State R&D Tax Credits:

Social and Economic Outcomes

by

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ABSTRACT

Research and Development (R&D) tax credits are one of the most widely adopted policies state governments use to incentivize R&D spending by firms operating in a state. R&D spending is associated with increases in firm productivity, innovation, and higher wages. However, most studies into these tax credits examine only the effect the credit has on firm-based R&D spending and assume the increases in R&D spending mean states are receiving the social and economic benefits endogenous growth theory predicts. This dissertation connects R&D tax credits with the expected outcomes of R&D spending increases to evaluate the efficacy of the tax credits. Specifically, the dissertation connects R&D tax credits to the movement of researchers between states, innovative activity, and state fiscal health. The study uses a panel of Doctorate of Philosophy (PhD) recipients from United States universities and a fixed-effects linear probability model to show R&D tax credits have a small but statistically significant impact on PhDs moving to states that have the tax credit. Using a structural equation model and a latent innovation variable, the dissertation shows R&D tax credits have a small but significant impact on innovative activity mediated by R&D spending. Finally, the dissertation examines the effect of R&D tax credits on a state's short- and long-run fiscal health by using a distributed lag model to illustrate R&D tax credits are associated with decreases with fiscal health.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Overview

This three-paper dissertation examines the effect of state research and development (R&D) tax credits on the movement of researchers between states, innovative activity in a state's economy, and state fiscal health. State R&D tax credits are an economic-development policy that incentivizes firms to increase their R&D spending within a state. Theoretically, R&D produces positive externalities, like increased productivity, wages, and innovation (Döring & Schnellenbach, 2006; Koo, 2005). Additionally, businesses underprovide R&D because its benefit cannot be captured solely by the firm that produces it. These two conditions justify the use of a Pigouvian subsidy to incentivize firms to invest in R&D (Fichtner & Michel, 2015; Lucas, 1988; Romer, 1989). While this same logic can be applied to a variety of economic-development policies, the literature is generally pessimistic about the efficacy of most of them. Specifically, companies may respond to competing for state tax credits by relocating operations without increasing their overall economic activity in the country. In effect, companies are receiving windfalls for what they would have done anyway (Bozeman & Link, 1984).

R&D tax credits as an incentive for knowledge creation are one of the few categories of economic-development policies that may produce their intended benefit (Jones, 1995; Mathur, 1999; Sterlacchini, 2008). This dissertation focuses on R&D tax policies at the state level. State-level R&D tax policies sit at the intersection of a positive outlook on R&D tax policies specifically and a pessimistic view of most other economic development policies in general. Thus, the dissertation contributes to a crowded body of literature by attempting to bridge the gap between the optimistic and pessimistic views on R&D tax credits (Döring & Schnellenbach, 2006). While there has been considerable work done regarding the effectiveness of government R&D tax policies, most have either focused on the national level or the firm level.

R&D tax incentives may provide considerable potential benefits to a state's economy, but they are certainly not immune to criticism. Wilson (2009) finds increases in R&D spending due to tax credits in one state almost always come at the expense of neighboring states, meaning the net national effect of R&D tax credits sits near zero. Another major problem with R&D tax credits is firms that may increase their R&D spending even without the credit receive an unintended windfall with the credit (Bozeman & Link, 1984). Companies taking advantage of incentive programs for behavior they would have done without the subsidy is a plague of economic-development policies (Döring & Schnellenbach, 2006). Finally, new arrivals rather than current residents tend to fill the majority of jobs created by economic-development policies (Döring & Schnellenbach, 2006). The migratory effect aligns with Wilson's findings that the tax credit has a net national effect of zero. However, the states may see an internal benefit of utilizing R&D tax policies if they result in a state attracting firms and knowledge-producing human capital that spur endogenous growth within a state's economy (Romer, 1989).

When states offer competing credits, larger firms can respond to the credit by changing where they perform R&D rather than by increasing the amount of R&D they perform (Wilson, 2009). If the credit increases R&D in one state at the expense of other states, this motivates states to evaluate the credit not in terms of increases to R&D, but rather in terms of the spillover effects generated by increased R&D spending. The problem is less of a concern at the national level because legal, cultural, and geographic barriers make the movement of R&D activities and workers across national borders more difficult than at the state level.

Research Question

Every year, states forgo billions of dollars in tax revenue to incentivize firms within their jurisdiction to invest in R&D. R&D is associated with increased economic activity due to its connection to innovation, productivity, high wages, and knowledge spillovers. Ample evidence connects R&D tax credits to R&D spending within firms, but few efforts have been made to examine the second- and third-order effects of R&D tax credits. This dissertation seeks to understand if the increase in R&D spending from these tax credits translates into tangible benefits for a state government, its economy, or its citizens. In broad strokes, this dissertation seeks to answer the following question:

What are some social and economic returns of R&D tax credits to states?

This question is especially salient as state governments have been dealing with increased fiscal constraints and will soon likely be faced with rebuilding an economy devastated by the Coronavirus pandemic. Specifically, the dissertation looks at how R&D tax credits can influence a state's labor market for highly skilled workers, whether increases in innovative activity by state firms can be attributed to R&D tax credits, and whether the tax credit can actually help a state's fiscal condition.

Dissertation Structure

Each of the following three papers examines a different outcome associated with R&D tax credits. These three papers are designed to be stand-alone journal articles that can be read without the context provided by the other papers. As a result, there may be some redundant information presented in each paper. Specifically, each paper introduces the background and structure of the tax credit and reviews related literature. The abstract for each paper is presented below:

Paper 1: R&D Tax Credits and the Interstate Mobility of PhDs

Research Question: What is the effect of state R&D tax credits on the movement of PhDs?

As the United States economy evolves, states require more highly skilled labor to fill science, technology, engineering, and math (STEM) jobs. Over the next decade, states across the U.S. are projected to need an additional one million STEM workers. One strategy for states to fulfill their STEM needs is to develop an economy that is attractive to STEM workers. States particularly desire one subset of STEM workers, individuals with PhDs, because they contribute to a state's economy by producing knowledge and increasing innovation. States use R&D tax credits to incentivize R&D spending in the state, which may be related to the movement of PhDs. This paper explores the relationship between R&D tax credits and the movement of PhDs between states using panel data from the *Survey of Doctoral Recipients*. This paper uses a fixed-effects linear probability model to test the relationship between state R&D tax credits and the movement of PhDs. The findings from this paper suggest incentivizing industry R&D spending may attract PhDs to move to their states.

Paper 2: State Economic Innovation and R&D Tax Credits

Research Question: Do R&D tax credits increase the levels of innovation in a state's economy?

State R&D Tax Credits are the most popular way for states to incentivize R&D spending. R&D spending is associated with increases in innovative activity and knowledge spillovers predicted by endogenous growth theory (Arrow, 1962; Romer 1986, 1990). While there is a preponderance of research connecting these tax credits to R&D spending, little effort has been made to connect them to innovation. This paper uses a structural equation model to understand the direct and indirect effects of R&D tax credits on innovation.

Paper 3: The Cost of State R&D Tax Credits

Research Question: Do R&D Tax Credits increase net tax revenue for a state?

One argument for tax credits is they are an investment by a government into the economy. The logic of this argument is tax credits should increase economic activity, which improves the tax base and ultimately increases tax revenue. Most literature on tax expenditures that are direct transfers to firms found they hurt a state's fiscal condition.

However, R&D tax credits may be more effective at boosting economic activity than other types of credits. Therefore, this paper seeks to explore both the short-term and long-term impacts of R&D tax credits on state fiscal health, using a repeated measures panel composed of all 50 states.

Methods

The dissertation utilizes many different quantitative techniques to assess the impact of R&D tax credits on the outcome variables of interest. The first paper utilizes a repeated measure design of people with PhDs and a linear probability model to assess this impact. This paper is novel in the use of individual-level data to assess the impact of state-level policies. The second paper uses a structural equation model to analyze a cross-lagged model and a latent variable to capture innovation. This is one of the first papers to attempt to connect the indirect effect of the tax credit with its implementation. The final paper utilizes a distributed lag model to look at the short-term and long-term implications of the tax credit on a state's fiscal health. Most other papers connecting tax expenditures like tax credits to fiscal health only examine the expenditure in terms of the short-term or annual implication and not in terms of multiple years (McDonald, 2018; Wang et al., 2007a).

Themes

Several themes connect each of the three papers. The first is the idea that R&D tax credits serve as a policy mechanism to incentivize firm behavior toward some positive economic or societal benefit. New knowledge, the product of R&D, is likely produced below the socially optimal level (Fichtner & Michel, 2015; Lucas, 1988;

Romer, 1989). New knowledge cannot be entirely captured or monetized by firms that create knowledge; instead, it spills over into other parts of the economy. Therefore, R&D tax credits are useful in incentivizing the production of this knowledge, which has positive economic and social benefits. This dissertation attempts to explore some of those benefits.

The second theme connecting these papers emerges from an attempt not only to determine if the tax credits have a significant impact on the variable of interest but if that impact is substantively meaningful. The results of the first two papers demonstrate the tax credits have a statistically significant but substantively small relationship with the variable outcome interest. The first paper reveals the effect of R&D tax credits is positively related to PhDs moving to a state, but this effect is several orders of magnitude smaller than the main drivers of labor force migration, the economy, and direct R&D spending. The second paper shows R&D tax credits create a statistically significant effect on innovation, but this effect is so substantively small, it is almost negligible. The dissertation seeks to understand not only if the credit has an impact, but also if the size of that impact justifies the cost. The third paper takes that question head-on in assessing the tax credits' impact on the short-term and long-term fiscal health of the state implementing the credit.

The third theme connecting these papers is endogenous growth theory, the primary theoretical framework that makes the case why R&D spending is desirable. All three papers draw on this theory to explain R&D tax credits' connection to economic development, both to inform the papers and connect the tax credit to the outcome variable of the paper. In the first paper, endogenous growth theory explains both why PhDs are desirable for a state's economic growth and why the tax credit should grow the economy in a way that attracts researchers to move there. The second paper explores the connection between R&D tax credits, R&D spending, and innovation, assuming firms are both directly benefiting from R&D spending and indirectly benefiting through spillovers. While these are not directly captured in the paper, endogenous growth theory provides the underlying justification for the structural model used in the paper. The final paper uses endogenous growth theory's assumption that R&D tax credits have spurred economic growth to assess the effect of the tax credit on a state's fiscal condition. It is worth taking a moment to explore the literature surrounding endogenous growth theory because of the pivotal role the theory plays in the development of this dissertation.

