total Government Support in OECD Countries



The source is http://oe.cd/rdtax, December 2021

Appendix A. International Comparison of Research and Development Expenditures in 2020

Country	YEAR	R&D Tax Incentives as a Percentage of GDP	R&D incentives (in billion dollars and 2015 US$)
Australia	2020	0.130%	1.94
Austria	2020	0.275%	1.07
Belgium	2020	0.230%	1.08
Canada	2020	0.143%	2.42
Chile	2020	0.008%	0.02
China	2017	0.069%	8.66
Czech Republic	2020	0.037%	0.08
Denmark	2020	0.040%	0.13
France	2020	0.291%	7.03
Greece	2020	0.029%	0.05
Hungary	2020	0.038%	0.05
Iceland	2020	0.177%	0.03
Ireland	2020	0.177%	0.70
Italy	2020	0.101%	1.77
Japan	2020	0.094%	4.10
Korea	2020	0.143%	2.33
Lithuania	2020	0.034%	0.02
Mexico	2020	0.001%	0.01
Netherlands	2020	0.154%	1.24
New Zealand	2020	0.045%	0.09
Norway	2020	0.108%	0.43
Poland	2020	0.029%	0.16
Portugal	2020	0.238%	0.48
Romania	2020	0.008%	0.02
Russia	2019	0.112%	1.64
Slovak Republic	2020	0.043%	0.04
Slovenia	2020	0.082%	0.04
South Africa	2020	0.002%	0.01
Sweden	2020	0.029%	0.16
Türkiye	2020	0.126%	1.28
United Kingdom	2020	0.307%	8.66
United States	2019	0.119%	23.76
European Union	2020	0.098%	13.58

Source: OECD INNOTAX portal, https://stip.oecd.org/innotax/, March 2023.

Appendix B. Main Features of R&D Tax Incentives in OECD and EU Economies 2022

Country	Year	Incentive Name	Type1	Type2
Australia	2022	R&D tax incentive	Tax credit	V
Austria	2021	Research premium	Tax credit	V
Belgium	2022	Accelerated depreciation for R&D capital assets	Accelerated depreciation	V
	2022	Payroll Withholding Tax Credit	Payroll/SSC incentives	V
	2022	R&D Investment Deduction	Tax allowance	V
	2022	Refundable tax credit for R&D	Tax credit	V
Brazil	2022	Accelerated depreciation for R&D capital assets	Accelerated depreciation	V
	2022	R&D tax allowance	Tax allowance	V
Canada	2022	Scientific research and experimental development (SR&ED) tax credit	Tax credit	V
Chile	2021	R&D tax credit for intramural and extramural expenses	Tax credit	V
China	2022	Accelerated depreciation for R&D capital assets	Accelerated depreciation	V
	2022	R&D tax allowance	Tax allowance	V
Cyprus	2022	Enhanced tax deduction for R&D expenses	Tax allowance	V
Czech Republic	2022	R&D tax allowance	Tax allowance	Hybrid
Denmark	2022	Accelerated depreciation for R&D capital assets	Accelerated depreciation	V
	2022	Enhanced Tax allowance on R&D capital	Tax allowance	V
	2022	R&D tax credit for deficit related R&D expenses	Tax credit	V
France	2022	Accelerated depreciation for R&D capital assets (Machinery and Equipment)	Accelerated depreciation	V
	2022	Payroll withholding tax credit for young innovative firms (JEI) and young university firms (JEU)	Payroll/SSC incentives	V
	2022	R&D tax credit	Tax credit	V
	2022	Tax credit for collaborative research	Tax credit	V
Greece	2022	R&D tax allowance	Tax allowance	V
Hungary	2022	Development tax incentive	Tax credit	V
	2022	Payroll withholding tax remission (SSC exemption)	Payroll/SSC incentives	V
	2022	R&D tax allowance in innovation contribution	Tax allowance	V
	2022	R&D tax credit in Small Business Tax (KIVA)	Payroll/SSC incentives	V
Iceland	2022	R&D tax credit	Tax credit	V
Ireland	2022	Accelerated depreciation for R&D capital assets	Accelerated depreciation	V
Italy	2022	Tax allowance for R&D expenses related to eligible intangible assets	Tax allowance	V
	2022	V R&D tax credit (Law 160/2019, Law 178/2020, Law 234/2021)	Tax credit	V
Japan	2021	General type R&D tax credit	Tax credit	V
	2021	High R&D intensity-based R&D tax credit	Tax credit	I
	2021	Open innovation activity-based R&D tax credit	Tax credit	V
Korea	2022	R&D investment credit	Tax credit	V
Korea	2022	R&D tax credit	Tax credit	Hybrid

Lithuania	2022	Accelerated Depreciation for R&D capital assets	Accelerated depreciation	V
Lithuania	2022	R&D tax allowance	Tax allowance	V
Mexico	2022	R&D tax credit	Tax credit	I
Netherlands	2022	WBSO	Payroll/SSC incentives	V
New Zealand	2021	Research and Development Tax Incentive	Tax credit	V
	2021	Tax Credit for research and development tax losses	Tax credit	V
Norway	2022	SKATTEFUNN R&D tax credit	Tax credit	V
Poland	2022	R&D tax allowance	Tax allowance	V
Portugal	2022	SIFIDE tax credit	Tax credit	Hybrid
Romania	2022	R&D tax allowance	Tax allowance	V
Russian	2022	Accelerated depreciation provision for R&D capital assets	Accelerated depreciation	V
	2022	R&D tax allowance	Tax allowance	V
	2022	VAT exemption and property tax credit	Tax credit	V
Slovak Republic	2022	R&D tax allowance (grant recipients)	Tax allowance	V
	2022	R&D tax allowance	Tax allowance	Hybrid
Slovenia	2022	R&D tax allowance	Tax allowance	V
South Africa	2022	R&D tax allowance	Tax allowance	V
Spain	2022	Accelerated depreciation for R&D capital assets	Accelerated depreciation	V
	2022	R&D&I tax credit	Tax credit	Hybrid
	2022	SSC exemption	Payroll/SSC incentives	V
Sweden	2022	Partial exemption of social security contributions	Payroll/SSC incentives	V
Türkiye	2022	Accelerated depreciation of R&D capital	Accelerated depreciation	V
	2022	Compensation for social security contributions	Payroll/SSC incentives	V
	2022	R&D tax allowance	Tax allowance	I
United Kingdom	2022	Corporate Tax Credit for Research & Development	Tax allowance	V
	2022	Research and development allowance (RDA)	Accelerated depreciation	V
	2022	Research and Development Expenditure Credit (RDEC) Scheme	Tax credit	V
United States	2022	Federal research and experimentation (R&E) tax credit	Tax credit	Hybrid

Source: OECD R&D Tax Incentives Database, April 2022.

Appendix C. Variable Definition

Variable Name	Definition
State-level Variables	
Credit	Indicator variable, which equals 1 in year t and subsequent years if a state introduces R&D credits in year t, and 0 otherwise.
IDD	Indicator variable, which equals 1 in year t and subsequent years if a state has valid IDD, and 0 otherwise.
GSPGrowth	State GDP growth rate.
GSP	Log (1+state-level real gross state product in a year).
UnempGrowth	State unemployment rate in year a year.
StateEMP	Log (1+total number of employees in a state and a year).
LaborC	The sum of the squared labor shares for a state and a year.
CorpTaxR	Total corporate tax / state GDP in a year.
IndTaxR	Total individual tax / state GDP in a year.
TaxToGDPR	Total state revenue received from tax/ state GDP in a year.
Information Transparency	
StateInfo	A weighted average of the sector-level public firms' percentage in a state
CPCInfo	A weighted average of the public firms' presence in 3-digits NAICS industries for all Patents applied in a year and in a CPC class. The industry-level presence of public firms Is measured as the number of public firms/the total number of firms in an industry.
CPC_PubR	An alternative of CPCInfo. THE industry-level presence of public firms is measured as the total sales of public firms/the total production of firms in an industry.
CPC_NAnalyst	An alternative of CPCInfo. The industry-level presence of public firms is measured as the average number of analysts' forecasts per firm in this industry.
IndustryInfo	The number of public firms in a 3-digits NACIS industry/total number of firms in the industry.
Firm-level Variables	
TPat	Log (1+ number of patents applied by a firm in a year).
TNvalue	Log(1+sum(patvalue) for all patents applied by a firm in year t). Patvalue is a firm's idiosyncratic stock market return on the day of patent grant.
TRvalue	Log(1+sum(real-patvalue) for all patents applied by a firm in year t). Real-patvalue is measured by: 1) get a firm's idiosyncratic stock market return on the day of patent grant. 2) deflated to 1982-dollar value using CPI.
RDSale	Replace missing xrd with zero and then scaled by sales.
R&D Missing	Missing xrd from compustat.
ROA	obibdp/at_{t-1}
Size	Log(1+at).
TobinQ	Max((abs(prcc_f) *csho + dltt +max (0, dlc)/(lt+ceq)), 0).
Age	Log (1+Compustat age).
Leverage	lt/at_{t-1}
Tangibility	ppent/at_{t-1}
Sale	Log(1+sale)

SaleGrowth	$(\text{sale}_t - \text{sale}_{t-1})/\text{sale}_{t-1}$
Capex	$\text{capx}/\text{at}_{t-1}$
Innovation Outcomes	
Pat	Number of patents filed in a state and in year t.
L3Pat	Log (1+ number of total patents filed in state and in year t+3).
CpcTPat	Number of patents filed in a CPC patent class, a state, and year t.
L3CpcTPat	Log (1+ number of patents filed in a CPC patent class, a state, and in year t +3).
PatPub	Number of patents filed by all public firms in a state and in year t.
L3PatPub	Log (1+ number of patents filed by all public firms in a state and in year t+3).
CpcPubPat	Number of patents filed by all public firms in a CPC patent class, a state, and year t.
L3CpcPubPat	Log (1+number of patents filed by all public firms in a CPC patent class, a state, and year t+3).
PatPri	Number of patents filed by all private firms in a state and in year t.
L3PatPri	Log (1+number of patents filed by all private firms in a state and in year t+3).
CpcPriPat	Number of patents filed by all private firms in a CPC patent class, a state, and year t.
L3CpcPriPat	Log (1+number of patents filed by all private firms in a CPC patent class, a state, and year t+3).
Cite	Number of citations received by patents filed by all firm in a state and year t.
L3Cite	Log (1+number of citations received by patents filed by all firm in a state and year t+3).
CpcTCite	Number of citations received by patents filed by all firm in a CPC patent class, state, and year t.
L3CpcTCite	Log (1+number of citations received by patents filed by all firm in a CPC patent class, state, and year t+3).
CitePub	Number of citations received by patents filed by all public firm in a state and year t.
L3CitePub	Log (1+number of citations received by patents filed by all public firm in a state and year t+3).
CpcPubCite	Number of citations received by patents filed by all public firm in a CPC patent class, state, and year t.
L3CpcPubCite	Log (1+number of citations received by patents filed by all public firm in a CPC patent class, state, and year t+3).
CitePri	Number of citations received by patents filed by all private firm in a state and year t.
L3CitePri	log (1+number of citations received by patents filed by all private firm in a state and year t+3).
CpcPriCite	Number of citations received by patents filed by all private firm in a CPC patent class, state, and year t.
L3CpcPriCite	Log (1+number of citations received by patents filed by all private firm in a CPC patent class, state, and year t+3).
top-cited patents	1, when a patent has citations that are higher than the 90 percentiles of citations associated with patents of the same CPC class and application year.
TopPat	Number of top-cited patents in a state and year t.
L3TopPat	Log (1+number of top-cited patents in a state and year t+3).
CpcTop	Number of top-cited patents in a CPC class, a state, and year t.
L3CpcTop	Log (1+ number of top-cited patents in a CPC class, a state, and year t).
TopPatPub	Number of top-cited patents applied by all public firms in a state and year t.
L3TopPatPub	Log (1+number of top-cited patents applied by all public firms in a state and year t +3).
CpcPubTop	Number of top-cited patents applied by all public firms in a CPC class, a state, year t.