Endogenous Growth Theory

Endogenous growth theory contends regions can generate internal economic growth through the promotion of feedback loops or positive externalities. It was originally conceived as part of the amalgamation literature, which suggests regional economies should be arranged in clusters that limit transaction costs and maximize spillovers (Audretsch, 1998; Bresnahan et al., 2001; Gordon & McCann, 2005). Examples include the concentration of car manufacturers in Detroit, Michigan or steel foundries in Pittsburg, Pennsylvania. Romer (1989) proposes feedback loops enable regions to experience increasing returns from both physical and human capital. The economic benefit of externalities allows regions to experience internal growth, despite firms experiencing diminishing returns from expanding in the region. Endogenous growth theorists posit that human capital, not firms, are the primary drivers of economic growth because of positive externalities that arise from the creation of knowledge (Henderson, 2010; Lucas, 1988; Mathur, 1999).

Endogenous growth contends increasing levels of human capital lead to higher wages and higher levels of firm productivity through the production of knowledge and knowledge spillovers (Lucas, 1988; Romer, 1986). One mechanism of knowledge production is research and development (R&D) (Oort *et al*, 2009). Scholars have associated R&D with increased firm productivity, higher wages, and innovation (Hewitt-Dundas & Roper, 2011; Koo, 2005; Koo & Kim, 2009; Sterlacchini, 2008). Technological change and innovation are dependent on the production of new knowledge, and the production of new knowledge is contingent on technological change and innovation (Audretsch & Keilbach, 2004b).

Knowledge spillovers enable economic growth by allowing new knowledge, technical expertise, and innovations to spread through a region (Audretsch, 1998). Human capital facilitates knowledge spillovers by allowing individuals to recognize and apply useful knowledge when they see it (Audretsch & Keilbach, 2004a). For Romer (1986), knowledge spillovers are the result of non-rivalrous knowledge production by firms. Lucas (1988) argues knowledge spillovers are spatially concentrated into regions and part of the region’s growth process because knowledge spills over as individuals interact with one another. Knowledge spillovers enable technology and innovations to diffuse through a region and thus are one of the most important benefits of regional human capital (Henderson, 2010; Porter, 2003).

Scholars have empirically linked human capital to knowledge spillovers and economic growth. Audretsch (1998) connects innovations to the education level of the labor force to find industries with high levels of human capital receive larger increases in productivity and wage growth from knowledge spillovers than regions with low levels of human capital. Bettencourt et al. (2007) finds patents, a proxy for innovation (Acs et al., 2002), are granted disproportionately in larger urban centers, suggesting increasing returns in innovation relative to population size. Sterlacchini (2008) supports the endogeneity of knowledge production (through R&D), regional growth, and higher education by examining the economic output of twelve European Union countries from 1995–2002. Additionally, Sterlacchini finds R&D spending and worker education only impact economic growth when per capita GDP is above a given threshold. While scholars have explored the economic benefit of knowledge production and spillovers, they understand less about exactly how and why knowledge spillovers occur (Currid-Halkett & Stolarick, 2011).

There is ambiguity regarding the cost and mechanisms of knowledge spillovers. Scholars stress spillovers are neither costless nor automatic (Döring & Schnellenbach, 2006; Acs & Plummer, 2005; Grosmann & Helpman, 1991). The geographical and regional economics literature provides evidence knowledge spillovers do not diffuse instantaneously across a region. Scholars question whether regional economic growth is due to higher numbers of firms or the concentration of knowledge (M. P. Feldman & Audretsch, 1999a; Glaeser et al., 1992).

Critics of endogenous growth theory argue the theory does not have articulated mechanisms of growth regarding both the arrangement of firms and how knowledge spillovers work. Furthermore, endogenous growth theory assumes a closed system in firms, and individuals can neither enter nor leave a system. In Lucas's (1988) seminal piece, he articulates endogenous growth theory assumes a closed economic system, but few scholars have attempted to relax this assumption. Nationally, this is a reasonable assumption because legal and geographic barriers make movement across international borders challenging. At the subnational level, the assumption of a closed system is more problematic because individuals, firms, and regional economies freely cross jurisdictional lines.

Contributions

This dissertation makes several important contributions to the literature. The most important empirical contribution is the operationalization of the R&D tax-credit variable used in the dissertation. R&D tax credits are measured in terms of the number of dollars claimed by companies each year. This variable represents the extent to which firms utilize the tax credits and is a measure of policy uptake. Other attempts to measure R&D tax credits have either operationalized the credit as a binary variable (the state has a tax credit or does not) or in terms of the rate of the tax credit. However, using a binary variable does not allow for much nuance or variation in comparing credits across states (Bloom et al., 2002; Wilson, 2005).

Using the rate of the tax credits raises a different problem because each state structures its tax credit differently. For instance, New Mexico offers a very generous tax credit for new and small firms (≈50%). In contrast, Delaware offers a tax credit that is regressive: small firms receive a smaller credit, while large firms receive a more generous credit. This paper's method of measuring R&D tax credits is superior because it is agnostic to the peculiarities of each state's implementation. This data is drawn from annual tax expenditure reports from all 50 states. However, this approach is limited because it cannot determine if the structure of a state's tax credit is responsible for the implications of the policy.

The dissertation's other main contribution is testing the connection of R&D tax credits to second- and third-order outcomes that theoretically exist. Still, scholars have not connected to the tax credit. R&D tax credits have been evaluated primarily in terms of their effect on R&D spending, with the theory then used to explain the benefits of this connection (Becker, 2015; Chiang et al., 2012; Hearn et al., 2014). This dissertation tests some of these theoretical connections by attempting to isolate the effect of the tax credit. This is empirically difficult because of the small population of states. However, it is substantively important to consider if there is any external benefit of these tax credits or if the only beneficiaries are the firms and the people who work for them.

CHAPTER 2

R&D TAX CREDITS AND INTERSTATE MOBILITY OF PHDS

Introduction

As the United States economy evolves, states require more highly skilled labor to fill science, technology, engineering, and math (STEM) jobs. Since 2008, the number of STEM jobs has increased seven times as fast as non-STEM jobs, 14% versus 2%, and this trend of above-average growth for STEM employment does not appear to be slowing in the next decade (Castleman et al., 2018). One strategy for states to fulfill their STEM needs is to develop an economy that is economically attractive to STEM workers, which involves incentivizing firm investment in research and development (R&D) (Medicine et al., 2016). The most common policy for incentivizing R&D is the use of state R&D tax credits. PhDs are one subset of STEM workers who are trained as researchers and are particularly desirable for conducting research specifically and economic development more broadly because of their role in knowledge production (Foray, 2004; Jones, 1995).

State and federal governments employ policies to produce and attract highly skilled labor to address the STEM labor shortage. The federal government has attempted to address the shortfall of STEM workers by expanding the H-1B visas program to attract skilled labor from other countries (Rothwell & Ruiz, 2013). States have sought to address the shortfall by expanding STEM offerings at public universities (Zucker, Darby, & Brewer, 1994). However, the success of a state gaining more STEM workers from increasing university production of PhDs is limited because PhDs can move freely between states and there is no guarantee a state will be able to encourage doctoral graduates to stay (Stephan, 2006). To compound this issue, states heavily subsidize graduate education, and when a PhD leaves, the state loses both the economic investment in the student and the benefits of that student's knowledge spillover on the local economy (Jones, 1995). Traditionally, states have placed limited emphasis on attracting workers via economic development policies, preferring to focus primarily on attracting businesses, especially STEM businesses. An R&D tax credit is the most common state-level policy aimed at creating a STEM-centric economy (Biggins et al. 2017). Initially, it may seem like R&D tax credits are unrelated to the movement of PhDs; it is certainly unlikely policy makers were concerned with the movement of PhDs when they implented these policies. After all, these tax credits are designed to be taken advantage of by firms, not individuals. However, both R&D spending and workers with PhDs are inputs of knowledge production in a state's economy (Foray, 2004). By connecting tax credits and the migration of PhDs, this paper argues targeted state economic-development policies might be able to attract workers with highly specialized forms of human capital to a local economy.

The remainder of the paper constitutes the following: first, it provides background on R&D tax credits and the economic-development impacts of both these tax policies and PhDs. Second, it describes the data and methodology used to explore empirically this relationship link. Following the discussion of the data and methods, it presents the results of the empirical model. The penultimate section discusses the results, policy implications, and avenues for additional research, before the final section concludes the paper.

Background

R&D Tax Credits

Minnesota adopted the first state R&D tax credit in 1982. The policy has since expanded to 37 states (Wilson, 2005). Though the exact structure and rate of R&D tax credits vary by state, the credit generally allows firms to receive a discount on taxes owed as a percentage of incremental increases in annual R&D spending. Firms can receive both state and federal tax credits. When designing tax credits, most states use the federal R&D tax credit as a basis for determining what qualifies as R&D spending, with the added caveat that firms can only claim credit for R&D spending within the state. Firm expenditures on process improvement, elimination of uncertainty, development of new technology, and generation of knowledge as R&D are eligible for the federal credit. Activities like reverse engineering, product improvement after commercialization, software development, and market research do not qualify as R&D spending. Additionally, only R&D spending primarily on wages for either an employee or a contractor is eligible for the federal credit (Chiang, Lee, & Anandarajan, 2012).

Extensive literature on R&D tax credits exists, making it one of the most well-studied tax incentives (Fichtner & Michel, 2015). Scholars have examined the conditions that lead to the adoption of these tax credits, their impact on private sector R&D spending, their diffusion by state, and their impact on innovation (Chiang et al., 2012; Finley et al., 2014; Hearn et al., 2014; Miller & Richard, 2010; Wu, 2008). The literature has investigated these issues at the international, national, and state level (Duguet, 2012; Nam, 2009). Though large firms benefit the most from R&D tax credits, the credits have a spillover effect of improving the innovation of all firms in a state (Chiang et al., 2012). The literature concurs that R&D tax credits improve economic growth for the state that implements them.

R&D tax credits are the most common way for states to incentivize R&D spending by firms (Biggins, 2017; Wu, 2005). States incentivize research-and-development spending because of its link to economic growth (Jones, 1995; Stokey, 1995; Sylwester, 1995). R&D spending directly improves firm performance through increasing the availability of technology, productivity, and innovation (Mansfield, 1972). More importantly for economic development, R&D spending has positive externalities for state residents because these performance benefits for firms spill over into the rest of an economy (Coe & Helpman, 1995; Klaassen et, al., 2005; Mairesse & Mohnen, 2004). Public subsidies for R&D funding improve firm innovativeness (Almus & Czarn, 2012) and encourage a higher amount of spending in R&D (Hans, 2004; Lööf & Hesmati, 2004).

R&D tax incentives may provide considerable positive benefits to a state's economy, but they are certainly not immune to criticism. Wilson (2009) finds increases in R&D spending due to tax credits in one state almost always come at the expense of neighboring states, meaning the net national effect of R&D tax credits sits near zero. Another major problem with R&D tax credits can be seen when firms may increase their R&D spending even without the credit then receive an unintended windfall with the credit (Bozeman & Link, 1984). Finally, jobs created by economic-development policies are filled primarily by in-migration rather than current state residents (Döring & Schnellenbach, 2006). However, this migratory effect may prove to be a strength for

R&D tax policies, since attracting PhDs and other types of highly skilled human capital has many benefits for economic development.

PhDs and Economic Development

Doctorate recipients are quite desirable for local economic development. First, individual PhDs contribute their highly skilled human capital to the local economy. Second, they serve as an input in knowledge production, which has many positive externalities for the economy. Finally, they are instrumental in ensuring technology transfer between university and industry.

Individuals with a large amount of human capital, like PhDs, contribute to the local economy through increasing state productivity and receiving higher wages (Benhabib & Spiegel, 1994; Carnevale, Rose & Cheah, 2013; Frank, 1960; Prime, Grimes, & Walker, 2016; Mincer, 1984). Becker (1994) contends the most important type of human capital is educational attainment, and PhDs have among the highest levels of human capital. The personal economic benefit of a PhD is evident in earnings statistics. A PhD earns on average 43% more than someone with a Bachelor's or 21% more than someone with a Master's over the course of their lifetime (Rothwell, 2013). At the most basic level, individuals who receive a high wage contribute more to economic development, since economic development is an aggregation of individual-level effects (Becker, 1994),

PhDs contribute to their local economy because they produce knowledge, which has several positive spillovers (Foray, 2004). Knowledge production, whether from R&D

or PhDs, increases levels of innovation throughout an economy (Shaw & Allison, 2010). This is one reason why PhDs are an indicator of the innovative capacity of an economy (Furman, Porter, & Stern, 1999). The majority of patents held by individuals, an indicator of economic performance and innovation, is held by people with PhDs (Furman, Porter, & Stern, 2002; Marx, Singh, & Fleming, 2015). Furthermore, PhDs tend to work locally with other peers—despite globalization enabling long-distance collaboration—to create knowledge, patents, and innovation (Breschi & Lissoni, 2009). For instance, concentrations of highly skilled labor are associated with the birth of the biotechnology industry in North Carolina (Zucker, Darby, & Brewer, 1994) and the prominence of Silicon Valley (Bresnahan, Gambardella, & Saxenian, 2001).

In addition to the knowledge spillovers associated with PhDs in a local economy, PhDs are drivers of technology transfer—an economic benefit states receive from research universities (Bresnahan, Gambrdella, and Saxenian, 2001; Feldman, 2002). They are instrumental in facilitating research universities in two primary ways: increased human capital and technology transfer (Lee, 1996; Thune, 2009). Research universities' contributions to the local economy through developing of PhDs is predominantly measured in the short run and does not account for the mobility of the new PhDs (Johansen & Arano, 2016). Universities also use PhD candidates to interface with local industry to spread technical knowledge and technology between universities and industry (Bozeman, 2000).

PhDs contribute to economic development through both high wages and the production and diffusion of knowledge. Consequently, their contribution mirrors that of R&D spending through a direct and indirect mechanism. The two are connected directly via employment: as Table 3 demonstrates, R&D is the most common job activity of PhDs (40.8%), and the for-profit sector is the second most common employer (31.4%). An indirect connection between R&D and PhDs exists because both contribute to the local economy through the creation of new knowledge that improves productivity and encourages innovation. It is necessary to understand why PhDs migrate if one is to understand if policies that increase R&D spending can affect that migration.

Doctoral Mobility

For a state to receive the benefit of PhDs and other types of STEM workers, it needs the ability to attract these highly skilled workers. Highly educated workers like PhDs tend to be among the most mobile in terms of moving between either jobs or geographic locations (Sicherman & Galor, 1990). Movement of highly skilled labor has received considerable attention in the literature at the international level. Interest at this level has focused primarily on concepts such as brain drain and factors that affect PhDs returning to their home country. At the local level, there has been a growing movement to understand what factors attract these workers to cities (Clark, 2003; Niedomysl & Hansen, 2010). Outside of a few works (Borjas, Bronars, & Trejo, 1992; Greenwood, 1969), examination of state-level factors affecting the mobility of PhDs has been conspicuously absent.

The migration pattern of the general workforce within the U.S. has been extensively studied to determine the factors affecting that migration. Such factors include economic outcomes, family conditions, and distance (DaVanzo, 1976; Schwartz, 1973).

Individuals who feel the career opportunities in their state do not match their skill levels tend to leave the state, which is a fundamental economic theory of migration (Bronars & Trejo, 1991). Highly skilled workers are more likely to migrate than low-skilled workers due to receiving higher wages and being in higher demand (Greenwood, 1969). Stephan (2006) confirms that U.S. PhDs are highly mobile and settle primarily along the coast and in large urban centers.

Initial attempts to understand the migration of workers focuses on the influence of economic conditions that lead to higher wages (Greenwood, 1997). Scholars have challenged this notion as the demand for STEM workers has outstripped supply and led to research exploring the role of amenities in the movement of highly skilled workers (Florida, 2006). The literature has yet to reach a consensus concerning the role amenities play in the movement of workers. Gottlieb and Joseph (2006) find PhDs pay more attention to amenities than economic factors when compared with other recent college graduates. Their study is cross-sectional, and the authors admit their measure of city level amenities is weak—they are more concerned with social diversity and the level of crime than specific physical amenities. Niedomysl & Hansen (2010), using a more robust measure of amenities, find economic conditions are more important than amenities as a driver for the mobility of labor.

The international migration literature has paid considerable attention to the migration of highly skilled workers and their benefit to national economies. Highly skilled labor benefits national economies through enhancing innovation, technology, human capital, and it encourages R&D spending and hiring by firms (Regets, 2001; Solimano, 2008). Within the literature on highly skilled labor, PhDs have received special attention for their unique combination of high levels of human capital and research capability (Grogger & Hanson, 2015; Roh, 2014). The migration of PhDs out of the U.S. is a concern because governments highly subsidize the education of PhDs; if graduates leave this country, the country loses the investment made in training a PhD (Regets, 2001). The literature categorizes this problem as a brain drain—the outward flow of highly educated workers from one country to another (Stark, Helmensteinc, & Prskawetzd, 1997; Straubhaar, 2000). Scholars have studied the brain drain in a number of fields, including engineering and medicine (Johnson & Regets, 1998; Mullan, 2005). States face a problem similar to that of foreign countries in regards to PhD movement but have access to fewer policy options than national governments.

Data and Methods

This research uses an unbalanced panel with individual, year, and state fixed effects in a linear probability model to predict the movement of a sample of PhD holders (people who have already graduated with a doctoral degree) based on the amount of R&D credits claimed by firms in a state while controlling for individual characteristics and state economic factors.

Data

The data for this study come from the National Science Foundation (NSF), state tax expenditure reports, the State Higher Education Executive Officers Association (SHEEO), and the Bureau of Economic Analysis (BEA). NSF provided the *Survey of Doctoral Recipients* (SDR), and the *Business Research and Development and Innovation*

Survey (BRDIS). The SDR is a biennial longitudinal study of a repeated random sample of individuals who received a research doctorate from accredited U.S. institutions (National Science Foundation, 2017).

Multiple years of the SDR are used to form a repeated unbalanced panel of PhD holders. Though the SDR surveys the same individual in each iteration, there is some turnover in participants as recent graduates are added to the survey and senior scholars are removed due to attrition. Since NSF conducted the SDR in 2006, 2008, 2010, and 2013, the panel also has gaps between survey years. The SDR collects data on individual characteristics, including educational background, demographics, and employment. The SDR had 75,349 observations from these years across 34,245 individuals. After dropping singletons and cases with missing observations, the study includes 59,276 observations of 27,477 individuals from 49 states. Illinois is missing from the analysis because SHEEO removes Illinois' data due to that state revising its data-collection standards. An individual's employment location is used to match individual observations to the state variables.

The dependent variable for this study, move, measures whether an individual moved to a new state between two observed years in the panel. Move is defined as a change of status in which an individual received a 1 if their place of employment changed states between responses. If their place of employment did not change states, move remained a 0. By necessity, the initial observation of a person is used to establish a baseline location but not used in the analysis. Consequently, the years 2008, 2010, and 2013 are used in the models, though 2006 is used to form the initial movement comparison. For the move variable, the location of a person's employment address instead of home address is used, because states design R&D tax credits for firms, not individuals. In the three years of the study, 6,843 moves took place, which accounted for 10.89% of all observations. Table 1 shows how many individuals stayed vs. moved in each of the years of the study.

Table 1: Move By Year

		Freq.		*Percent*	
Year	Annual Total	Stayed	Moved	Stayed	Moved
2008	19,440	17,072	2,368	87.82	12.18
2010	21,219	19,190	2,029	90.44	9.56
2013	22,172	19,726	2,446	88.97	11.03
Total	62,831	55,988	6,843	89.11	10.89

The key independent variables in this study are R&D credit, R&D claimed, and industry R&D spending. R&D credit is a binary variable where individuals receive a 1 if they live in a state with an R&D tax credit and a 0 otherwise. R&D claimed is a continuous variable measuring the aggregate amount of R&D tax credits claimed within a state. The binary R&D credit variable is useful for measuring treatment effects, while the continuous R&D claimed variable allows for measuring the dosage effect of the policy. Both the R&D credit and R&D claimed variables are generated from examining annual state expenditure reports. A state tax expenditure report is a detailed report of the amount of tax revenue a state does not collect by offering tax credits and exemptions. Though several states offered a sales tax exemption on R&D purchases (equipment and capital), this analysis does not include those policies, because it does not directly translate into employing R&D workers. Using the raw amount of R&D tax expenditures over the legislatively mandated rates provides the benefit of measuring policy uptake and is agnostic to each state's particular policy implementation. Industry R&D spending is the amount of spending companies perform within a state and is provided by BRDIS. Given the skewed distribution of both the R&D tax credits claimed and R&D spending by industry, the natural logarithm is used in the empirical analysis.

Control variables

The control variables consist of state-level economic variables and individual level control variables. State economic variables include higher education revenue, unemployment, and state GDP per capita. Higher education revenue measures the amount of revenue public universities in a state received from tuition and state contribution and is provided by SHEEO. Unemployment rates and state GDP per capita is provided by BEA. The analysis uses the natural log of state GDP per capita and higher education revenue to aid in interpretability.

The individual level controls include demographic variables and work variables. All individual and demographic control variables are provided by the SDR. Demographic control variables include age, years since graduation, marital status, and children by age category. Age is an individual's age when the survey was taken. Years since graduation is a continuous variable measuring how many years since someone graduated. Marital status is a binary variable where married individuals receive a 1 and unmarried individuals receive a 0. Children is a categorical variable distinguishing between a person having no children, any children younger than 6, and children between the ages of 6 and 18. Individuals with children in both age categories are coded into the younger than 6 category. These variables serve as a proxy for family conditions that might impact an individual's mobility decisions.