L3CpcPubTop	Log (1+number of top-cited patents applied by all public firms in a CPC class, a state, and year t+3).
TopPatPri	Number of top-cited patents applied by all private firms in a state and year t.
L3TopPatPri	Log (1+number of top-cited patents applied by all private firms in a CPC class, a state, and year t+3).
CpcPriTop	Number of top-cited patents applied by private firms in a CPC class, a state, and year t.
L3CpcPriTop	Log (1+number of top-cited patents applied by all private firms in a CPC class, a state, and year t+3).
Patent Sales and the Number of Acquisitions	
PatSale	Number of patents generated in a state and year and sold at least once.
LPatSale	Log (1+number of patents generated in a state and year and sold at least once).
CpcPatSale	Number of patents generated in a state, a CPC class, and year, and sold at least once.
LCpcPatSale	Log (1+the number of patents generated in a state, a CPC class, and a year and sold at least once).
LPriPubPsale	Number of patents generated in a state and year by private firms and sold to public firms.
PriPubPsale	Log (1+number of patents generated in a state and year by private firms and sold to public firms).
CpcPriPSale	Number of patents generated in a state, a CPC class, and a year by private firms and sold to public firms.
LCpcPriPSale	Log (1+the number of patents generated in a state, a CPC class, and a year by private firms and sold to public firms).
TM&A	Number of acquisition deals with the target in a state and year.
TPubM&A	Number of acquisition deals with the target as a public firm in a state and year.
LTPubM&A	Log (1+number of acquisition deals with the target as a public firm in a state and year).
TPubTechM&A	Number of acquisition deals with the target as a public firm in a state and year, and has at least one patent.
LTPubTechM&A	Log (1+number of acquisition deals with the target as a public firm in a state and year, and has at least one patent).
TPubOperM&A	Number of acquisition deals with the target is a public firm, in a state, in a year, and has no patents.
LTPubOperM&A	Log (1+number of acquisition deals with the target as a public firm in a state and year and has no patents).
TPriM&A	Number of acquisition deals with the target as a private firm in a state and year.
LTPriM&A	Log (1+number of acquisition deals with the target as a private firm in a state and year).
TPriTechM&A	Number of acquisition deals with the target as a private firm in a state and year and has at least one patent.
LTPriTechM&A	Log (1+number of acquisition deals with the target as a private firm in a state and year and has at least one patent).
TPriOperM&A	Number of acquisition deals with the target as a private firm in a state and year and has no patents.
LTPriOperM&A	Log (1+number of acquisition deals with the target as a private firm in a state and year and has no patents).

Appendix D. List of Changes in State R&D Tax Credits

Notes: The source of this table is from Falato and Sim (2014) and Schmidt (2021).

State	Year Enacted	R&D Tax Credit Rate	Tax Base	Limit	Cap	Refundable	Carry Forward
Alaska	1998	18% of allocated federal credit	No	No	No	No	20 Years
Arizona	1994	15%-24% of incremental research expenditures in-state	Incremental	No	$5 million for refundable portion	Yes, for qualified small business only.	15 years
Arkansas	2003	10% incremental research expenditures	Incremental	No	No	No	No
Arkansas	2007	20%-33% of incremental research expenditures	Incremental	Yes, $10,000-$50,000 per year	No	No	9 Years
California	1988	8% incremental research expenditures	Incremental	No	No	No	Until utilized
California	1997	11% incremental research expenditures	Incremental	No	No	No	Until utilized
California	2000	15% incremental research expenditures	Incremental	No	No	No	Until utilized
Colorado	1989	3% incremental research expenditures	Incremental	25% of credit amount	No	No	Until utilized
Connecticut	1993	20% incremental research expenditures	Hybrid	70% of liability	No	Yes, up to 65% of credit for qualified small business only.	15 years
Delaware	2000	10% of incremental re-search expenditures or 50% of allocated federal research tax credit computed under alternative simplified method	Incremental	No	No	Yes (Effective January 1 2017)	No
Florida	2012	10% of incremental research expenditures	Incremental	50% of liability. For businesses less than four years old, limits apply.	$9 million in 2015. $23 million in 2016. $9 million in 2017 and after. (First come, first served.)	No	5 Years
Georgia	1998	10% of incremental research expenditures	Incremental	50% of liability after all other credits have been applied.	No	No	10 Years
Hawaii	2000	20% of incremental	Incremental	No	No	Yes, up to $5 million	No

		research expenditures					
Hawaii	2011	Let R&D tax credit expire					
Hawaii	2013	20% of incremental research expenditures	Incremental	No	No	Yes, up to $5 million	No
Idaho	2001	5% of incremental research expenditures	Incremental	No	No	No	14 Years
Illinois	1990	6.5% of incremental research expenditures	Incremental	No	No	No	5 Years
Illinois	2004	6.5% of incremental research expenditures	Incremental	No	No	No	5 Years
Indiana	1991	10% of incremental research	Incremental	1 million	No	No	10 Years
Indiana	2005	10%-15% of incremental research expenditures	Incremental	1 million	No	No	10 Years
Iowa	1985	4.55% - 6.5% of incremental research expenditures	Incremental	No	No	Yes	No
Kansas	1988	6.5% of incremental research expenditures	Incremental	25% of credit	No	No	Until utilized
Kentucky	2002	5% of the qualified cost for “construction of research facilities” for “qualified research”	Incremental	Limited to construction of research facilities	No	No	10 years
Louisiana	2003	5% of incremental research expenditures	Incremental	No	No	Yes	10 Years
Maine	1996	5% of incremental research expenditures	Hybrid	75% of liability beyond $25,000	No	No	15 Years
Maryland	2000	10% of incremental research expenditures	Incremental	Yes, up to $250,000	$12 million statewide cap (Prorated); $3.5 million for small businesses	Yes, (effective December 15 2012) for small businesses	7 years
Massachusetts	1991	10% of incremental research expenditures	Incremental	75% of liability beyond $25,000	No	Yes, partially refundable.	15 years
Michigan	2008	1.9% of in-state research expenditures	Incremental	65% of liability	NA	NA	NA
Michigan	2012	Let R&D tax credit expire					
Minnesota	1982	4% - 10% of incremental	Incremental	No	No	No	15 years

		research expenditures					
Missouri	1994	6.5% of incremental research expenditures	Incremental	NA	NA	NA	NA
Missouri	2004	Let R&D tax credit expire					
Montana	1987	5% of incremental research expenditures	Incremental	NA	NA	NA	NA
Montana	2010	Let R&D tax credit expire					
Nebraska	2006	15%-35% of allocated federal credit	Hybrid	No	No	Yes	No
New Hampshire	2007	10% of incremental research expenditures	Incremental	Yes, up to $50,000	$7 million statewide cap (Prorated)	No	5 years
New Jersey	1994	10% of incremental research expenditures	Hybrid	No	No	No	7 Years. 25 Years for certain types of research
New Mexico	2000	5% of incremental research expenditures	Incremental	No	No	No	99 years
New York	2005	50% of allocated federal credit or 6% of expenditures (8% for qualified projects)	Incremental	No	$250 million statewide (First come, first served.)	Yes	No
North Carolina	1996	1.25% to 20% of incremental research expenditures	Incremental	NA	NA	NA	NA
North Carolina	2015	expired on December 31 2015.					
North Dakota	1988	25% of incremental research up to $100,000. 8% of incremental research beyond $100,000.	Incremental	No	No	No	15 Years or 3 Year Carry Back
Ohio	2001	7% of incremental research expenditures	Incremental	No	No	No	7 years
Oregon	1989	5% of incremental research expenditures	Incremental	NA	NA	NA	NA
Oregon	2017	expired on December 31 2017.					
Pennsylvania	1997	10% of incremental research expenditures	Incremental	75% of liability	Statewide $55 million cap, $11 million for small businesses (Prorated)	No	15 Years
Rhode Island	1994	16.9% - 22.5% of incremental	Incremental	50% of liability	No	No	7 Years

		research expenditures					
South Carolina	2001	5% of incremental research expenditures	Incremental	50% of liability	No	No	10 Years
Texas	2014	5% of incremental research expenditures	Incremental	No	No	No	20 Years
Utah	2008	5% of incremental qualified research expenditures and 7.5% of total qualified research expenditures	Hybrid	No	No	No	14 Years for incremental based credits
Vermont	2011	27% of allocated federal credit		No	No	No	10 Years
Virginia	2011	15%-20% of first $300,000 of incremental research expenses	Incremental	No	$7 million statewide cap (Prorated)	Yes	No
Virginia	2016	10% of incremental research expenses	Incremental	75% of liability	$20 million statewide cap (Prorated)	No	10 Years
Washington	1995	1.5% of incremental research expenses	Incremental	4 million	NA	NA	14 years
West Virginia	2003	10% of incremental research expenses	Incremental	NA	NA	NA	NA
Wisconsin	1986	5.75% - 11.5% of incremental research expenditures	Hybrid	No	No	Yes, (effective 2018) up to 10%	15 years

Table 1 Summary Statistics

Note: Table 1, Panel A, shows the state-level descriptive statistics. *Credit* is an indicator variable equal to 1 if a state provides an RTC and 0 otherwise. Please refer to Appendix C for further variable definitions.

Panel A. Summary Statistics of State-level Observations

	Mean	SD	25th	Median	75th	Obs
Credit	.38	.49	.00	.00	1	2294
IDD	.4119	.4923	.00	.00	1	2294
StateInfoQ	.0016	.0022	.0004	.0008	.0018	2141
Pat	1243.48	2381.37	82.00	347.50	1447.00	2294
PatPub	508.91	1183.06	2.00	50.00	388.00	2294
PatPri	687.02	1283.05	60.00	216.00	748.00	2294
Cite	18862.92	37914.06	606.00	3837.50	18535.00	2294
CitePub	9871.85	23072.96	17.00	821.50	6893.00	2294
CitePuri	8917.13	15988.79	492.00	2533.00	9910.00	2294
TopPat	231.37	490.16	13.00	59.50	248.00	2294
TopPatPub	72.66	149.79	.00	8.00	65.00	2294
TopPatPri	142.67	315.00	10.00	36.00	131.00	2294
PatSale	802.87	1471.92	39.00	211.00	810.00	2294
PriPubPsale	487.98	919.85	30.00	143.50	534.00	2294
TM&A	36.18	51.20	7.00	18.00	44.00	2012
TPubM&A	7.82	13.94	1.00	2.00	8.00	2012
TPriM&A	28.42	40.15	5.00	14.00	34.00	2012
GSPGrowth	5.76	4.17	3.40	5.40	8.30	2294
GSP	11.43	1.23	10.56	11.41	12.35	2294
UnempGrowth	.0005	.0141	-.007	-.002	.004	2243
StateEMP	14.43	.99	13.59	14.51	15.11	2244
LaborC	.184	.042	.158	.174	.196	2294
CorpTaxR	.0159	.0091	.0113	.0031	.0042	2294
IndTaxR	.016	.009	.011	.0177	.0221	2294
TaxToGDPR	.054	.012	.047	.053	.0601	2294

.

Table 1 Continued

Panel B. Summary Statistics of State-level Observations by Treatment

	Control	Credit	Credit-Control
IDD	0.3747	0.4721	0.0973***
StateInfo	0.0006	0.0027	0.0021***
Pat	759.9301	2024.7685	1264.8384***
PatPub	371.5984	730.7719	359.1735***
PatPri	388.3317	1169.6294	781.2977***
Cite	14570.0995	25798.9943	11228.8948***
CitePub	7701.1807	13379.0673	5677.8866***
CitePuri	6802.0296	12334.5724	5532.5428***
TopPat	121.3769	409.0798	287.7030***
TopPatPub	51.1757	107.3763	56.2006***
TopPatPri	68.8207	261.9897	193.1690***
PatSale	654.7071	1042.2691	387.5620***
PriPubPsale	356.6704	700.1448	343.4744***
TM&A	27.3927	47.8187	20.4260***
TPubM&A	5.1763	11.3176	6.1413***
TPriM&A	22.1998	36.6478	14.4480***
GSPGrowth	6.6361	4.3536	-2.2825***
GSP	11.0395	12.0715	1.0320***
UnempGrowth	-0.0002	0.0010	0.0012*
StateEMP	14.2565	14.7140	0.4575***
LaborC	0.1868	0.1787	-0.0082***
CorpTaxR	0.0034	0.0032	-0.0002*
IndTaxR	0.0133	0.0201	0.0068***
TaxToGDPR	0.0535	0.0556	0.0021***
Observations	1417	877	2294

Note: *StateInfo* is measured by a weighted average of the sector-level public firms' percentage in a state. High *StateInfo* takes a value of 1 if a state's *StateInfo* is in the top tercile, while Low *StateInfo* takes a value of 1 if a state's *StateInfo* is in the bottom tercile. Sector is the classification used by the Bureau of Economic Analysis (BEA) to report the GDP by state.