Work variables like salary, job satisfaction, sector of employment, job activity and degree relevance are used to control for an individual's working conditions. Salary is a self-reported continuous variable of their salary in the survey year. The natural log of salary is used to aid in interpretation and address concerns of heteroskedasticity. Job satisfaction is a self-reported survey measure on a 4-point Likert scale ranging from very satisfied (1) to very unsatisfied (4). Sector of employment is a categorical variable defining which sector an individual works in. Categories include 4-year college, 2-year college, for-profit, self-employed, non-profit, and government. Job activity is a self-reported categorical variable of someone's primary job activity, divided into R&D, teaching, management/admin, computer application, and other. Degree relevance is a self-reported measure of how relevant someone's PhD is to their job. Table 2 displays descriptive statistics for all the continuous and binary variables, and Table 3 includes descriptive statistics for all categorical variables.

Table 2: Descriptive Statistics of Continuous and Binary Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Move	62,831	0.1089	0.3115	0	1
R&D Credit	75,349	0.6366	0.4648	0	1
R&D Claim	75,349	2.54E+08	5.52E+08	0	1.80E+09
Log R&D Credit	75,349	12.0898	8.4083	0	21.3113
R&D Industry Spending	75,349	1.51E+10	2.09E+10	2.10E+07	7.69E+10
Log R&D Industry Spending	75,349	22.5190	1.5341	16.8600	25.06513
Higher Education Revenue	71,455	5.56E+09	4.46E+09	7.30E+07	1.43E+10
Log Higher Education Revenue	71,455	22.0737	0.94323	18.1058	23.3825
State Unemployment	75,349	7.5957	2.0796	2.9	13.5
State GDP Per Capita	75,349	52,673.07	18,921.48	31,688	17,0687
Log State GDP Per Capita	75,349	10.8363	0.2357	10.3637	12.0476
Married	75,349	0.7657	0.42355	0	1
Age	75,349	48.5634	11.4346	23	75
Years Since	75,349	23.43533	11.50874	5	59
Salary	75,274	103,380.6	6,6021.12	0	980,000
Log Salary	75,080	11.3566	0.7183	0	13.7953

Table 3: Descriptive Statistics of Categorical Variables

	Freq.	Percent	Cum.
Children			
No Children	40,212	53.37	53.37
Children under 6	13,910	18.46	71.83
Children aged 6-18	21,227	28.17	100
Total	75,349	100	
Sector			
4 year colleges	32,359	42.95	42.95
2 year colleges	2,765	3.67	46.62
For-Profit	23,656	31.4	78.01
Self-Employed	4,264	5.66	83.67
Non-Profit	5,005	6.64	90.31
Federal Govt	5,311	7.05	97.36
State and Local Govt	1,989	2.64	100
Total	75,349	100	
Primary Work Activity			
R&D	30,731	40.78	40.78
Teaching	15,121	20.07	60.85
Management/Administration	14,369	19.07	79.92
Computer Applications	2,861	3.8	83.72
Other	12,267	16.28	100
Total	75,349	100	
Job Relevance			
Not Relevant	6,044	8.02	8.02
Somewhat Relevant	19,761	26.23	34.25
Highly Relevant	49,544	65.75	100
Total	75,349	100	
Job Satisfaction			
Very Satisfied	38,600	51.23	51.23
Satisfied	30,281	40.19	91.42
Unsatisfied3	5,196	6.9	98.31
Highly Unsatisfied4	1,272	1.69	100
Total	75,349	100	

Methodology

This research uses a linear probability model with individual, state, and year fixed effects with an unbalanced repeated measure panel to conduct the empirical analysis. Robust standard errors are used to account for heteroskedasticity and serial correlation. Post regression analysis revealed 98% of the predicted values fell between 0 and 1. Using individual and year fixed effects allows for control of all time-invariant unobserved variables of the individuals such as race or gender. State fixed effects also control for unobserved time-invariant variables at the state level and are particularly advantageous for controlling for time-invariant amenities such as culture or climate. As an important note, when individuals move between states, the state-level variables are observed as an individual's current state of residence, including state fixed effects. This, combined with the state fixed affects, means most of the variance in the state-level variables is attributed to individuals moving between states.

This paper uses two general empirical models, the first of which is as follows:

$$Move_{ist} = \beta_0 + \beta_1 R\&DCredit_{st} + \beta_2 R\&D_{st} + \beta_3 STATE_{ist} + \beta_3 X_{ist} + \delta_s + \delta_t + \delta_i + \varepsilon_{ist}$$

Move is the probability a PhD moves to a new state, where *i* indexes the individual, *s* the state, and *t* the year. R&DCredit measures if the state has an R&D tax credit in order to test if states with this tax credit are more likely to have PhDs move to their state. R&D measures the amount of R&D spending by industry. STATE is a factor of state-level economic control variables, and *X* is a factor of individual-level control variables. δ_s controls for the impact of state fixed effects, δ_t controls for time fixed effects and δ_i controls for individual fixed effects. The second model uses R&DClaim to test for the dosage effect of the tax policy. The second empirical model is as follows:

$$Move_{ist} = \beta_0 + \beta_1 R\&DClaim_{st} + \beta_2 R\&D_{st} + \beta_3 STATE_{ist} + \beta_3 X_{ist} + \delta_s + \delta_t + \delta_i + \varepsilon_{ist}$$

One concern for this model is R&D tax credits and R&D firm spending in a state are co-linear and potentially endogenous due to R&D tax credits increasing R&D spending by firms. However, R&D spending is necessary for controlling for a state's R&D infrastructure and determining the unique contribution of R&D tax credits to movement. Wilson (2009) suggests lagging R&D spending to correct for this potential endogeneity. Unfortunately, the gapped and unbalanced nature of the panel means correctly lagging R&D spending and other economic variables becomes highly problematic, as it is impossible to know in which year an individual moved. By not correcting for this potential endogeneity, the models should underestimate the relationship between the R&D credit variables and movement.

Results

Analysis is begun by presenting the results of the two general linear probability models in Table 4. Column 1 displays the results of using the binary variable R&D credit. The magnitude of having a tax credit is minimal and significant: individuals are 1.49% more likely to move to a state with an R&D tax credit. Column 2 displays the result of the dosage model with similarly minimal but significant findings: a 1% increase in the amount of R&D taxes claimed increases the probability someone moves to a state by 0.08%. In both models, 1% increases in state R&D spending is associated with a 6.8% increase in the probability of moving to a state. Additionally, PhDs moving to a state is negatively associated with increasing state revenues for higher education but positively associated with state GDP per capita. State unemployment rates do not have a significant relationship with the movement of PhDs.

While the effect of R&D credits appears to be minimal, it is substantive for two reasons. First, the R&D tax credits coefficient is an order of magnitude lower than the R&D spending coefficient, which is an order of magnitude lower than the GDP per capita coefficient. This suggests R&D tax credits have a third-order effect on the movement of PhDs, and R&D spending has a second-order effect. Second, the coefficient of the R&D

credit is its unique contribution when controlling for R&D spending and all other state variables, which may be underestimated due to issues of multicollinearity with R&D spending.

Table 4: Linear Probability Model

	Dependent variable:	
	Move	
	(1)	(2)
R&D Credit	0.0149**	
	(0.0064)	
Log R&D Claim		0.0008**
		(0.0004)
Log R&D Spending	0.0680***	0.0678***
	(0.0139)	(0.0139)
State Unemployment	0.0027	0.0027
	(0.0023)	(0.0023)
Log Higher Education Revenue	-0.0948***	-0.0940***
	(0.0301)	(0.0301)
Log State GDP Per Capita	0.1684***	0.1656***
	(0.0593)	(0.0593)
Constant	0.2289	0.2485***
	(0.9458)	(0.9490)
Observations	59,276	59,276
Individuals	27,477	27,477
R^2 within	0.0505	0.0512
R^2 between	0.0004	0.0008
R^2 overall	0.0044	0.0053
Fixed Effects		
Individual	Y	Y
Year	Y	Y
State	Y	Y

Notes: *p<0.1;**p<0.05;***p<0.01
Models included but did not report individual control variables
Models presented with robust standard errors

Two types of subgroup analyses are conducted, one by dividing the sample by primary work activity and the other by dividing the sample by work sector. Conducting these subgroup analyses eliminates the potential for spurious correlation, wherein individuals move to states with large R&D tax credits for reasons completely unrelated to the state's R&D infrastructure or policy. This is particularly important given the small observed effects of both R&D tax credit variables.

Table 5: Work Activity Robustness Check

	R&D Workers		*Teachers*	
	(1)	(2)	(3)	(4)
R&D Credit	0.0308***		-0.0024	
	(0.0120)		(0.0105)	
Log R&D Claim		0.0021***		-0.0003
		(0.0007)		(0.0007)
Log R&D Spending	0.1370***	0.1371***	0.0317	0.0317
	(0.0266)	(0.0266)	(0.0262)	(0.0262)
Unemployment	0.0045	0.0044	-0.0017	-0.0017
	(0.0044)	(0.0044)	(0.0044)	(0.0044)
Log Higher Education Revenue	-0.0268	-0.0246	-0.1188**	-0.1196*
	(0.0535)	(0.0535)	(0.0631)	(0.0632)
Log State GDP per Capita	0.1736*	0.1776*	0.0112	0.0052
	(0.1049)	(0.1049)	(0.1186)	(0.1186)
Constant	-2.4154	-2.498	4.7679**	4.8477**
	(1.7292)	(1.7334)	(1.9041)	(1.9116)
Observations	23,059	23,059	12,221	12,221
Individuals	13,323	13,323	6,812	6,812
R^2 within	0.0832	0.0833	0.1314	0.1314
R^2 between	0.0038	0.0041	0.0071	0.0071
R^2 overall	0.0099	0.0103	0.0096	0.0096
Fixed Effects				
Individual	Y	Y	Y	Y
Year	Y	Y	Y	Y
State	Y	Y	Y	Y

Notes: *p<0.1;**p<0.05;***p<0.01
Models included but did not report individual control variables
Models presented with robust standard errors

The first subgroup analysis divides the sample into two mutually exclusive groups according to primary job activity, comparing individuals who primarily perform R&D

and individuals who primarily teach. In theory, R&D tax credits should only affect the movement of people who primarily perform R&D. Table 5 presents the results of this analysis. Columns 1 and 2 display the results for the R&D worker subgroup and show both R&D credit variables (dummy and dosage) and R&D spending have a stronger and more significant relationship with moving to a state than the general analysis. Column 3 and Column 4 display the results of the teacher subgroup analysis and show no relationship between movement and either R&D tax credit variables or R&D spending in general for individuals who primarily teach. Higher education revenue is an insignificant predictor of movement for R&D workers but almost doubles in magnitude for teachers. There is no notable change in the individual control variables. These results support the finding that the relationship between R&D tax credits and the movement of PhDs is theoretical and not spurious.

The second subgroup analysis divides the original sample into two different mutually exclusive subgroups according to sector: individuals who only work for a for-profit company and individuals who work in either a 2-year or 4-year college. Theoretically, R&D tax credits should have more of an effect on individuals working in a for-profit sector. Table 6 reports the results of the sector subgroup analysis with the for-profit subgroup displayed in Columns 1 and 2 and the college sector subgroup in Columns 3 and 4. The for-profit group is slightly more likely to move to states with R&D tax credits, though the dosage effect is insignificant. High Education Revenue is significant for this subgroup but not the college subgroup. Moreover, state GDP per capita ceases to be significant at the 95% level for the college subgroup, though state unemployment remains significant. Unlike the first subgroup analysis, the results from this analysis are less clear. The ambiguity is likely due to individuals in the for-profit sector not necessarily performing R&D and individuals working in universities potentially interfacing with industry. While further subgroup analysis may be able to untangle this ambiguity, further dividing the sample into increasingly smaller subgroups is ill-advised.

Table 6: Sector Robustness Check

	For-Profit		*College*	
	(1)	(2)	(3)	(4)
R&D Credit	0.0291**		0.0149*	
	(0.0141)		(0.0078)	
Log R&D Claim		0.0016*		0.0008*
		(0.0009)		(0.0005)
Log R&D Spending	0.1291***	0.1284***	0.0660***	0.0658***
	(0.0300)	(0.0300)	(0.0184)	(0.0184)
State Unemployment	0.0018	0.0016	0.0079***	0.0079**
	(0.0049)	(0.0049)	(0.0031)	(0.0031)
Log Higher Education Revenue	-0.1715***	-0.1699***	-0.0699*	-0.0696
	(0.0593)	(0.0593)	(0.0424)	(0.0424)
Log State GDP per Capita	0.2834**	0.2772**	0.1414*	0.1386*
	(0.1246)	(0.1246)	(0.0748)	(0.0749)
Constant	-4.9862	-4.9429	-4.9862	0.8852
	(3.0447)	(3.0485)	(3.0446)	(1.2372)
Observations	18,705	18,705	27,579	27,579
Individuals	9,546	9,546	13,200	13,200
R^2 within	0.0585	0.0584	0.0972	0.0972
R^2 between	0.0098	0.0098	0.0061	0.0062
R^2 overall	0.0056	0.0056	0.0127	0.0128
Fixed Effects				
Individual	Y	Y	Y	Y
Year	Y	Y	Y	Y
State	Y	Y	Y	Y

Notes: *p<0.1;**p<0.05;***p<0.01
Models included but did not report individual control variables
Models presented with robust standard errors

Limitations

One should consider several limitations when interpreting these results. First, the use of state-level fixed effects means most of the variance in state-level indicators results from an individual moving between states rather than from changes within a state. While this is useful for interrogating how R&D tax credits can result in in-migration, it is difficult to tell whether R&D tax credits can retain someone in the state. Second, these findings have limited generalizability beyond which factors affect the movement of PhDs. Though PhDs certainly have high levels of human capital, the uniqueness of the academic labor market makes the findings less generalizable to other forms of highly educated workers (e.g., lawyers, medical doctors, or engineers). Third, using a PhD's employer's address instead of home address to determine moves exposes the paper to measurement errors resulting from PhDs working remotely or commuting between multiple states. In a similar vein, the model cannot consider factors that lead to someone moving to a different local economy within a state, such as moving from southern California to northern California. Fourth, the state economic variables only capture a small aspect of a state economy, ignoring cultural or technological changes within the state. The model assumes states do not significantly change these unobserved factors from year to year. Additionally, state-level economic variables are aggregate measures of a state's economy and do not control for local-level economic conditions. Fifth, the panel is unbalanced with gaps in both the reference years and responses by individuals; this exposes the findings to cross-sectional issues.

Discussion

Evidence supports a positive relationship between state R&D tax credits and the probability PhDs move. This significant finding demonstrates state economic development policy has the potential to impact the movement of highly skilled laborers, in addition to their intended purpose of improving R&D spending. The observed relationship between R&D tax credits and PhDs moving to a state implies R&D tax credits may incidentally help states address STEM worker shortages. Furthermore, this demonstrates the potential economic development policies must affect the movement of labor between states.

The relationship between R&D tax credits and the movement of PhDs is further confirmed by the subgroup analysis. The subgroup analysis demonstrates these tax credits affect the movement of R&D workers but not PhDs who primarily teach. If an equivalent relationship between the tax credits and the movement of PhDs across both subgroups existed, the correlation between movement and tax credits could be considered spurious. However, because the relationship holds only for PhDs whose employment is directly affected by the tax credit, there is evidence a relationship between tax credits and PhD movement exists that warrants further exploration.

This study also finds the positive relationship between R&D spending by firms in a state and PhDs moving to that state to be significant. Given the larger magnitude of R&D spending on movement over tax credits, this finding suggests policies that incentivize R&D spending (e.g., sales tax exemptions, R&D job credits) by firms can also alter the movement of workers. Scholars suggest local economic conditions play an important role in the movement of workers (Borjas, Bronars, & Trejo, 1992; Gottlieb &

Joseph, 2006; Mathur, 1999; Regets, 2001; Salt, 1992; Schwartz, 1973; Stark & Bloom, 1985). However, this study's findings suggest some local economic conditions (namely unemployment) may have a smaller impact on the movement of highly skilled labor like PhDs. The lack of significance of unemployment suggests PhDs are subject to different economic conditions than more conventional workers. This is likely due to a PhD facing a different labor market than workers with less human capital. The implication of PhDs not being responsive to certain labor market conditions warrants research into alternative explanations for the mobility of highly skilled workers (e.g., amenities).

This study found, surprisingly, a strongly negative and significant relationship between higher education revenues in a state and PhDs moving to that state. This variable should be a proxy for the state's production of human capital from education, which implies a high supply of skilled labor. This finding suggests one possible explanation: as a state's level of human capital increases, achieving a PhD level of education gives a worker a smaller advantage over less well-educated peers. Alternatively, states might increase their spending on higher education because they are suffering a brain drain. This explanation is consistent with Stephan's (2006) finding that midwest states lose a high number of PhDs to coastal states despite spending more on higher education and producing more PhDs.

Extensions for Future Research

The findings in this paper suggest several new directions for research. While the research establishes a connection between R&D tax credits and the movement of PhDs, other state economic-development policies can be evaluated similarly. States that subsidize PhD education lose their investment when the PhD moves away. This problem is alleviated if a state attracts a corresponding number of PhDs. Moving the unit of analysis to the state level can help assess how state policies affect the aggregate amount of PhDs and other forms of highly skilled labor. Another extension of this study is testing the impact of R&D tax credits on workers with lower levels of human capital, specifically workers with Master's and Bachelor's degrees in STEM fields. Another approach could be exploration of the factors and policies that determine which states a PhD moves to immediately following graduation. This would allow states to focus on attraction and retention before the PhD joins the workforce.

It should be noted a few states have implemented policies aimed directly at attracting researchers to move there. Georgia, New York, and California among others have all adopted programs aimed at attracting "star" scientists. These programs work by providing state funding to universities to recruit world-renowned researchers to state universities. The hope is these stars will attract other researchers. This study did not directly control for these programs, but a natural extension would be consideration of the R&D credits in the evaluation of star science programs.

Conclusion

This paper found a positive relationship between state R&D tax credits and PhDs moving to a state. The findings suggest states with economic-development policies (R&D

tax credits) can draw highly skilled labor (PhDs) to move to those states. While the magnitude of the unique effect of tax credits on mobility is small, the findings suggest policies incentivizing R&D spending in the private sector can increase the probability PhDs move to a particular state. Furthermore, increasing economic prosperity has an even larger effect on the movement of PhDs. This adds to the literature confirming state policies can affect migration and should encourage scholars to think about economic development in terms of attracting human capital. The findings also encourage human-capital scholars to consider how workers with different levels of human capital respond to certain economic conditions. These findings suggest a few key implications for policymakers. State-level policies aimed at increasing R&D spending by firms generate a positive effect on the mobility of highly skilled labor. Consequently, states facing STEM worker shortfalls may find other policies aimed at incentivizing firm behavior can attract highly skilled labor.

CHAPTER 3

R&D TAX CREDITS AND INNOVATION

Introduction

States incentivize research and development (R&D) because it encourages companies to innovate. Innovation and R&D provide several positive economic-development implications in terms of new jobs, increased productivity, and higher wages (Audretsch & Feldman, 1996; Bolívar-Ramos, 2017; M. P. Feldman & Audretsch, 1999b; Romer, 1989). The most common form of state incentive aimed at increasing R&D spending by firms is the R&D tax credit (Hearn et al., 2014). Researchers have found R&D tax credits are effective in boosting R&D spending and R&D spending is associated with higher levels of innovation, but there have been few attempts to measure or estimate the impact of R&D tax credits on innovation (B. Becker, 2015; Chiang et al., 2012; Hearn et al., 2014; Wu, 2005, 2008).

The majority of states have implemented a form of R&D tax credits and spend an average of $1.54 billion on R&D tax credits annually. In a time of increased fiscal constraints for governments and increased public scrutiny of economic development policies, it is necessary to evaluate whether tax expenditures are having the intended outcome for the states that implement them (Campbell & Sances, 2013; Hall & Van Reenen, 2000). High-profile cases like Amazon’s H2 bidding have only increased this scrutiny and should push public officials to reexamine economic-development policies. The literature has long been skeptical of the efficacy of most economic development policies that are cash transfers to corporations, like tax credits (Amin, 1999; Jimenez, 2018; McDonald et al., 2019). However, the literature has a more optimistic view of R&D tax credits because the evidence suggests they increase R&D spending, which has positive economic-development implications due to endogenous growth (Audretsch & Feldman, 1996; Bolívar-Ramos, 2017; Romer, 1989).

Most studies into the efficacy of R&D tax credits look only at the impacts of these credits on R&D spending but are unable to connect the credit to innovation directly (Acs et al., 2002; Wilson, 2009; Wu, 2008). Instead, these studies rely on literature that demonstrates R&D spending is associated with innovation and assume R&D tax credits lead to higher levels of innovation. Becker (2015) raises the concern that the increased R&D spending brought on by these tax credits is not enough to produce new knowledge but instead generates slack associated with R&D, such as more funding for administrative costs and supplies. This paper seeks to address these concerns by examining the indirect relationship between R&D tax credits and innovation within a state's economy.

In this study, a structural equation model measures the indirect effect of R&D tax credits on innovation using data drawn from all U.S. states over 15 years. Structural equation modeling is particularly useful for answering this question because it allows one to estimate indirect effects and to consider innovation as a latent variable constructed from a factor of related measures (Kline, 2016). The paper examines this relationship using a cross-lag model, which reveals the indirect effect of R&D tax credits on innovation is positive.

The rest of the paper is structured as follows: first, background on the structure of R&D tax credits is presented and the literature on the tax credit's effect on R&D

spending—and how past studies have measured innovation—is reviewed. A hypothesis motivating the indirect relationship between R&D tax credits and innovation is then developed. The data used in this study is presented and the analytical strategy is justified. Next, the results of the empirical analysis are discussed. Finally, the results and the implications for future research are presented.