Table 1 Continued

Panel C. Summary Statistics of State-Patent_Class level Observations

	Mean	SD	25th	Median	75th	Obs
Credit	.40	.49	.00	.00	1.00	255366
IDD	.45	.50	.00	.00	1.00	255366
CPC_PubR	.02	.01	.01	.02	.03	217060
CPC_NAnalyst	.46	.33	.22	.38	.61	196828
CPC_SaleR	.13	.05	.10	.13	.16	217060
CpcTPat	20.96	161.73	.00	2.00	8.00	255366
CpcPubPat	8.20	76.02	.00	.00	1.00	255366
CpcPriPat	12.76	120.46	.00	1.00	5.00	255366
CpcTCite	328.59	3078.37	.00	6.00	78.00	255366
CpcPubCite	170.07	1877.59	.00	.00	10.00	255366
CpcPriCite	158.52	1357.34	.00	3.00	46.00	255366
CpcTop	4.78	46.07	.00	.00	2.00	255366
CpcPubTop	1.48	12.79	.00	.00	.00	255366
CpcPriTop	3.31	41.68	.00	.00	1.00	255366
CPCPatSale	13.56	110.63	.00	1.00	5.00	255366
CPCPriPubSale	8.84	97.45	.00	1.00	3.00	255366

Note: The Cooperative Patent Classification (CPC) is a patent classification system jointly developed by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO). It is divided into nine sections, A-H and Y, which are further sub-divided into classes, sub-classes, groups, and sub-groups. The CPC classification used in the analysis is at the sub-classes level.

Panel D. Summary Statistics State-Patent_Class Observations by Treatment

	Control	Credit	Credit-Control
IDD	0.4147	0.4985	0.0838***
CPC_PubR	0.0229	0.0256	0.0027***
CPC_NAnalyst	0.3929	0.5431	0.1502***
CPC_SaleR	0.7635	0.7231	-0.0404***
CpcTPat	0.3929	0.5431	12.3178***
CpcPubPat	0.1348	0.1264	3.9231***
CpcPriPat	12.0903	34.1457	8.3948***
CpcTCite	5.6792	11.9570	103.6395***
CpcPubCite	6.4112	22.1887	55.5421***
CpcPriCite	237.2868	464.2470	48.0974***
CpcTop	124.3782	237.9665	1.9395***
CpcPubTop	112.9086	226.2805	0.4858***
CpcPriTop	2.2962	8.4823	1.4536***
CPCPatSale	0.9274	2.2976	7.8841***
CPCPriPubSale	1.3688	6.1847	7.6015***
Observations	152634	102732	

Note: *CPCPubNfirmR* is measured by a weighted average of the three-digit NAICS-level public firms' percentage in a CPC of a state. *CPCAvgAnalystR* is measured by a weighted average of the three-digit NAICS-level average number of analysts per firm in a CPC of a state. Following Shroff, Verdi, and Yost (2017), the average values of 1) the percentage of public firms operating in the NAICS 3-digit industry 2) the average analyst coverage for firms in the industry, and 3) the ratio of sales from public firms to the total production in the industry, measure the peer information environment.

Table 2. Correlation Matrix

Notes:This matrix is based on the state-level observations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Credit	1.000											
(2) StateInfo	0.226*	1.000										
(3) Pat	0.258*	0.853*	1.000									
(4) PatPub	0.148*	0.767*	0.797*	1.000								
(5) PatPri	0.296*	0.752*	0.899*	0.505*	1.000							
(6) Cite	0.144*	0.677*	0.697*	0.843*	0.463*	1.000						
(7) CitePub	0.120*	0.658*	0.658*	0.856*	0.396*	0.973*	1.000					
(8) CitePuri	0.168*	0.640*	0.684*	0.740*	0.516*	0.942*	0.840*	1.000				
(9) TopPat	0.285*	0.741*	0.899*	0.617*	0.890*	0.567*	0.523*	0.575*	1.000			
(10) TopPatPub	0.182*	0.762*	0.795*	0.975*	0.524*	0.875*	0.876*	0.788*	0.623*	1.000		
(11) TopPatPri	0.298*	0.620*	0.754*	0.345*	0.885*	0.326*	0.269*	0.377*	0.925*	0.353*	1.000	
(12) PatSale	0.128*	0.765*	0.854*	0.659*	0.787*	0.750*	0.708*	0.734*	0.752*	0.684*	0.645*	1.000
(13) PriPubPsale	0.181*	0.707*	0.839*	0.474*	0.918*	0.528*	0.452*	0.586*	0.798*	0.502*	0.786*	0.908*
(14) TM&A	0.198*	0.847*	0.823*	0.727*	0.706*	0.757*	0.700*	0.771*	0.737*	0.727*	0.585*	0.754*
(15) TPubM&A	0.218*	0.736*	0.712*	0.723*	0.554*	0.685*	0.629*	0.703*	0.569*	0.703*	0.392*	0.569*
(16) TPriM&A	0.178*	0.831*	0.814*	0.691*	0.716*	0.738*	0.685*	0.750*	0.754*	0.695*	0.616*	0.766*
(17) GSPGrowth	-0.250*	-0.114*	-0.101*	-0.055*	-0.126*	-0.014	-0.018	-0.007	-0.128*	-0.065*	-0.144*	-0.033
(18) GSP	0.408*	0.749*	0.635*	0.477*	0.649*	0.467*	0.423*	0.489*	0.611*	0.510*	0.590*	0.553*
(19) UnempGrowth	0.057*	0.013	-0.039	-0.006	-0.054*	-0.036	-0.024	-0.049*	0.037	-0.013	0.053*	-0.069*
(20) StateEMP	0.224*	0.747*	0.625*	0.511*	0.606*	0.539*	0.489*	0.564*	0.566*	0.546*	0.514*	0.607*
(21) LaborC	-0.106*	0.067*	0.093*	0.135*	0.046*	0.199*	0.201*	0.178*	0.059*	0.149*	0.029	0.199*
(22) CorpTaxR	-0.058*	-0.040	0.029	0.071*	-0.015	0.102*	0.096*	0.103*	0.012	0.076*	-0.028	0.089*
(23) IndTaxR	0.363*	0.113*	0.187*	0.152*	0.161*	0.161*	0.136*	0.179*	0.191*	0.171*	0.165*	0.175*
(24) TaxToGDPR	0.085*	-0.209*	-0.093*	-0.060*	-0.121*	-0.045*	-0.034	-0.058*	-0.073*	-0.051*	-0.095*	-0.076*

Variables	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(13) PriPubPsale	1.000											
(14) TM&A	0.691*	1.000										
(15) TPubM&A	0.501*	0.856*	1.000									
(16) TPriM&A	0.710*	0.985*	0.760*	1.000								
(17) GSPGrowth	-0.055*	-0.009	-0.048*	0.006	1.000							
(18) GSP	0.567*	0.699*	0.574*	0.694*	-0.286*	1.000						
(19) UnempGrowth	-0.078*	-0.049*	-0.053*	-0.044*	0.038	0.060*	1.000					
(20) StateEMP	0.583*	0.704*	0.558*	0.709*	-0.101*	0.910*	-0.013	1.000				
(21) LaborC	0.113*	0.045*	-0.035	0.067*	0.013	-0.026	-0.007	-0.065*	1.000			
(22) CorpTaxR	0.030	-0.013	-0.028	-0.006	0.073*	-0.115*	-0.047*	-0.097*	0.264*	1.000		
(23) IndTaxR	0.157*	0.054*	0.078*	0.042	-0.124*	0.195*	0.006	0.172*	0.043*	0.082*	1.000	
(24) TaxToGDPR	-0.088*	-0.195*	-0.156*	-0.194*	-0.095*	-0.220*	0.008	-0.285*	0.048*	0.306*	0.379*	1.000

*** p<0.01, ** p<0.05, * p<0.1

Table 3. R&D Tax Credits and State Innovation

Note: Table 3 presents the regression results of the effect of the state R&D tax credit on innovation using state-level data. *L3Pat* is the total number of patents applied by all firms in a state in year t+3 after log transformation. *L3Cite* is the total number of citations received by all patents applied by all firms in a state in year t+3 after log transformation. *L3TopPat* is the log transformation of the total number of patents with citations that are higher than the 90th percentile of patents of the same technology class and application year. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit and 0 otherwise.

	(1)	(2)	(3)
VARIABLES	L3Pat	L3Cite	L3TopPat
Credit	0.055*	0.055	0.070**
	(1.974)	(1.636)	(2.424)
GSPGrowth	0.005	0.001	0.007
	(1.472)	(0.216)	(1.602)
GSP	0.006	-0.079	0.105
	(0.051)	(-0.315)	(0.940)
UnempGrowth	-3.009	-1.315	-0.884
	(-1.518)	(-0.572)	(-0.493)
StateEMP	3.389***	3.026***	2.366***
	(21.838)	(10.581)	(13.496)
LaborC	-1.595***	-2.623***	-0.804*
	(-3.730)	(-4.326)	(-1.868)
CorpTaxR	-17.644***	-42.412**	-10.647
	(-3.163)	(-2.577)	(-1.348)
IndTaxR	-6.357**	-12.094**	4.025
	(-2.702)	(-2.179)	(1.116)
TaxToGDPR	3.264**	3.480	4.528**
	(2.324)	(1.293)	(2.517)
Constant	-39.648***	-32.800***	-33.405***
	(-22.740)	(-13.409)	(-15.356)
Observations	2,090	2,090	2,090
Adjusted R-squared	0.964	0.960	0.952
Control Innovation at t	YES	YES	YES
State FE	YES	YES	YES
Year FE	YES	YES	YES
SE Clustering	By year	By year	By year

Table 4. IDD and the Effectiveness of R&D Tax Credits

Note: Table 4 presents the regression results of the effect of the state-level IDD on the effectiveness of R&D tax credits. *L3Pat* is the total number of patents applied by all firms in a state in year t+3 after log transformation. *L3Cite* is the total number of citations received by all patents applied by all firms in a state in year t+3 after log transformation. *L3TopPat* is the log transformation of the total number of patents with citations that are higher than the 90th percentile of patents of the same technology class and application year. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit and 0 otherwise. *IDD* is set to one if a state has adopted the Inevitable Disclosure Doctrine.

	(1)	(2)	(3)
VARIABLES	L3Pat	L3Cite	L3TopPat
Credit	0.105***	0.089***	0.136***
	(3.977)	(2.818)	(4.551)
IDD×Credit	-0.201***	-0.133**	-0.245***
	(-4.229)	(-2.496)	(-5.084)
IDD	0.209***	0.125***	0.161***
	(6.586)	(3.168)	(4.510)
GSPGrowth	0.005	0.001	0.006
	(1.373)	(0.168)	(1.484)
GSP	-0.006	-0.066	0.153
	(-0.050)	(-0.266)	(1.351)
UnempGrowth	-3.019	-1.319	-0.878
	(-1.532)	(-0.578)	(-0.492)
StateEMP	3.377***	3.006***	2.262***
	(21.915)	(10.569)	(13.049)
LaborC	-1.774***	-2.744***	-1.043**
	(-4.158)	(-4.416)	(-2.405)
CorpTaxR	-19.748***	-43.773**	-13.015
	(-3.445)	(-2.634)	(-1.586)
IndTaxR	-8.542***	-13.372**	2.545
	(-3.603)	(-2.387)	(0.686)
TaxToGDPR	3.556**	3.632	4.587**
	(2.582)	(1.325)	(2.589)
Constant	-39.780***	-32.796***	-32.906***
	(-22.765)	(-13.271)	(-15.392)
Observations	2,090	2,090	2,090
Adj R-squared	0.964	0.960	0.953
State FE	YES	YES	YES
Year FE	YES	YES	YES
SE Clustering	By year	By year	By year

Table 5. Heterogeneous Effects of State IDD

Note: Table 5 presents the regression results of the effect of the state-level IDD on the effectiveness of R&D tax credits based on the innovation generated by public or private firms. *L3PatPub*, *L3CitePub*, and *L3TopPatPub* measure the total number of patents applied, the total number of citations received by all patents applied, and the top cited patents applied by all public firms in a state in year t+3 after log transformation, respectively. *L3PatPri*, *L3CitePri*, and *L3TopPatPri* measure the total number of patents applied, the total number of citations received by all patents applied, and the top cited patents applied by all private firms in a state in year t+3 after log transformation, respectively. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit and 0 otherwise. *IDD* is set to one if a state has adopted the Inevitable Disclosure Doctrine.

	# Patents		# Citations		# Top Cited Patents	
	By Public Firm	By Private Firm	By Public Firm	By Private Firm	By Public Firm	By Private Firm
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	L3PatPub	L3PatPri	L3CitePub	L3CitePri	L3TopPatPub	L3TopPatPri
Credit	0.082	0.031	-0.040	-0.013	0.161***	0.059**
	(1.347)	(1.598)	(-0.381)	(-0.474)	(3.215)	(2.194)
IDD×Credit	-0.737***	0.111***	-0.723***	0.142***	-0.682***	0.044
	(-3.668)	(2.853)	(-2.882)	(3.403)	(-3.479)	(1.079)
IDD	0.412***	0.059*	0.325***	-0.012	0.318***	0.063*
	(7.103)	(1.868)	(4.054)	(-0.320)	(4.902)	(1.823)
GSPGrowth	-0.008	0.004	-0.010	0.002	-0.004	0.006
	(-0.656)	(1.364)	(-0.571)	(0.490)	(-0.395)	(1.600)
GSP	-0.054	-0.037	-0.079	0.275	-0.061	0.709***
	(-0.136)	(-0.364)	(-0.133)	(1.325)	(-0.177)	(6.176)
UnempGrowth	5.616	-2.839	8.462	-2.208	6.960	-0.540
	(0.973)	(-1.652)	(1.145)	(-1.004)	(1.470)	(-0.268)
StateEMP	3.194***	2.524***	2.946***	2.102***	2.265***	1.356***
	(8.387)	(20.371)	(4.521)	(7.610)	(5.932)	(9.829)
LaborC	-0.471	-1.508***	-3.480**	-2.945***	1.220**	-1.230***
	(-0.674)	(-3.965)	(-2.569)	(-4.390)	(2.079)	(-3.240)
CorpTaxR	-55.048***	-10.608*	-80.079***	-41.894**	-29.116**	-9.216
	(-3.021)	(-1.905)	(-2.951)	(-2.295)	(-2.370)	(-1.052)
IndTaxR	-14.039	-5.035*	-22.548*	-4.939	-9.328	4.553
	(-1.392)	(-1.968)	(-1.806)	(-0.833)	(-1.193)	(1.081)
TaxToGDPR	18.098**	-0.891	29.694***	-0.987	10.252*	0.187
	(2.587)	(-0.677)	(3.158)	(-0.326)	(1.922)	(0.084)
Constant	-42.092***	-30.220***	-35.906***	-25.083***	-30.028***	-23.871***
	(-7.710)	(-20.270)	(-4.275)	(-10.052)	(-5.636)	(-15.037)
Observations	2,090	2,090	2,090	2,090	2,090	2,090
Adj R-squared	0.868	0.966	0.867	0.955	0.844	0.950
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SE Clustering	By year	By year	By year	By year	By year	By year

Table 6. State Information Transparency and the Effectiveness of R&D Tax Credits

Note: Table 6 presents the regression results of the effect of the state-level information transparency on the effectiveness of R&D tax credits. *L3Pat* is the total number of patents applied by all firms in a state in year t+3 after log transformation. *L3Cite* is the total number of citations received by all patents applied by all firms in a state in year t+3 after log transformation. *L3TopPat* is the log transformation of the total number of patents with citations that are higher than the 90th percentile of patents of the same technology class and application year. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit and 0 otherwise. The state-level information transparency (*StateInfo*) is measured by the weighted average of the aggregated industry-level information transparency in a state. The aggregated industry-level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3-digit NAICS industry. High *StateInfo* takes the value of 1 if a state's *StateInfo* is in the top tercile. Low *StateInfo* takes the value of 1 if a state's *StateInfo* is in the bottom tercile.

	StateInfo		StateInfo		StateInfo	
	(1)	(2)	(3)	(4)	(5)	(6)
	L	H	L	H	L	H
VARIABLES	L3Pat	L3Pat	L3Cite	L3Cite	L3TopPat	L3TopPat
Credit	0.073*	0.101***	0.055	0.238***	0.184**	0.161***
	(1.984)	(3.756)	(0.833)	(3.732)	(2.627)	(3.654)
GSPGrowth	-0.000	0.003	-0.000	-0.012	-0.005	-0.001
	(-0.062)	(0.595)	(-0.009)	(-1.503)	(-0.708)	(-0.215)
GSP	0.292	0.628***	0.582	0.050	0.928***	0.256
	(1.026)	(3.153)	(1.144)	(0.121)	(3.343)	(0.613)
UnempGrowth	-0.707	-2.040	1.638	-2.338	2.914	-1.865
	(-0.277)	(-1.643)	(0.590)	(-0.877)	(1.094)	(-0.918)
StateEMP	1.291***	0.897***	1.556**	1.931***	1.211***	1.633***
	(3.932)	(2.897)	(2.392)	(3.186)	(2.843)	(3.496)
LaborC	-1.583**	0.901*	-4.059***	0.186	-2.540***	0.856
	(-2.701)	(1.926)	(-3.380)	(0.152)	(-3.195)	(1.100)
CorpTaxR	-10.330	-32.419***	-41.958	-16.124	-5.375	-36.147***
	(-1.242)	(-3.628)	(-1.262)	(-0.922)	(-0.444)	(-3.039)
IndTaxR	7.655	-12.022***	11.210	-18.028**	25.288**	-19.631***
	(1.118)	(-4.616)	(0.746)	(-2.411)	(2.255)	(-4.810)
TaxToGDPR	-1.178	10.572***	1.537	9.299*	-0.084	12.966***
	(-0.438)	(3.553)	(0.355)	(1.893)	(-0.024)	(3.559)
Constant	-18.443***	-18.039***	-22.320***	-23.545***	-24.693***	-23.993***
	(-7.145)	(-5.143)	(-4.223)	(-3.549)	(-5.951)	(-5.699)
Observations	610	612	610	612	610	612
Adj R-squared	0.981	0.983	0.964	0.969	0.964	0.966
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SE Clustering	By year	By year	By year	By year	By year	By year
Coefficients Differences	0.028		0.183		-0.023	
Prob>chi2	0.5666		0.0372		0.7283	

Table 7. PatClass Information Transparency and the Effectiveness of R&D Tax Credits

Notes: Table 7 presents the regression results of the effect of the state-patent_class level information transparency on the effectiveness of R&D tax credits. *L3CpcTPat* is the total number of patents applied by all firms in a state and a CPC class in year t+3 after log transformation. *L3CpcTCite* is the total number of citations received by all patents applied by all firms in a state and a CPC class in year t+3 after log transformation. *L3CpcTop* is log transformed total number of patents in a state and a CPC class, which have citations that are higher than the 90th percentile of patents of the same technology class and application year. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. The CPC-level information transparency (*CPCInfo*) is measured by the weighted average of the aggregated industry-level information environment in a CPC patent class. The aggregated industry-level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3-digit NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tertile, and *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tertile.

	CPCInfo		CPCInfo		CPCInfo	
	(1)	(2)	(3)	(4)	(5)	(6)
	L	H	L	H	L	H
VARIABLES	L3CpcTPat	L3CpcTPat	L3CpcTCite	L3CpcTCite	L3CpcTop	L3CpcTop
Credit	0.026	0.058**	0.017	0.022	0.028	0.053**
	(1.082)	(2.098)	(0.268)	(0.340)	(1.362)	(2.247)
GSPGrowth	0.001	0.003	0.005	0.006	0.001	0.001
	(0.480)	(1.366)	(1.267)	(1.170)	(0.547)	(0.492)
GSP	0.372**	0.175	0.126	-0.235	0.350**	0.209
	(2.481)	(1.007)	(0.435)	(-0.573)	(2.295)	(1.214)
UnempGrowth	-0.508	-0.550	-0.493	0.360	-0.590	-0.001
	(-1.048)	(-0.773)	(-0.361)	(0.213)	(-1.137)	(-0.002)
StateEMP	0.393	0.954***	1.710***	2.561***	-0.089	0.515*
	(1.586)	(3.680)	(5.308)	(4.718)	(-0.404)	(2.017)
LaborC	-0.316	0.113	0.638	0.973	-0.420	-0.047
	(-0.621)	(0.271)	(0.676)	(1.038)	(-1.175)	(-0.132)
CorpTaxR	-8.243	-11.350	-7.951	-14.746	-7.856	-8.090
	(-1.045)	(-1.387)	(-0.670)	(-0.843)	(-0.883)	(-0.974)
IndTaxR	-4.012	-4.249	-17.743**	-12.599	-0.029	-3.079
	(-1.028)	(-0.993)	(-2.170)	(-0.898)	(-0.007)	(-0.934)
TaxToGDPR	-1.220	0.350	10.094***	14.589***	-2.045	-2.115
	(-1.073)	(0.213)	(3.311)	(2.760)	(-1.604)	(-1.481)
Constant	-8.954***	-14.674***	-24.849***	-32.679***	-2.183	-9.080***
	(-3.415)	(-5.942)	(-6.513)	(-5.594)	(-1.008)	(-3.871)
Observations	67,266	66,287	67,266	66,287	67,266	66,287
Adj R-squared	0.850	0.921	0.723	0.817	0.742	0.868
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass

Table 8. Heterogeneous Effects of PatClass Information Transparency

Notes: Table 8 presents the regression results of the effect of the state-patent_class level information transparency on the innovation generated by public firms (Panel A) and private firms (Panel B) following the introduction of an R&D tax credit. *L3CpcPubPat*, *L3CpcPubCite*, and *L3CpcPubTop* measure the total number of patents applied, the total number of citations received by all patents applied, and the top cited patents applied by all public firms in a state and a CPC class in year t+3 after log transformation, respectively. *L3CpcPriPat*, *L3CpcPriCite*, and *L3CpcPriTop* measure the total number of patents applied, the total number of citations received by all patents applied, and the top cited patents applied by all private firms in a state and a CPC class in year t+3 after log transformation, respectively. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. The CPC-level information transparency (*CPCInfo*) is measured by the weighted average of the aggregated industry level information environment in a CPC patent class. The aggregated industry level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3-digit NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tercile, and *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tercile.