Literature Review

Minnesota adopted the first state R&D tax credit in 1982. The policy has since expanded to 37 states (Hearn, Lacy, & Warshaw, 2014; Wilson, 2005) Though the exact structure and rate of these credits vary by state, the credit generally allows firms to receive a discount on taxes owed as a percentage of incremental increases in annual R&D spending. Firms can receive both state and federal tax credits. When designing tax credits, most states use the federal R&D tax credit as a basis for determining what qualifies as R&D spending, with the added caveat that firms can only claim credit for R&D spending within the state. Firm expenditures on process improvement, elimination of uncertainty, development of new technology, and generation of knowledge are eligible for the federal credit. Activities like reverse engineering, product improvement after commercialization, software development, and market research do not qualify as R&D spending (Chiang et al., 2012).

Extensive literature on R&D tax credits exists, making it one of the most well-studied tax incentives (Fichtner & Michel, 2015). Scholars have examined the conditions that lead to the adoption of these tax credits, their impact on private-sector R&D

spending, their diffusion by state, and how the structure of the tax credit changes its effectiveness (Chiang et al., 2012; Finley et al., 2014; Hearn et al., 2014; Miller & Richard, 2010; Wu, 2008). Hall and Reenen (2000) conduct an exhaustive study of the association between fiscal incentives and R&D spending in a wide range of industrialized countries; they conclude R&D tax credits are positively associated with R&D intensity, the ratio of R&D spending to sales. Wu (2008) performs a cross-state empirical study to measure the positive effects of R&D tax credits on R&D expenditures in states.

R&D tax credits are one of the most common ways for states to incentivize R&D spending by firms (Biggins et al., 2017; Wu, 2008). States incentivize research-and development spending because of its link to endogenous economic growth (Jones, 1995; Stokey, 1995). Endogenous growth is the theory that knowledge spillovers from activities such as R&D can generate internally driven growth (Romer, 1989). R&D spending directly improves firm performance through increasing the availability of technology, productivity, and innovation (Audretsch & Feldman, 1996; Audretsch & Keilbach, 2004b; Mansfield, 1972). More importantly for economic development, R&D spending has positive externalities for state residents because these performance benefits for firms spill over into the rest of an economy (Coe & Helpman, 1995; Klaassen et al., 2005).

The primary motive for incentivizing R&D spending is to increase innovative activity (Almus & Czarnitzki, 2003). Studies focusing on the effectiveness of R&D tax credits tend to consider these credits only in terms of R&D spending (B. Becker, 2015; Chiang et al., 2012). This approach is problematic because R&D spending represents a budgetary allocation of resources to generate new ideas and processes (i.e., innovation) but does not measure outcomes associated with increased R&D spending. This paper seeks to address this hole by connecting R&D credits to innovation using R&D spending as a mediating variable.

Most studies connecting R&D spending to innovation rely on patent counts as the sole measure of innovation (Acs et al., 2002; Becker, 2015). State patenting data are a relatively reliable measure of literature-based innovation counts, a direct indicator of innovative outputs (Acs et al., 2002). However, state patent data are susceptible to error because they do not measure the economic value of these technologies, not all new innovations are patented, and patents can vary greatly in their impact (Griliches, 1981; B. Hall et al., 2001; Pakes & Griliches, 1980). Patents only measure one aspect of innovation. To determine other indicators of innovation, it is useful to consider when firms attempt to innovate.

Firms innovate when they are seeking to build capacity for future growth, which occurs at two stages in a firm's life cycle: during startup and when they have become stagnant (Chiang et al., 2012; Mazzarol et al., 2010). During these stages, firms seek to leverage innovation to gain a competitive advantage (Schumpeter, 2003). When firms innovate, they seek to protect their competitive advantage through patents and to secure funding to marketize the innovation (Porter, 1980). One way for firms to secure funding for growth is through venture capital firms. Kortum and Lerner (2000) find increases in venture capital funding in industries are associated with significantly higher levels of patenting. Hirukawa and Ueda (2011) argue innovation and venture capital funding occur non-recursively, where higher levels of patenting lead to more venture capital funding, and the availability of venture capital funding stimulates innovative activity among firms. Government grants for small businesses are another source of funding that innovative firms can pursue.

The Small Business Industrial Research Program (SBIR) and Small Business Technology Transfer Program (STTR) are government grants administered by the Small Business Administration (SBA). They are available to small businesses and startups that have developed some innovation and are attempting to bring that innovation to market. SBA awards grants to companies whose innovation aligns with the strategic interests of participating federal agencies. These interests are either aligned with supporting the agency mission directly or with furthering economic activity along the lines of the agency's goals (Shepard, 2017). In effect, firms apply for these grants to receive funding that allows them to capitalize on innovation. Lanahan and Feldman (2019) connect Federal SBIR and STTR awards to innovation within a state.

This paper considers innovation in terms of the marketization of a new process or technology (Schumpeter, 2003) and thus seeks to measure innovation in terms of protecting the innovation through patenting and securing funding for bringing the innovation to market. This conceptualization provides a more robust understanding of innovation than previous studies that measure innovation by patent counts alone (Acs et al., 2002). The paper also significantly contributes to the conceptualization of innovation as a factor of patents and funding.

Hypothesis Development

The literature provides ample evidence demonstrating the positive relationship between R&D tax credits and R&D spending (Chiang et al., 2012; Wilson, 2009; Wu, 2005). Additionally, many scholars have connected R&D Spending to indictors of innovation like patents (Acs et al., 2002; Antonioli et al., 2014; B. Becker, 2015; Finley et al., 2014). The question therefore is, do R&D tax credits sufficiently boost R&D spending to result in increases in innovation? In other words, what is the indirect impact of R&D tax credits on innovation mediated by R&D spending?

There are reasons to suspect R&D tax credits do not sufficiently incentivize R&D spending to increase overall innovative activity. The structure of the tax credit means firms receive a relatively small decrease in tax liability in response to accelerating R&D spending (Hearn et al., 2014). Becker (2015) suggests this marginal cheapening of R&D spending results not in the pursuit of innovation but rather in additional slack in a firm's production function. Wilson (2009) argues large firms may be responding to state tax credits by relocating R&D spending toward states with more generous tax credits without significantly changing their overall level of R&D. However, if these critiques of R&D tax credits are valid, endogenous growth theory suggests the credits may still have an impact on innovation.

Endogenous growth theory suggests knowledge spills over in a quasi-random process that is accidental and not purposeful (Feldman & Lowe, 2015). R&D has an immediate benefit for the firms producing new knowledge. Spillovers occur when this new knowledge is applied to solve unrelated problems or by people external to the original researchers (Martin & Sunley, 1998). Even if R&D tax credits only increase slack in a firm's production function, it might allow researchers to take risks they did not have the resources to pursue otherwise. In the case of firms relocating R&D, increased research intensity by a firm in a state might interact with other research activities happening in the state to spur innovation. This theory supports the following hypothesis:

H1: R&D tax credits, mediated by R&D, have a positive and indirect effect on innovation.

Data & Methods

This study uses publicly available datasets of state-level science and technology (S&T) indicators to examine the relationship between R&D tax credits and innovation. This data is leveraged by a cross-lagged structural equation model that tests the indirect influence of R&D credits on innovation. This section discusses the data used in the study and the analytical approach used to estimate a latent innovation variable, the cross-lagged model, and the limitations of this analytical approach.

Data

Data for this study comes from two sources. The National Science Foundation biennially collects data on state S&T indicators (Khan, 2016). The National Center for Science and Engineering Statistics (NCSES) aggregates these variables drawn from many individual reports. The R&D tax credit variable discussed later is the only variable not drawn from NCSES's statewide indicators. Data come from all 50 states and Washington D.C. from 2000–2015, meaning the study has a total of 816 observations. Each variable in the study is divided by a state's population, which accounts for differences in population size between states. The results are standardized to aid in the convergence of the cross-lagged structural equation model (Hamaker et al., 2015; Kline, 2016). The major limitation of this standardization is it limits the interpretability of the model results. Table 1 displays the descriptive statistics of each variable.

Table 1: Descriptive Statistics

Variable	Obs.	mean	median	std.dev	min	max
Corporate.Rnd.Claimed	699	3.31E+07	8.70E+05	1.72E+08	0	2.20E+09
Company.RnD	810	3.93E+09	1.12E+09	8.50E+09	7.00E+06	9.50E+10
Patents.awarded	663	2.00E+03	8.42E+02	4.02E+03	1.80E+01	4.05E+04
Average.SBIR.and.STTR.funding	408	4.18E+07	1.62E+07	7.25E+07	3.69E+05	4.77E+08
Venture.capital.deals	765	9.68E+01	2.30E+01	2.96E+02	0	3.37E+03
Venture.capital.disbursed	765	7.41E+08	9.72E+07	2.95E+09	0	4.26E+10
State.GDP	765	2.79E+11	1.72E+11	3.47E+11	1.73E+10	2.51E+12

Innovation is a latent variable constructed using the number of patents filed in a state, the dollar value of SBIR and STTR grants awarded to new technology companies, the quantity of venture capital deals performed, and the amount of venture capital dollars awarded to companies in a state. The number of patents filed in a state in a given year is a standard measure associated with innovation (Acs et al., 2002; B. Becker, 2015). It captures the number of new technologies or processes protected by patents. SBIR and STTR are two federal programs designed to provide grant money to small businesses to aid these companies in bringing innovations to the market (Shepard, 2017). The SBA only awards these grants to companies that can demonstrate the viability of a new product or technology, and payments are structured to happen as companies reach milestones in commercializing their innovation (Lanahan & Feldman, 2017). Venture capital funding and deals both occur when firms are raising equity for growth, and most justify the potential of that growth to investors. As with the SBIR and STTR awards, firms should only be seeking this funding after an innovation has been developed (Shepard, 2017). The innovation factor has a Cronbach alpha of 0.966.

The variable R&D Spending measures the amount of R&D spending firms engage in within a state. The Business Research and Development Innovation Survey (BRDIS), an annual survey of state businesses, collected data on company R&D spending (*Business R&D and Innovation Survey*, 2018). The key exogenous variable is the amount of R&D tax credits claimed by companies within a state. This variable comes from annual tax expenditure reports published by each state. Measuring the R&D tax credit as an aggregate dollar amount has two benefits over measuring R&D tax credits in terms of the rate of the credit. First, the dollar amount claimed by firms within a state is agnostic to the structure of the tax credit in each state. Secondly, it measures the extent to which corporations utilize the policy.

The study uses state gross domestic product (GDP) as a covariate. This control variable accounts for the effects of the economy on R&D spending and innovation and is a common control variable in studies that examine R&D tax credits (Duguet, 2012; Finley et al., 2014; Hearn et al., 2014; Wilson, 2009). This variable comes from the Bureau of Economic Analysis (*GDP & Personal Income*, 2019).