Panel A. CPCInfo is Low

	CPCInfo = Low					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	L3CpcPubPat	L3CpcPriPat	L3CpcPubCite	L3CpcPriCite	L3CpcPubTop	L3CpcPriTop
Credit	0.011	0.032	0.022	0.040	0.015	0.024
	(0.312)	(1.091)	(0.251)	(0.784)	(0.805)	(0.934)
GSPGrowth	-0.001	-0.000	0.003	0.003	-0.001	0.001
	(-0.376)	(-0.097)	(0.641)	(0.827)	(-0.800)	(0.274)
GSP	0.121	0.336	-0.237	0.260	0.129*	0.280
	(0.722)	(1.668)	(-0.566)	(1.008)	(1.696)	(1.540)
UnempGrowth	0.967	-0.532	0.661	-0.132	0.592	-0.656
	(0.934)	(-0.964)	(0.385)	(-0.097)	(0.953)	(-1.067)
StateEMP	0.252	0.227	1.397***	1.246***	-0.028	-0.125
	(1.207)	(0.798)	(2.989)	(3.397)	(-0.275)	(-0.536)
LaborC	0.200	-0.426	1.939*	0.408	-0.131	-0.410
	(0.491)	(-0.822)	(1.892)	(0.484)	(-0.753)	(-1.070)
CorpTaxR	2.002	-8.875	9.603	-8.480	-0.743	-7.851
	(0.230)	(-0.807)	(0.467)	(-0.954)	(-0.238)	(-0.727)
IndTaxR	-15.311***	3.345	-28.883**	-8.100	-7.858***	5.014
	(-2.914)	(0.569)	(-2.503)	(-1.268)	(-3.031)	(0.973)
TaxToGDPR	1.783	-2.313	6.548	8.136***	0.379	-2.282
	(1.331)	(-1.406)	(1.686)	(3.507)	(0.678)	(-1.470)
Constant	-4.666**	-6.294**	-17.129***	-19.857***	-0.812	-1.003
	(-2.146)	(-2.285)	(-3.338)	(-5.031)	(-0.760)	(-0.447)
Observations	67,266	67,266	67,266	67,266	67,266	67,266
Adj R-squared	0.761	0.806	0.663	0.670	0.647	0.661
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass

Table 8. Continued

Panel B. CPCInfo is High

	CPCInfo = High					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	L3CpcPubPat	L3CpcPriPat	L3CpcPubCite	L3CpcPriCite	L3CpcPubTop	L3CpcPriTop
Credit	0.021	0.068**	0.033	0.046	0.028	0.048*
	(0.406)	(2.223)	(0.302)	(0.833)	(0.808)	(1.765)
GSPGrowth	-0.000	0.001	0.006	0.004	-0.001	-0.000
	(-0.100)	(0.278)	(0.827)	(0.836)	(-0.544)	(-0.035)
GSP	0.000	0.320	-0.485	0.112	-0.040	0.312
	(0.001)	(1.273)	(-0.781)	(0.280)	(-0.237)	(1.452)
UnempGrowth	1.955	-0.816	3.316	0.242	1.637	-0.177
	(1.175)	(-0.897)	(1.260)	(0.149)	(1.371)	(-0.246)
StateEMP	0.637**	0.526	2.127***	1.783***	0.421**	0.147
	(2.502)	(1.472)	(3.174)	(2.790)	(2.695)	(0.486)
LaborC	0.739	-0.312	2.870**	0.611	0.474	-0.431
	(1.405)	(-0.514)	(2.039)	(0.594)	(1.498)	(-0.941)
CorpTaxR	0.166	-14.125	5.658	-18.625	1.160	-10.700
	(0.012)	(-1.098)	(0.186)	(-1.584)	(0.153)	(-0.892)
IndTaxR	-15.823*	-0.773	-25.806	-11.358	-11.369**	1.662
	(-1.891)	(-0.142)	(-1.339)	(-1.244)	(-2.294)	(0.356)
TaxToGDPR	5.126*	-2.183	14.399**	11.896***	2.093	-3.523*
	(2.032)	(-1.128)	(2.297)	(2.804)	(1.585)	(-1.879)
Constant	-8.975***	-10.065***	-25.052***	-25.407***	-5.392***	-4.973*
	(-3.462)	(-3.110)	(-3.578)	(-3.892)	(-3.394)	(-1.811)
Observations	66,287	66,287	66,287	66,287	66,287	66,287
Adj R-squared	0.866	0.897	0.790	0.775	0.802	0.821
Control	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass	State Year TechClass

Table 9. PatClass Information Transparency and Cost of Capital

Notes: Table 9 presents the regression results of the effect of the state-patent_class level information transparency on the innovation generated by private firms (Panel A) and public firms (Panel B) following the introduction of an R&D tax credit and by the level of state bank competition and patent-class information. *L3CpcPriPat*, *L3CpcPriCite*, and *L3CpcPriTop* measure the total number of patents applied, the total number of citations received, and the top cited patents applied by all private firms in a state and a CPC class in year t+3 after log transformation, respectively. *L3CpcPubPat*, *L3CpcPubCite*, and *L3CpcPubTop* measure the total number of patents applied, the total number of citations received by all patents applied, and the top cited patents applied by all public firms in a state and a CPC class in year t+3 after log transformation, respectively. Credit is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. The CPC-level information transparency (*CPCInfo*) is measured by the weighted average of the aggregated industry level information environment in a CPC patent class. The aggregated industry level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3 digits NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tercile. *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tercile. I use the state interstate branching deregulation index developed by Rice and Strahan (2010) to proxy for the level of bank competition in a state and the accessibility to capital for firms in that state.

Panel A. The Innovation Produced by Private Firms

	Bank Competition = Low		Bank Competition = High	
	CPCInfo = Low	CPCInfo = High	CPCInfo = Low	CPCInfo = High
	(1)	(2)	(3)	(4)
VARIABLES	L3CpcPriPat	L3CpcPriPat	L3CpcPriPat	L3CpcPriPat
Credit	0.011	0.033**	-0.010	-0.019
	(0.698)	(2.045)	(-0.801)	(-1.003)
IDD×Credit	0.001	0.027	0.072***	0.2042***
	(0.061)	(1.104)	(3.419)	(6.806)
IDD	-0.009	0.006	0.068***	-0.2041***
	(-0.433)	(0.303)	(3.606)	(-7.584)
LCpcPriPat	0.633***	0.725***	0.730***	0.683***
	(90.230)	(114.208)	(130.479)	(124.766)
State Control	Yes	Yes	Yes	Yes
Constant	-2.153***	-0.692***	-2.001***	26.685***
	(-9.564)	(-3.061)	(-8.277)	(12.932)
Observations	14,275	14,016	19,793	19,460
Adj R-squared	0.750	0.866	0.788	0.889
FE	TechClass		TechClass	
FE	Year		Year	
SE Clustering	TechClass & Year & State		TechClass & Year & State	
Differences in Coefficients	0.026		0.1322	
Prob > Chi2	0.4549		0.0003	

Table 9. Continued

Panel B. The Innovation Produced by Public Firms

	Bank Competition = Low		Bank Competition = High	
	CPCInfo = Low	CPCInfo = High	CPCInfo = Low	CPCInfo = High
	(1)	(2)	(3)	(4)
VARIABLES	L3CpcPubPat	L3CpcPubPat	L3CpcPubPat	L3CpcPubPat
Credit	-0.019	0.009	0.094***	0.115***
	(-1.582)	(0.506)	(8.178)	(8.286)
IDD×Credit	-0.013	-0.054**	-0.231***	-0.285***
	(-0.703)	(-1.993)	(-11.797)	(-12.124)
IDD	0.010	0.032	0.187***	0.207***
	(0.668)	(1.466)	(10.735)	(9.879)
LCpcPubPat	0.586***	0.748***	0.700***	0.778***
	(97.629)	(148.008)	(153.411)	(173.997)
State Control	Yes	Yes	Yes	Yes
Constant	0.037	0.796***	0.178	0.003
	(0.215)	(3.267)	(0.810)	(0.012)
Observations	14,275	14,016	19,793	19,460
Adj R-squared	0.750	0.866	0.788	0.889
FE	TechClass		TechClass	
FE	Year		Year	
Year FE	TechClass & Year & State		TechClass & Year & State	
Differences in Coefficients	-0.041		-0.054	
Prob > Chi2	0.0003		0.4549	

Table 10. PatClass Information Transparency and Cost of Capital - Matched Sample

Notes: Using a matched sample, Table 10 presents the regression results of the effect of the state-patent_class level information transparency on the innovation generated by private firms (Panel A) and public firms (Panel B) following the introduction of an R&D tax credit and by the level of state bank competition and level of patent-class information. The matched sample is matched on the CPC class and the level of innovation at time t. *L3CpcPriPat*, *L3CpcPriCite*, and *L3CpcPriTop* measure the total number of patents applied, the total number of citations received, and the top cited patents applied by all private firms in a state and a CPC class in year t+3 after log transformation, respectively. *L3CpcPubPat*, *L3CpcPubCite*, and *L3CpcPubTop* measure the total number of patents applied, the total number of citations received by all patents applied, and the top cited patents applied by all public firms in a state and a CPC class in year t+3 after log transformation, respectively. Credit is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. The CPC-level information transparency (*CPCInfo*) is measured by the weighted average of the aggregated industry level information environment in a CPC patent class. The aggregated industry level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3 digits NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tercile. *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tercile. I use the state interstate branching deregulation index developed by Rice and Strahan (2010) to proxy for the level of bank competition in a state and the accessibility to capital for firms in that state.

Panel A. Innovation Produced by Private Firms

	Bank Competition = Low		Bank Competition = High	
	CPCInfo = Low	CPCInfo = High	CPCInfo = Low	CPCInfo = High
	(1)	(2)	(3)	(4)
VARIABLES	L3CpcPriPat	L3CpcPriPat	L3CpcPriPat	L3CpcPriPat
Credit	-0.035*	0.024	-0.019	-0.003
	(-1.770)	(1.249)	(-1.209)	(-0.155)
IDD×Credit	0.025	0.016	0.088***	0.217***
	(0.788)	(0.505)	(3.175)	(6.144)
IDD	-0.050*	0.004	0.035	-0.192***
	(-1.746)	(0.162)	(1.329)	(-5.741)
LCpcPriPat	0.633***	0.724***	0.731***	0.683***
	(82.560)	(103.076)	(117.599)	(110.689)
State Control	Yes	Yes	Yes	Yes
Constant	-3.137***	-1.216***	-2.226***	31.265***
	(-11.231)	(-4.359)	(-8.821)	(14.206)
Observations	11,699	11,451	16,201	15,791
Adj R-squared	0.771	0.874	0.796	0.895
FE	TechClass		TechClass	
FE	Year		Year	
SE Clustering	TechClass & Year & State		TechClass & Year & State	
Differences in Coefficients	-0.009		0.129	
Prob > Chi2	0.8265		0.0036	

Table 10. Continued

Panel B. Innovation Produced by Public Firms

	Bank Competition = Low		Bank Competition = High	
	CPCInfo = Low	CPCInfo = High	CPCInfo = Low	CPCInfo = High
	(1)	(2)	(3)	(4)
VARIABLES	L3CpcPubPat	L3CpcPubPat	L3CpcPubPat	L3CpcPubPat
Credit	0.042***	0.118***	0.130***	0.133***
	(2.582)	(5.296)	(8.800)	(7.767)
IDD×Credit	-0.024	-0.066*	-0.326***	-0.377***
	(-0.900)	(-1.860)	(-12.309)	(-12.583)
IDD	0.031	0.056*	0.303***	0.316***
	(1.290)	(1.808)	(12.139)	(11.275)
LCpcPubPat	0.588***	0.751***	0.699***	0.766***
	(87.791)	(134.837)	(139.055)	(152.346)
State Control	Yes	Yes	Yes	Yes
Constant	-0.271	0.432	0.591**	0.810***
	(-1.209)	(1.377)	(2.520)	(2.878)
Observations	14,275	14,016	19,793	19,460
Adj R-squared	0.750	0.866	0.788	0.889
FE	TechClass		TechClass	
FE	Year		Year	
Year FE	TechClass & Year & State		TechClass & Year & State	
Differences in Coefficients	-0.042		-0.051	
Prob > Chi2	0.3228		0.224	

Table 11. Industry Information Environment and Innovation Efficiency

Notes: Using firm-level observations, Table 11 presents the regression results of the effect of R&D tax credits on the innovation outcomes generated by an additional dollar of R&D under different levels of information environment. The sample is a matched sample, matching on the level of R&D, the innovation measures in year t, and size. *TPat* measures the aggregated number of patents applied and granted in t+3 after log transformation. *TRvalue* measures the aggregated relative value of patents applied and granted in t+3 after log transformation. *TNvalue* measures the aggregated nominal value of patents applied and granted in t+3 after log transformation. The relative value and the nominal value of each patent are from Kogan et al. (2017). Following Shroff, Verdi, and Yost (2017) and Badertscher, Shroff, and White (2013), I measure the industry information environment (*IndustryInfo*) as the ratio of the number of public firms to the total number of firms in a 3-digit NAICS industry. High industry information environment is equal to one when the *IndustryInfo* of a firm is in the top tercile, and *Low IndustryInfo* takes the value of one when the *IndustryInfo* of a firm is in the bottom tercile.

	IndustryInfo		IndustryInfo		IndustryInfo	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	TPat	TPat	TRvalue	TRvalue	TNvalue	TNvalue
R&D×Credit	-0.007	0.254***	-0.023	0.252***	-0.019	0.291***
	(-0.172)	(3.695)	(-0.335)	(3.012)	(-0.249)	(3.276)
R&D Missing	-0.177**	-0.099	-0.182	-0.223	-0.210*	-0.207
	(-2.198)	(-0.606)	(-1.680)	(-0.973)	(-1.715)	(-0.804)
ROA	-0.159**	-0.086	-0.125	0.123	-0.148	0.115
	(-2.405)	(-1.098)	(-1.312)	(1.222)	(-1.399)	(1.032)
Size	0.282***	0.275***	0.207***	0.089	0.239***	0.128
	(7.155)	(4.689)	(3.926)	(1.140)	(4.184)	(1.469)
TobinQ	0.034***	0.058***	0.056***	0.086***	0.061***	0.093***
	(3.914)	(5.921)	(4.442)	(5.457)	(4.531)	(5.522)
Age	0.076	-0.049	0.225	-0.045	0.149	-0.130
	(0.877)	(-0.487)	(1.661)	(-0.315)	(1.044)	(-0.871)
Leverage	-0.305***	-0.427***	-0.467***	-0.356**	-0.489***	-0.379**
	(-3.716)	(-3.451)	(-3.665)	(-2.283)	(-3.536)	(-2.281)
Tangibility	0.016	-0.020	0.181	0.178	0.158	0.153
	(0.165)	(-0.122)	(1.161)	(0.744)	(0.943)	(0.602)
Sale	0.018	0.051	0.084	0.119	0.092	0.131
	(0.546)	(0.915)	(1.475)	(1.583)	(1.462)	(1.614)
SaleGrowth	0.018	0.047**	0.027	0.063**	0.033	0.074**
	(1.305)	(2.284)	(1.329)	(2.213)	(1.469)	(2.413)
Capex	0.365	0.371	0.538	0.916*	0.565	0.812
	(1.573)	(1.072)	(1.521)	(1.983)	(1.465)	(1.634)
CorpTaxRatio	-26.384	48.560	-0.076	85.032*	-3.637	87.608
	(-1.431)	(1.416)	(-0.003)	(1.726)	(-0.116)	(1.691)
IndTaxRatio	-17.069**	2.205	-22.854**	-7.968	-24.569**	-6.127
	(-2.589)	(0.236)	(-2.303)	(-0.641)	(-2.326)	(-0.458)
GSP	-0.114	-0.434	-0.030	-0.997	-0.025	-0.763
	(-0.205)	(-0.522)	(-0.033)	(-0.859)	(-0.026)	(-0.626)
GSPGrowth	-0.001	0.000	-0.000	-0.006	0.001	-0.004
	(-0.227)	(0.061)	(-0.002)	(-0.625)	(0.075)	(-0.349)
StateEMP	1.675**	0.935	1.443	0.583	1.525	0.576
	(2.227)	(0.895)	(1.353)	(0.406)	(1.302)	(0.378)

UnemployR	5.231***	4.482*	6.046**	5.083	6.601**	6.417*
	(2.938)	(2.029)	(2.557)	(1.690)	(2.534)	(1.968)
PopuGrowth	-0.005	0.002	-0.007*	-0.000	-0.008*	-0.000
	(-1.506)	(1.197)	(-1.718)	(-0.038)	(-2.027)	(-0.107)
LaborC	-1.581	-2.589	-0.132	-4.257**	-0.157	-4.615**
	(-1.575)	(-1.674)	(-0.092)	(-2.374)	(-0.101)	(-2.293)
Constant	-24.221***	-8.636	-21.949**	5.474	-22.897**	2.810
	(-3.224)	(-0.862)	(-2.325)	(0.385)	(-2.231)	(0.187)
Observations	16,646	11,196	16,646	11,196	16,646	11,196
Adj R-squared	0.847	0.845	0.859	0.871	0.851	0.867
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
SE Clustering	By Firm & Year	By Firm & Year	By Firm & Year	By Firm & Year	By Firm & Year	By Firm & Year

Table 12. Effect of IDD and R&D Tax Credits on Number of M&A Deals

Notes: Table 12 presents the regression results of the effect of the state level IDD and R&D tax credits on the number of M&A deals in a state. The number of deals is measured by the total number of public firms, public firms with patents, public firms without patents, total private firms, private firms with patents, and private firms without patents acquired in a state during a year, respectively. *LTPubM&A*, *LTPubTechM&A*, and *LTPubOperM&A* measure the number of deals with public firms, public firms that have at least one patent, and public firms that have no patents being acquired after log transformation, respectively. *LTPriM&A*, *LTPriTechM&A,* and *LTPriOperM&A* measure the number of deals with private firms, private firms that have at least one patent, and private firms that have no patents being acquired after log transformation, respectively. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. *IDD* is set to one if a state has adopted the Inevitable Disclosure Doctrine.

Panel A. The Number of Deals with Firm from a State being Acquired

	Public	Public & Inventor	Public & Non-Inventor	Private	Private & Inventor	Private & Non-Inventor
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LTPubM&A	LTPubTechM&A	LTPubOperM&A	LTPriM&A	LTPriTechM&A	LTPriOperM&A
Credit	0.010	0.008	0.027	-0.018	0.011	-0.010
	(0.251)	(0.290)	(0.712)	(-0.586)	(0.310)	(-0.329)
IDD×Credit	0.180***	0.053	0.163**	0.122***	0.191***	0.107***
	(2.866)	(0.931)	(2.533)	(3.599)	(3.503)	(3.208)
IDD	-0.043	0.038	-0.038	-0.053*	-0.055	-0.051*
	(-0.798)	(0.848)	(-0.680)	(-1.775)	(-1.151)	(-1.700)
GSPGrowth	0.002	0.001	0.003	0.017***	0.004*	0.017***
	(0.603)	(0.601)	(0.805)	(3.584)	(1.711)	(3.672)
GSP	1.088***	0.623***	1.100***	0.563***	0.715***	0.571***
	(6.116)	(5.469)	(5.989)	(3.141)	(5.721)	(3.195)
UnempGrowth	-1.647	-1.749	-1.154	-0.529	-2.460*	-0.222
	(-0.877)	(-1.356)	(-0.641)	(-0.333)	(-1.800)	(-0.140)
StateEMP	-0.554***	-0.494***	-0.627***	0.246	-0.157	0.217
	(-3.265)	(-4.189)	(-3.695)	(0.902)	(-0.916)	(0.775)
LaborC	-1.400**	-1.154***	-1.388**	-0.749	-0.490	-0.787
	(-2.659)	(-3.895)	(-2.599)	(-1.568)	(-1.304)	(-1.668)
CorpTaxR	-12.819**	-8.707**	-14.752**	-3.818	-9.758*	-4.156
	(-2.216)	(-2.691)	(-2.492)	(-0.343)	(-1.760)	(-0.374)
IndTaxR	1.346	0.220	-0.393	-5.201	2.563	-6.154
	(0.406)	(0.075)	(-0.110)	(-1.044)	(0.740)	(-1.214)
TaxToGDPR	0.011	-0.681	0.148	0.299	-3.264***	0.595
	(0.007)	(-0.822)	(0.097)	(0.158)	(-2.720)	(0.310)
Constant	-3.345**	0.448	-2.447	-8.387***	-5.191***	-8.076***
	(-2.039)	(0.428)	(-1.468)	(-3.014)	(-3.036)	(-2.820)
Observations	2,192	2,192	2,192	2,192	2,192	2,192
Adj R-squared	0.851	0.544	0.843	0.913	0.700	0.909
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SE Clustering	By year	By year	By year	By year	By year	By year

Table 12. Continued

Panel B. StateInfo = Low

	Public	Public & Inventor	Public & Non-Inventor	Private	Private & Inventor	Private & Non-Inventor
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LTPubM&A	LTPubTechM&A	LTPubOperM&A	LTPriM&A	LTPriTechM&A	LTPriOperM&A
Credit	-0.045	-0.043	-0.036	-0.082	0.033	-0.084
	(-0.642)	(-0.936)	(-0.534)	(-1.420)	(0.669)	(-1.499)
IDD×Credit	0.067	-0.061	0.124	0.204*	0.021	0.216*
	(0.488)	(-0.402)	(0.829)	(1.913)	(0.109)	(1.961)
IDD	0.069	0.149	0.064	-0.005	0.036	-0.021
	(0.809)	(1.472)	(0.745)	(-0.084)	(0.398)	(-0.350)
GSPGrowth	0.002	-0.000	0.004	0.022***	-0.001	0.023***
	(0.270)	(-0.114)	(0.548)	(3.465)	(-0.280)	(3.582)
GSP	1.308***	0.577***	1.242***	0.742**	0.647***	0.761**
	(4.799)	(2.956)	(4.510)	(2.590)	(3.558)	(2.655)
UnempGrowth	-3.318	1.472	-2.974	-4.349*	-0.361	-4.311*
	(-1.291)	(0.671)	(-1.158)	(-1.842)	(-0.183)	(-1.760)
StateEMP	-0.298	-0.382*	-0.314	0.090	0.250	0.012
	(-0.871)	(-1.854)	(-0.915)	(0.239)	(1.044)	(0.034)
LaborC	-1.968**	-0.922*	-1.744**	-0.422	-0.789*	-0.403
	(-2.541)	(-2.007)	(-2.284)	(-0.790)	(-1.880)	(-0.744)
CorpTaxR	-14.477	-3.707	-15.962*	1.383	15.637**	0.087
	(-1.568)	(-0.672)	(-1.768)	(0.125)	(2.494)	(0.008)
IndTaxR	-6.053	-2.133	-9.045	-17.910**	0.720	-21.390**
	(-0.517)	(-0.325)	(-0.751)	(-2.048)	(0.098)	(-2.350)
TaxToGDPR	1.515	-1.892*	1.983	3.579	-5.107***	4.234
	(0.799)	(-1.717)	(1.019)	(1.304)	(-3.219)	(1.555)
Constant	-9.152**	-0.610	-8.289**	-7.521**	-9.988***	-6.682*
	(-2.468)	(-0.351)	(-2.253)	(-2.044)	(-5.040)	(-1.877)
Observations	644	644	644	644	644	644
Adj R-squared	0.868	0.561	0.862	0.921	0.786	0.918
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SE Clustering	By year	By year	By year	By year	By year	By year

Table 12. Continued

Panel C. StateInfo = High

	Public	Public & Inventor	Public & Non-Inventor	Private	Private & Inventor	Private & Non-Inventor
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LTPubM&A	LTPubTechM&A	LTPubOperM&A	LTPriM&A	LTPriTechM&A	LTPriOperM&A
Credit	0.002	-0.001	0.003	-0.061	-0.092	-0.043
	(0.027)	(-0.027)	(0.035)	(-1.155)	(-1.214)	(-0.845)
IDD×Credit	0.242**	0.122	0.236*	0.173**	0.302***	0.159**
	(2.126)	(1.353)	(1.980)	(2.408)	(2.812)	(2.291)
IDD	-0.090	-0.046	-0.079	-0.169**	-0.310***	-0.142**
	(-0.864)	(-0.619)	(-0.753)	(-2.600)	(-3.514)	(-2.258)
GSPGrowth	0.001	0.007	-0.003	0.022**	0.008	0.022**
	(0.087)	(0.864)	(-0.229)	(2.483)	(0.704)	(2.346)
GSP	0.629	0.243	0.570	1.104**	0.652	0.993*
	(1.099)	(0.494)	(0.958)	(2.196)	(1.239)	(1.965)
UnempGrowth	0.544	-2.508	1.410	0.976	-6.243*	1.864
	(0.128)	(-1.129)	(0.363)	(0.474)	(-2.017)	(0.943)
StateEMP	1.335	0.630	1.209	0.413	-0.519	0.713
	(1.276)	(0.976)	(1.077)	(0.501)	(-0.628)	(0.865)
LaborC	0.272	0.454	0.260	1.116	2.683**	0.980
	(0.138)	(0.323)	(0.133)	(0.729)	(2.039)	(0.677)
CorpTaxR	-13.897	-10.963	-15.313	-2.736	-8.723	-4.446
	(-0.570)	(-0.766)	(-0.581)	(-0.160)	(-0.487)	(-0.261)
IndTaxR	14.073	2.536	14.812	-7.428	-4.579	-6.367
	(1.414)	(0.365)	(1.507)	(-1.132)	(-0.519)	(-0.977)
TaxToGDPR	-10.147*	-4.893	-9.977*	1.440	-1.418	1.109
	(-1.734)	(-1.496)	(-1.698)	(0.313)	(-0.350)	(0.245)
Constant	-25.292**	-11.648*	-22.799*	-16.531*	0.346	-19.687**
	(-2.428)	(-1.881)	(-1.968)	(-2.013)	(0.039)	(-2.401)
Observations	646	646	646	646	646	646
Adj R-squared	0.789	0.254	0.776	0.858	0.448	0.855
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SE Clustering	By year	By year	By year	By year	By year	By year