Methods

A cross-lagged model, a type of structural equation modeling, is used to measure the effect of R&D tax credits on innovation. Structural equation modeling allows one to measure latent variables, like innovation, and predict the indirect effects of variables. The analysis of the structural equation model proceeds in two steps. First, a confirmatory factor analysis estimates the latent innovation variable. Next, a partial cross-lagged model is constructed to disentangle any potential non-recursive effects in the model.

The first step of the analytical approach uses a confirmatory factor analysis (CFA) to check the validity of the innovation measurement model. Confirmatory factor analysis is particularly useful in measuring a multi-faceted variable that cannot be measured directly (Kline, 2016). The measurement model includes only the innovation latent variable and its indicators. This model confirms each latent variable is successfully estimated (Anderson & Gerbing, 1988). The strength of using a latent variable for innovation is it allows for multiple measures of innovation and accounts for some measurement error (Denti, 2013; Kline, 2016). Figure 1 presents a diagram of the innovation factor.

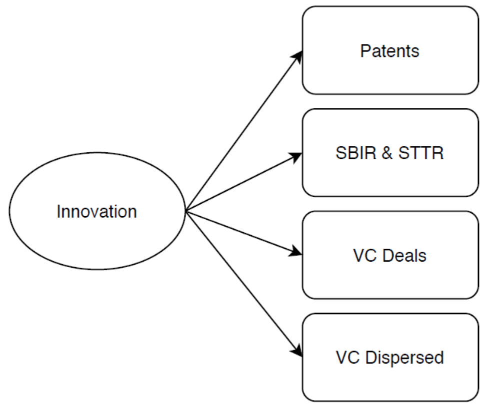

Figure 1: Innovation CFA Model

Patents refers to the number of patents filed within a state. SBIR & STTR refers to the value of federal grants awarded to companies each year through the SBIR and STTR programs. VC deals refer to the number of venture capital deals negotiated within a state, and VC funding refers to the amount of venture capital funding dispersed within a state.

The second step of analysis implements a cross-lag model. A cross-lag model regresses each variable in the *t-th* year against all variables of interest in year *t-1*. This process is then repeated for variables in year *t-1* against variables in *t-2*. The benefit of a cross-lag model is it can disentangle non-recursive relationships by examining the ability of lagged variables to predict contemporaneous variables (Pearl, 2009). The cross-lag model includes two years of lags because of issues associated with missing data in the

R&D tax credit variable and the loss of observations. Figure 2 presents the cross-lag model.

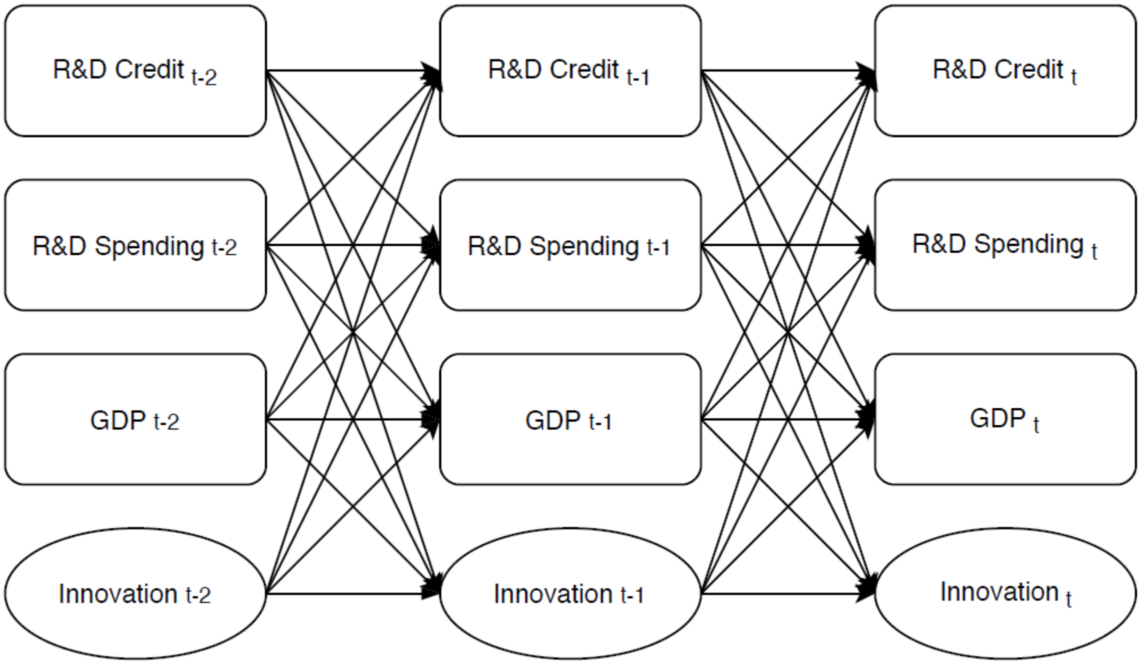

Figure 2: Cross-Lag Model

R&D credit refers to the dollar value of credits claimed by companies in the *i-th* state and in the *t-th* year. R&D refers to the amount of R&D spending by companies. Innovation refers to the latent measure of innovation discussed above, and State GDP serves as a control variable. The benefit of a cross-lag model is it accounts for temporal stability though the use of stabilization terms (Hamaker et al., 2015). In a cross-lag model, a stabilization term refers to the path between the same variable over two years, for instance, $R\&D_{t-1}$ and $R\&D_t$. The cross-lag model also has a considerable number of allowed covariances. The outcome variables in year *t* covary with all other variables in year *t*, as are all variables in year *t-1* and year *t-2*. Variables predicted by the latent innovation variable covary across years. For example, patents in year *t* covary with patents in year *t-1* and year *t-2*. The same is true for SBIR & STTR awards and the venture capital variables. This covariance strategy follows accepted practices for cross-lag models (Kline, 2016).

Models are estimated in R using the *Lavaan* package (version 0.6-3) with a maximum likelihood estimator with robust standard errors. The maximum likelihood estimator is a full information estimator, meaning the model attempts to estimate missing values where possible. This approach is used when the data are missing at random (Kline, 2016), which is a reasonable assumption because the bulk of missing variables are due to the uneven adoption of tax expenditure reports by states. In addition to the parameter estimates, the results include a variety of model fit indices. First, an X^2 test of perfect model fit is employed. Then the models are evaluated according to their comparative fit index (CFI) and root means square error approximation (RMSEA). The results report the RMSEA as both the mean RMSEA and 90% confidence interval because it is an approximation. The model fit is also assessed using the standardized root mean square residual (SRMR).

Limitations

The analytical strategy pursued in this paper has several limitations that need to be addressed. Ideally, a cross-lag panel model would have a different variable for each year of the study, which was not possible due to both the inability to sample more states and missing tax expenditure reports for some states in the early years of the study. Additionally, the stabilization terms in a cross-lag model only measure temporal stability and do not account for trait-level stability. In other words, the model can account for differences in time trends but not for static differences between states. This may bias the results depending on the strength of the stability terms. Stability terms that approach zero tend to over-estimate the effects, while stability terms approaching one understate them. (Hamaker et al., 2015). The cross-lag model also sacrifices any contemporaneous effects of variables, which are absorbed by the stability terms.

The model is also limited by omitted variable bias, such as information on industries within states. Another limitation is the inability to model firm-level decisions. The study aggregated data to the state level, which means it is not possible to discuss how firms or industries responded to the tax credit; instead, the analysis is limited to discussing the state-level trends. This approach misses some important details, such as answering Wilson's (2009) concern that firms are moving R&D to states with generous tax credits versus producing new R&D. In a similar vein, the innovation factor is only capturing one aspect of innovation. That aspect is probably the most applicable to R&D spending and tax credits; however, this approach misses other ways scholars have conceptualized innovation, like innovative culture (Florida, 2014; Tabellini, 2010).

Results

The first step of the analysis is a CFA of the latent innovation variable. Patents are used as the scaling term for the innovation factor because of patents' long history of being used as a proxy of innovation (Acs et al., 2002; B. Becker, 2015). Factor loadings for SBIR & STTR awards, venture capital deals, and venture capital dispersed are all greater than 1 and significant. With an X^2-test statistic of 24.543, the model does not pass the X^2 test of perfect model fit. The CFA model has a CFI of 0.994, and an SRMR of 0.012, which both suggest the model is an excellent but not perfect fit for the data. A CFI of 0.95 indicates an ideal level of fit, and a CFI of 0.90 indicates an acceptable level of fit. Likewise, an SRMR of 0.05 is a high level of fit, and an SRMR of 0.10 is an acceptable level of fit. Unfortunately, the model's RMSEA is higher than desirable. Ideally, the RMSEA upper confidence level is less than 0.05 but is acceptable if below 0.10 (Kline, 2016). Except for the RMSEA statistics, the CFA model has an acceptable level of fit. This process is repeated for a measurement model at *t-1* and *t-2* with similar results. The results of the CFA model are presented in Table 2. Table 3 presents the fit statistics of the two models.

Table 2: Innovation CFA

Variable	**Loading**
Patents	1
SBIR & STTR	0.953 ***
VC Deals	1.102 ***
VC Dispersed	1.055 ***

Table 3: Fit Statistics

	χ^2	CFI	SRMR	RMSEA	90% Conf. Interval
CFA Model	19.377	0.99	0.028	0.107	0.067 – 0.152
Cross-Lag model	1791.744	0.925	0.216	0.123	0.118 – 0.128

Estimating the cross-lag model is the second stage of empirical analysis. The cross-lag model has a CFI of 0.938 and an SRMR of 0.093, which suggests an acceptable level of fit. This model's RMSEA score is 0.110, which is less than ideal. The stabilization terms are positive and significantly related to the predicted variable in all cases. For instance, innovation at year *t-2* is significantly related to innovation in year *t-1*, and innovation in year *t-1* is significantly related to innovation in year *t.* This means State GDP, Innovation, and R&D tax credits are relatively stable over time. It is noticeable that only R&D spending has stabilization terms that are not approximately equal to 1. This implies R&D spending is less a function of the previous year's R&D spending than innovation, state GDP, or the R&D tax credits. The results of the cross-lag model are displayed in Table 4.