Table 13. State Information Transparency and Number of Patent Sales

Notes: Table 13 presents the regression results on how state R&D tax credits affect patent sales and whether information transparency matters for that effect. *LPatSale* measures the total number of patents generated in a state and year that have been sold at least once. *LPriPubPsale* measures the number of patents generated in a state and year by private firms that have been sold to public firms. Both measures are log-transformed. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit and 0 otherwise. *StateInfo* is measured by a weighted average of the percentage of public firms at the sector level in a state. *High StateInfo* takes the value of 1 if a state's *StateInfo* is in the top tercile, while *Low StateInfo* takes the value of 1 if a state's *StateInfo* is in the bottom tercile.

	Full Sample		StateInfo = Low		StateInfo = High	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LPatSale	LPriPubPsale	LPatSale	LPriPubPsale	LPatSale	LPriPubPsale
Credit	0.060	0.119***	0.093	0.129*	0.264***	0.282***
	(1.617)	(2.700)	(1.560)	(1.940)	(5.780)	(4.589)
GSPGrowth	0.008	0.007	0.006	0.006	0.011	0.005
	(1.435)	(1.057)	(0.789)	(0.767)	(1.349)	(0.499)
GSP	0.167	0.628*	-0.090	-0.157	1.648**	1.590**
	(0.571)	(1.867)	(-0.237)	(-0.358)	(2.625)	(2.546)
UnempGrowth	-4.902*	-5.321*	-5.483	-5.906	-1.810	-0.945
	(-1.890)	(-1.715)	(-1.273)	(-1.241)	(-0.874)	(-0.386)
StateEMP	3.550***	2.573***	5.295***	5.305***	3.039***	1.245
	(15.495)	(9.758)	(12.945)	(11.882)	(3.853)	(1.652)
LaborC	-2.078***	-3.322***	-2.930***	-3.272***	1.248	-5.076***
	(-4.334)	(-6.389)	(-3.126)	(-3.367)	(1.238)	(-3.892)
CorpTaxR	-22.884**	-16.309	28.248***	44.722***	-112.401***	-133.691***
	(-2.413)	(-1.542)	(2.788)	(3.392)	(-4.460)	(-4.193)
IndTaxR	6.028	9.479*	28.078*	33.694**	-37.098***	-45.434***
	(1.579)	(1.972)	(1.897)	(2.165)	(-6.682)	(-6.442)
TaxToGDPR	1.773	-2.521	-12.523***	-14.504***	36.133***	40.958***
	(0.811)	(-1.017)	(-3.956)	(-4.301)	(6.085)	(6.770)
Constant	-47.738***	-38.935***	-68.976***	-68.576***	-59.303***	-31.803***
	(-36.292)	(-26.260)	(-19.778)	(-16.202)	(-8.235)	(-4.278)
Observations	2,193	2,193	645	645	646	646
Adj R-squared	0.926	0.904	0.943	0.919	0.940	0.917
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SE Clustering	By year	By year	By year	By year	By year	By year

Table 14. PatClass Information Transparency and Number of Patent Sales

Notes: Table 14 presents the regression results of how state R&D tax credits affect patent sales in a CPC technology class and whether information transparency in that class matters for the effect. *LCpcPatSale* measures the total number of patents generated in a state, a CPC class, and a year that are sold at least once. *LCpcPriPSale* measures the number of patents generated in a state, a CPC class, and a year by private firms that are sold to public firms. Both measures are log transformed. Credit is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. *CPCInfo* is measured by the weighted average of the aggregated industry-level information environment in a CPC patent class. The aggregated industry-level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3-digit NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tercile. *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tercile.

	Full Sample		CPCInfo = Low		CPCInfo = High	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LCpcPatSale	LCpcPriPSale	LCpcPatSale	LCpcPriPSale	LCpcPatSale	LCpcPriPSale
Credit	0.035	0.035	0.038	0.101*	0.056*	0.106**
	(0.866)	(0.866)	(0.932)	(1.953)	(1.715)	(2.338)
GSPGrowth	0.008***	0.008***	0.007**	0.010**	0.007**	0.007
	(2.953)	(2.953)	(2.189)	(2.125)	(2.243)	(1.603)
GSP	0.012	0.012	0.038	0.116	0.154	0.437
	(0.043)	(0.043)	(0.146)	(0.320)	(0.661)	(1.196)
UnempGrowth	-1.525*	-1.525*	-0.584	-0.572	-0.458	-0.141
	(-1.702)	(-1.702)	(-0.733)	(-0.571)	(-0.530)	(-0.125)
StateEMP	1.415***	1.415***	1.219***	1.862***	0.717*	0.828
	(3.336)	(3.336)	(3.287)	(3.342)	(2.021)	(1.367)
LaborC	-0.041	-0.041	0.203	0.247	-0.206	-0.961
	(-0.038)	(-0.038)	(0.281)	(0.205)	(-0.260)	(-0.760)
CorpTaxR	-13.481	-13.481	-2.465	-12.299	-5.334	-17.128
	(-1.460)	(-1.460)	(-0.375)	(-1.222)	(-0.781)	(-1.203)
IndTaxR	-4.253	-4.253	-5.751	-7.090	3.190	-0.703
	(-0.710)	(-0.710)	(-1.124)	(-0.696)	(0.604)	(-0.090)
TaxToGDPR	5.252**	5.252**	4.923***	7.077**	3.436**	3.706
	(2.691)	(2.691)	(2.871)	(2.404)	(2.667)	(1.514)
Constant	-19.877***	-19.877***	-17.588***	-27.434***	-11.777***	-16.082***
	(-5.049)	(-5.049)	(-5.043)	(-5.477)	(-3.772)	(-2.996)
Observations	247,953	247,953	67,802	66,804	67,802	66,804
Adj R-squared	0.825	0.825	0.777	0.872	0.722	0.839
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass

Table 15. Treated PatClass and Neighboring State Control Across State Borders

Notes: Table 15 presents the regression results of the effects of R&D tax credits on innovation using a matched sample by matching the innovation within a CPC class in a state with the innovations generated in the same CPC class and from neighboring states. Neighboring states are states that share a border with a focal state. *L3CpcTPat* is the total number of patents applied by all firms in a state and a CPC class in year t+3 after log transformation. L3CpcTCite is the total number of citations received by all patents applied by all firms in a state and a CPC class in year t+3 after log transformation. *L3CpcTop* is log transformed the total number of patents in a state and a CPC class, which have citations that are higher than the 90 percentiles of patents of the same technology class and application year. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. The CPC-level information transparency (*CPCInfo*) is measured by the weighted average of the aggregated industry level information environment in a CPC patent class. The aggregated industry level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3 digits NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tercile. *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tercile.

	CPCInfo = Low			CPCInfo = High		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	L3CpcTPat	L3CpcTCite	L3CpcTop	L3CpcTPat	L3CpcTCite	L3CpcTop
Credit	0.028	-0.008	0.031	0.050*	-0.021	0.051**
	(1.193)	(-0.128)	(1.567)	(1.966)	(-0.314)	(2.262)
GSPGrowth	0.001	0.006	0.001	0.003	0.005	0.001
	(0.690)	(1.551)	(0.875)	(1.397)	(0.920)	(0.281)
GSP	0.226*	0.123	0.249*	0.107	-0.055	0.131
	(1.706)	(0.452)	(1.893)	(0.743)	(-0.136)	(0.954)
UnempGrowth	-0.352	-0.265	-0.514	-0.072	0.721	0.220
	(-0.820)	(-0.202)	(-1.073)	(-0.099)	(0.393)	(0.359)
StateEMP	0.450*	1.618***	-0.037	0.797***	2.228***	0.491**
	(1.985)	(5.013)	(-0.184)	(3.552)	(4.281)	(2.291)
LaborC	-0.178	0.408	-0.315	0.128	0.591	-0.006
	(-0.404)	(0.449)	(-1.011)	(0.351)	(0.645)	(-0.018)
CorpTaxR	-7.669	-6.590	-8.304	-8.014	-11.426	-6.267
	(-0.935)	(-0.522)	(-0.884)	(-0.998)	(-0.669)	(-0.828)
IndTaxR	-4.330	-16.328*	-0.638	-2.871	-8.185	-2.429
	(-1.240)	(-1.996)	(-0.171)	(-0.734)	(-0.621)	(-0.770)
TaxToGDPR	-0.803	9.206***	-1.306	0.187	12.786***	-1.185
	(-0.795)	(3.782)	(-1.412)	(0.141)	(3.099)	(-1.230)
Constant	-8.162***	-23.393***	-1.843	-11.728***	-29.851***	-7.924***
	(-3.424)	(-6.293)	(-0.912)	(-5.326)	(-5.606)	(-3.999)
Observations	88,633	88,633	88,633	87,806	87,806	87,806
Adj R-squared	0.848	0.723	0.740	0.917	0.814	0.860
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass

Table 16. R&D Tax Credits and State-level Innovation Dynamics

Notes: Table 16 presents the regression results of the dynamic effect of state R&D tax credits on state-level innovation. *LPat* is the natural logarithm of the total number of patents applied by all firms in a state in year t. *LPatPub* is the natural logarithm of the total number of patents applied by all public firms in a state in year t. *LPatPri* is the natural logarithm of the total number of patents applied by all private firms in a state in year t. *LCite* is the natural logarithm of the total number of citations received by all patents applied by all firms in a state in year t. *LCitePub* is the natural logarithm of the total number of citations received by all patents applied by all public firms in a state in year t. LCitePri is the natural logarithm of the total number of citations received by all patents applied by all private firms in a state in year t. LTopPatPub is the natural logarithm of the total number of top cited patents applied by all public firms in a state in year t. *LTopPatPri* is the natural logarithm of the total number of top cited patents applied by all private firms in a state in year t. *Credit* is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. t-2 (t-1) denotes an indicator variable equal to 1 in the t-2 (t-1) year of the introduction of R&D tax credit, and 0 otherwise. Similarly, t (t+1, t+2, t+3) represents an indicator variable equal to 1 in the t (t+1, t+2, t+3) year of the introduction of R&D tax credit, and 0 otherwise. After 3 years represents an indicator variable equal to 1 in t+4 of the introduction of R&D tax credit and all subsequent years, and 0 otherwise.

Panel A. The Innovation Dynamics Relative to the Introduction of State R&D Tax Credits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	LPat	LPatPub	LPatPri	LCite	LCitePub	LCitePri	LTopPatPub	LTopPatPri
t-2	0.015	-0.138	0.040	-0.049	-0.261	-0.054	-0.182	0.052
	(0.245)	(-0.872)	(0.759)	(-0.621)	(-1.168)	(-0.709)	(-1.352)	(0.822)
t-1	0.011	-0.083	0.027	0.007	-0.117	0.026	-0.159	0.045
	(0.179)	(-0.526)	(0.507)	(0.087)	(-0.523)	(0.345)	(-1.178)	(0.700)
t	-0.021	-0.200	0.006	0.011	-0.240	0.025	-0.067	0.036
	(-0.352)	(-1.264)	(0.120)	(0.135)	(-1.070)	(0.328)	(-0.498)	(0.569)
t+1	0.027	-0.194	0.064	0.089	-0.202	0.099	-0.172	0.116*
	(0.450)	(-1.219)	(1.207)	(1.114)	(-0.899)	(1.300)	(-1.272)	(1.804)
t+2	0.037	-0.226	0.052	0.073	-0.344	0.092	-0.184	0.062
	(0.615)	(-1.419)	(0.983)	(0.906)	(-1.525)	(1.201)	(-1.355)	(0.957)
t+3	0.012	-0.261	0.018	0.011	-0.422*	0.031	-0.164	0.060
	(0.205)	(-1.640)	(0.331)	(0.132)	(-1.871)	(0.404)	(-1.205)	(0.933)
After 3 years	0.047	-0.090	0.054**	0.060	-0.205*	0.018	-0.019	0.079**
	(1.605)	(-1.156)	(2.103)	(1.534)	(-1.859)	(0.481)	(-0.287)	(2.512)
Control	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,193	2,193	2,193	2,193	2,193	2,193	2,193	2,193
Adj R-squared	0.964	0.874	0.965	0.956	0.865	0.950	0.854	0.951
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
SE Clustering	By year	By year	By year	By year	By year	By year	By year	By year

Table 16. Continued

Notes: *LPatSale* measures the total number of patents generated in a state and a year that are sold at least once, and *LPriPubPsale* measures the number of patents generated in a state and a year by private firms that are sold to public firms. Both measures are log transformed. In Table 12, *TPubTechM&A* and *TPubOperM&A* measure the number of deals with public firms that have at least one patent and public firms that have no patents being acquired after log transformation, respectively. *TPriTechM&A* and *TPriOperM&A* measure the number of deals with private firms that have at least one patent and private firms that have no patents being acquired after log transformation, respectively.

Panel B. Patent Sales or Technology Acquisitions Relative to the Introduction of State R&D Tax Credits

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LPatSale	LPriPubPsale	TPubTechM&A	TPubOperM&A	TPriTechM&A	TPriOperM&A
t-2	0.049	0.066	-0.095	-0.018	-0.023	-0.048
	(0.533)	(0.672)	(-1.577)	(-0.192)	(-0.379)	(-0.857)
t-1	0.025	0.030	-0.010	0.023	-0.030	0.020
	(0.277)	(0.303)	(-0.192)	(0.251)	(-0.378)	(0.355)
t	-0.013	0.017	-0.000	0.069	-0.090	0.008
	(-0.144)	(0.178)	(-0.003)	(0.972)	(-1.217)	(0.126)
t+1	-0.002	0.020	-0.064	0.165**	-0.008	0.022
	(-0.026)	(0.207)	(-1.303)	(2.090)	(-0.119)	(0.328)
t+2	0.027	0.069	-0.083	0.035	0.129*	0.037
	(0.288)	(0.705)	(-1.210)	(0.470)	(1.970)	(0.544)
t+3	-0.034	0.032	-0.044	-0.005	0.126*	0.019
	(-0.366)	(0.329)	(-0.777)	(-0.056)	(1.729)	(0.297)
After 3 years	0.103**	0.179***	0.059*	0.090	0.084**	0.015
	(2.294)	(3.716)	(1.694)	(1.539)	(2.192)	(0.397)
Control	YES	YES	YES	YES	YES	YES
Observations	2,193	2,193	2,192	2,192	2,192	2,192
Adj R-squared	0.926	0.904	0.552	0.845	0.701	0.909
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
SE Clustering	By year	By year	By year	By year	By year	By year

Table 17. R&D Tax Credits with Maximum Restrictions

Notes: Table 17 presents the regression results of the effects of R&D tax credits on innovation using a sample that only includes observations from states with the least generous R&D tax credits and observations from states without R&D tax credits. *L3CpcTPat* is the total number of patents applied by all firms in a state and a CPC class in year t+3 after log transformation. *L3CpcTCite* is the total number of citations received by all patents applied by all firms in a state and a CPC class in year t+3 after log transformation. L3CpcTop is log transformed the total number of patents in a state and a CPC class, which have citations that are higher than the 90th percentile of patents of the same technology class and application year. Credit is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. The CPC-level information transparency (*CPCInfo*) is measured by the weighted average of the aggregated industry-level information environment in a CPC patent class. The aggregated industry-level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3-digit NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tercile. *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tercile.

	CPCInfo = L			CPCInfo = H		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	L3CpcTPat	L3CpcTCite	L3CpcTop	L3CpcTPat	L3CpcTCite	L3CpcTop
Credit	0.068	-0.074	0.077	0.114*	-0.006	0.088*
	-1.044	(-0.450)	-1.663	-1.985	(-0.034)	-1.918
GSPGrowth	0.002	0.011*	0.002	0.004	0.013	0.002
	-0.753	-2.117	-1.133	-1.382	-1.721	-0.73
GSP	0.123	0.622	0.039	0.307	1.184*	0.158
	-0.753	-1.322	-0.429	-1.521	-1.953	-1.024
UnempGrowth	0.591	-0.062	0.124	0.443	2.828*	0.941
	-0.611	(-0.023)	-0.173	-0.527	-1.858	-1.065
StateEMP	0.065	-0.023	0.068	-0.072	-0.482	0.012
	-0.413	(-0.050)	-0.775	(-0.374)	(-0.832)	-0.08
LaborC	-0.033	-0.647	0.248	-0.202	-1.115	0.154
	(-0.050)	(-0.399)	-0.571	(-0.280)	(-0.553)	-0.26
CorpTaxR	4.47	14.659	3.807	-0.451	3.991	1.796
	-0.891	-0.715	-1.204	(-0.070)	-0.161	-0.379
IndTaxR	-0.357	1.808	-0.183	0.921	9.014	-0.174
	(-0.132)	-0.237	(-0.094)	-0.333	-1.295	(-0.081)
TaxToGDPR	-2.345	-7.846	-0.839	-5.441**	-15.981**	-2.915*
	(-1.209)	(-1.308)	(-0.713)	(-2.401)	(-2.356)	(-1.818)
Constant	-1.967***	-5.499**	-1.315***	-1.774**	-4.472*	0.088*
	(-3.302)	(-2.868)	(-3.993)	(-2.444)	(-2.090)	-1.918
Observations	17,942	17,942	17,942	17,449	17,449	17,449
Adj R-squared	0.786	0.615	0.652	0.861	0.716	0.749
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass

Table 18. R&D Tax Credits with Preferential Incentives for Small Firms

Notes: Table 18 presents the regression results of the effects of R&D tax credits on innovation using a sample consistent with samples from states with the preferential incentives for small firms and the observations from the states without R&D tax credits. *L3CpcPriPat* is the total number of patents applied by all private firms in a state and a CPC class in year t+3 after log transformation. *L3CpcPriCite* is the total number of citations received by all patents applied by all private firms in a state and a CPC class in year t+3 after log transformation. *L3CpcPriTop* is log transformed the total number of patents applied by private firms in a state and a CPC class, which have citations that are higher than the 90 percentiles of patents of the same technology class and application year. Credit is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. The CPC-level information transparency (*CPCInfo*) is measured by the weighted average of the aggregated industry level information environment in a CPC patent class. The aggregated industry level information environment is measured by the ratio of the number of public firms to the total number of firms in a 3 digits NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tercile. *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tercile.

	CPCInfo = L			CPCInfo = H		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	L3CpcPriPat	L3CpcPriCite	L3CpcPriTop	L3CpcPriPat	L3CpcPriCite	L3CpcPriTop
Credit	0.139***	0.168*	0.116***	0.157***	0.241**	0.122***
	(3.117)	(1.858)	(3.686)	(3.519)	(2.369)	(3.557)
GSPGrowth	0.004	0.016**	0.003	0.007**	0.024**	0.005**
	(1.561)	(2.650)	(1.491)	(2.207)	(2.800)	(2.303)
GSP	0.098	0.027	0.106	0.106	0.307	0.114
	(0.767)	(0.096)	(1.468)	(0.879)	(1.005)	(1.282)
UnempGrowth	1.922**	2.880	0.373	1.281	4.026	1.541
	(2.246)	(1.178)	(0.684)	(1.077)	(1.334)	(1.609)
StateEMP	0.063	0.475	-0.016	0.084	0.297	0.021
	(0.479)	(1.593)	(-0.223)	(0.696)	(0.939)	(0.236)
LaborC	0.686	3.310***	0.293	1.347***	4.453***	0.817***
	(1.566)	(3.088)	(1.259)	(3.215)	(3.472)	(2.986)
CorpTaxR	1.155	-1.072	0.254	-1.850	-15.164	-1.412
	(0.241)	(-0.094)	(0.077)	(-0.264)	(-0.733)	(-0.338)
IndTaxR	4.127	5.631	2.236	5.486*	9.476	3.340
	(1.415)	(0.939)	(1.241)	(1.813)	(1.255)	(1.591)
TaxToGDPR	-2.280	-0.389	-1.005	-3.486	-1.267	-1.780
	(-1.303)	(-0.084)	(-1.003)	(-1.401)	(-0.210)	(-0.995)
Constant	-1.826***	-7.052***	-0.909***	-2.192***	-7.511***	-1.535***
	(-3.048)	(-4.478)	(-3.069)	(-3.259)	(-3.885)	(-3.277)
Observations	24,480	24,480	24,480	23,791	23,791	23,791
Adj R-squared	0.679	0.497	0.469	0.834	0.669	0.711
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass

Table 19. Alternative Measures of Information Transparency

Notes: Table 19 presents the regression results of the effects of R&D tax credits on innovation using alternative measures of information transparency within a CPC technology class. *L3CpcTPat* is the total number of patents applied by all firms in a state and a CPC class in year t+3 after log transformation. L3CpcTCite is the total number of citations received by all patents applied by all firms in a state and a CPC class in year t+3 after log transformation. *L3CpcTop* is log transformed the total number of patents in a state and a CPC class, which have citations that are higher than the 90 percentiles of patents of the same technology class and application year. Credit is an indicator variable equal to 1 if a state provides an R&D tax credit, and 0 otherwise. The CPC-level information transparency (*CPCInfo*) is measured by the weighted average of the aggregated industry level information environment in a CPC patent class. In Panel A, the aggregated industry level information environment is measured by the ratio of total sales of public firms to the GDP in a 3 digits NAICS industry. In Panel B, the aggregated industry level information environment is measured by the average number of analysts following in a 3 digits NAICS industry. *High CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the top tercile. *Low CPCInfo* takes the value of 1 if the *CPCInfo* of a CPC class is in the bottom tercile.

Panel A. CPCInfo is Aggregated from the Industry-level Total Sale of Public Firms/Total Production in the Industry

	CPCInfo = Low			CPCInfo = High		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	L3CpcTPat	L3CpcTCite	L3CpcTop	L3CpcTPat	L3CpcTCite	L3CpcTop
Credit	0.028***	0.005	0.026***	0.066***	0.045**	0.058***
	(2.965)	(0.227)	(3.343)	(6.588)	(1.997)	(6.570)
Control	YES	YES	YES	YES	YES	YES
Observations	72,233	72,233	72,233	70,380	70,380	70,380
Adjusted R-squared	0.849	0.720	0.741	0.916	0.805	0.865
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass

Panel B. CPCInfo is Aggregated from the Industry-level Average number of analysts' forecasts in the Industry

	CPCInfo = Low			CPCInfo = High		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	L3CpcTPat	L3CpcTCite	L3CpcTop	L3CpcTPat	L3CpcTCite	L3CpcTop
Credit	0.015	0.017	0.011	0.046***	0.012	0.039***
	(1.526)	(0.723)	(1.314)	(4.277)	(0.502)	(3.990)
Control	YES	YES	YES	YES	YES	YES
Observations	60,005	60,005	60,005	58,677	58,677	58,677
Adj R-squared	0.859	0.743	0.754	0.928	0.828	0.881
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
TechClass FE	YES	YES	YES	YES	YES	YES
SE Clustering	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass	By Year & State & TechClass