Table 4: Cross Lag Model

T-2 → T-1		T-1 → T	
Path	**Estimate**	**Path**	**Estimate**
$Innovation_{t-2} \rightarrow Innovation_{t-1}$	1.094 ***	$Innovation_{t-1} \rightarrow Innovation_{t}$	1.059 ***
$R\&D\ Spending_{t-2} \rightarrow Innovation_{t-1}$	-0.015	$R\&D\ Spending_{t-1} \rightarrow Innovation_{t}$	0.017 **
$State\ GDP_{t-2} \rightarrow Innovation_{t-1}$	0.009	$State\ GDP_{t-1} \rightarrow Innovation_{t}$	-0.009
$R\&D\ Credit_{t-2} \rightarrow Innovation_{t-1}$	0.008	$R\&D\ Credit_{t-1} \rightarrow Innovation_{t}$	0.007
$Innovation_{t-2} \rightarrow State\ GDP_{t-1}$	-0.022	$Innovation_{t-1} \rightarrow State\ GDP_{t}$	0.006
$R\&D\ Spending_{t-2} \rightarrow State\ GDP_{t-1}$	-0.012	$R\&D\ Spending_{t-1} \rightarrow State\ GDP_{t}$	0.022 **
$State\ GDP_{t-2} \rightarrow State\ GDP_{t-1}$	0.994 ***	$State\ GDP_{t-1} \rightarrow State\ GDP_{t}$	1.003 ***
$R\&D\ Credit_{t-2} \rightarrow State\ GDP_{t-1}$	0.022	$R\&D\ Credit_{t-1} \rightarrow State\ GDP_{t}$	-0.003
$Innovation_{t-2} \rightarrow R\&D\ Spending_{t-1}$	0.130 ***	$Innovation_{t-1} \rightarrow R\&D\ Spending_{t}$	0.152 ***
$R\&D\ Spending_{t-2} \rightarrow R\&D Spending_{t-1}$	0.693 ***	$R\&D\ Spending_{t-1} \rightarrow R\&D Spending_{t}$	0.705 ***
$State\ GDP_{t-2} \rightarrow R\&D\ Spending_{t-1}$	0.015	$State\ GDP_{t-1} \rightarrow R\&D\ Spending_{t}$	0.002
$R\&D\ Credit_{t-2} \rightarrow R\&D\ Spending_{t-1}$	0.126 ***	$R\&D\ Credit_{t-1} \rightarrow R\&D\ Spending_{t}$	0.119 ***
$Innovation_{t-2} \rightarrow R\&D\ Credit_{t-1}$	0.02	$Innovation_{t-1} \rightarrow R\&D\ Credit_{t}$	0.037
$R\&D\ Spending_{t-2} \rightarrow R\&D\ Credit_{t-1}$	-0.023	$R\&D\ Spending_{t-1} \rightarrow R\&D\ Credit_{t}$	0.018
$State\ GDP_{t-2} \rightarrow R\&D\ Credit_{t-1}$	0.042	$State\ GDP_{t-1} \rightarrow R\&D\ Credit_{t}$	-0.024
$R\&D\ Credit_{t-2} \rightarrow R\&D\ Credit_{t-1}$	0.952 ***	$R\&D\ Credit_{t-1} \rightarrow R\&D\ Credit_{t}$	0.96 ***
		Path	**Estimate**
Indirect effects:		$R\&D\ Credit_{t-2} \rightarrow R\&D\ Credit_{t-1} \rightarrow Innovation_{t}$	0.002**

Outside of the stabilization terms, R&D spending at year *t-1* is the only variable significantly predicted by variables from year *t-2*. R&D tax credits are positively and significantly related to R&D spending in these years. Innovation in year *t-2* is only significant and positively related to R&D spending in year *t-1 (*β = 0.130). R&D spending and State GDP are only significant predictors of themselves from year *t-1* to *t-2*.

There are more significant paths between the variables at year *t* and year *t-1*. R&D tax credits in the previous year is a significant predictor of current R&D spending (β = 0.119) and does not have a significant relationship with any of the other current variables. R&D spending at *t-1* is a positive and significant predictor of State GDP (β = 0.022) and innovation. State GDP in year *t-1* does not predict any variables in year *t*. Innovation in *t-1* is a significant predictor of current R&D spending (β = 0.152).

In the cross-lag model, there is not a significant direct effect of R&D tax credits on innovation in either of the two years. However, it is possible to calculate the indirect effect of these credits on innovation, as mediated by R&D spending. The relationship between R&D tax credits at *t-2* and R&D spending at *t-1* is positive and significant (β = 0.126). R&D spending at *t-1* is significant and positively related to innovation at *t (*β = 0.017). The indirect effect of R&D tax credits on innovation, as mediated by R&D spending, is positive and significant but has a minimal effect (β = 0.002). This result provides evidence that R&D tax credits do have a positive impact on innovative activity within a state's economy, but that effect is mediated through its effect on R&D spending.

Discussion

The confirmatory factor analysis performed on the latent innovation variable finds innovation can be modeled in terms of patents, federal grants for small businesses marketizing innovations, and venture capital activity occurring within the state. While this approach only captures one aspect of innovation—the marketization of new technologies and processes—it provides a way of examining state-level innovative activity in a more robust manner than looking at patents alone, which is how innovation has traditionally been measured (Acs et al., 2002; Almus & Czarnitzki, 2003; Balzat, 2006). The findings suggest the measure of innovation is relatively robust, as evidenced by the CFA model's high level of fit and the stability of the measure over time.

The results of the cross-lag models suggest R&D tax credits incentivize R&D spending, which aligns with the literature (Chiang et al., 2012; Wilson, 2009; Wu, 2005, 2008). The model also suggests R&D spending is associated with innovative activity occurring within a state. There is evidence of an indirect effect between R&D credits and innovation, mediated through R&D spending, but there is not a direct effect between these two variables. Additionally, the significant and positive relationship between R&D spending and innovation only occurs between the two most recent years in the study. These results suggest the connection between R&D spending and innovation is more tenuous than the connection between R&D tax credits and R&D spending.

The results of the cross-lag model provide evidence that R&D tax credits have a significant indirect relationship with innovative activity within a state's economy. Innovation's stability term being near 1 may result in the model estimating more conservative results (Hamaker et al., 2015), which when combined with the issues of interpretability of the latent variable means it is difficult to estimate the extent of the indirect relationship between these tax credits and innovation. This is not to say the findings are not meaningful, but caution should be taken in making policy and budgeting decisions based on these findings alone.

The stabilization terms in the cross-lag model provide some interesting results. It is not surprising the past trends are significant and positive predictors of future trends; however, what is surprising is the strength of these relationships. Except for R&D spending, the stabilization terms explain most of the variance in their related terms. Importantly, innovation does not have a significant direct or indirect effect on State GDP, a measure of economic activity. Furthermore, State GDP is only a significant predictor of other years of State GDP. These results should not be taken to mean there is no relationship between innovation and economic activity, but it does suggest innovation does not have an immediate impact on the economy. Part of this finding may be due to this study estimating innovation in terms of events that occur when firms develop technology and processes but before they bring them to market. This result implies R&D tax credits likely are not able to provide short-term economic growth and more research is needed to understand the long-term effects of R&D tax credits on the economy.

Conclusion

The study leverages data on R&D tax credits drawn from state tax expenditure reports to determine the impact of R&D tax credits on innovation. It uses structural equation modeling and repeated observations from all 50 states and Washington D.C. to measure this effect. This study also leverages a way of measuring innovation in terms of a latent variable predicted by an aggregation of events associated with innovative periods in a firm's life cycle.

The results suggest R&D tax credits have a significant but potentially small impact on innovative activity occurring within the state that implements them. This relationship appears to be mostly mediated by the impact these tax credits have on R&D spending, which in turn increases innovation within the state that implements the tax credit. Scholars have long measured the efficacy of R&D tax credits on R&D spending and previous studies associated R&D spending with higher levels of innovation (Chiang et al., 2012; Wilson, 2009; Wu, 2005, 2008). This study is one of the first to attempt to determine if the tax credits provide a sufficient increase in R&D spending to impact innovation, and its main contribution to the literature is confirmation of this connection.

It is important to note the results of this study are not causal. While the models do have relatively high levels of model fit, there are too many omitted variables and too many limitations to claim increases in R&D tax credits cause increases in innovation. This study uses data collected over a 16-year period that includes major fluctuations in the nation's economy. The time-period begins in the waning years of the dot-com tech bubble and includes the 2008 financial crisis and resulting recovery. These events also limit the generalizability of the study.

The results of this study provide many avenues for future research. First, the construction of the innovation variable provides a more robust way of measuring innovation. This variable could be extended and applied to a variety of relevant contexts. Additionally, it might be interesting to consider the impacts of tax policies on other components of innovation, such as culture. One way to confirm the findings in this paper would be to gather firm- or industry-level data to gain a more granular understanding of the implications of the tax credit.

CHAPTER 4

R&D TAX CREDITS AND STATE FISCAL HEALTH

Introduction

States offer corporations Research and Development (R&D) tax credits to incentivize R&D, which has beneficial economic-development implications for a state's economy. In economic development, state and local governments seek two outcomes: first, the local economy grows in a way that is beneficial to their citizens; and second, this economic growth increases the government's tax revenue, which improves a state's fiscal health (Bartik, 1992). Scholars have found mixed support for the efficacy of tax credits on economic development. Tax credits and other cash-transfer economic-development policies have dubious efficacy because they can create competition between state and local governments that companies can play off of each other to receive the most generous subsidy possible for activities they were planning to perform without the subsidy (Buss, 2001). Additionally, even if corporate tax credits successfully stimulate economic development, the evidence suggests these policies can hurt the fiscal position of a state. McDonald et al. (2019) argues this is due to economic growth increasing the demand for government services while the tax credit constrains the government's ability to collect revenue off this added growth.

Research and Development tax credits differ from more traditional corporate tax credits such as job creation credits or economic opportunity zones because they incentivize R&D. Targeting R&D may be more effective at stimulating economic growth than efforts that incentivize general economic activity (Audretsch & Feldman, 1996). R&D generates knowledge spillovers, which Romer (1989) contends is a primary mechanism of endogenous growth theory. Endogenous growth theory is one of the few economic development strategies that generates net economic growth (Amin, 1999; Henderson, 2010; Martin & Sunley, 2006). R&D tax credits bring about increases in R&D spending within a local economy (Chiang et al., 2012; Finley et al., 2014), which is associated with both traditional economic growth measures—wages and productivity—but also increases innovation.

While scholars have found evidence supporting R&D tax credits' impact on the economic development of a state, there are no studies that focus on the relationship of these credits to a state's fiscal health (Bartik, 1992; Finley et al., 2014). However, there are theoretical reasons to suspect these tax credits may affect a state's fiscal health in both the short and long term. In the short term, it may take states years to see fiscal returns from R&D tax credits. Due to these competing explanations, this paper explores the question: what is the relationship between R&D tax credits and state fiscal health in both the short term and long term?

This paper offers several theoretical and empirical contributions to the literature and provides a new avenue for considering R&D tax credits as they relate to fiscal health. It is among the first studies to attempt to connect state tax expenditures to fiscal health (McDonald et al., 2019) and is the first to specifically look at the fiscal health implications of R&D tax credits. The paper explores this relationship in both the short term and long term, while other studies have focused primarily on the contemporaneous effects of tax incentives on state fiscal health.

The rest of the paper is structured as follows: first, information is provided regarding the background and structure of R&D tax credits. Next, the literature on the fiscal health implications of R&D tax credits is reviewed and a hypothesis is developed to test that relationship in the short term and long term. The Data & Methods section of the paper presents a novel way of measuring these tax credits, the dataset constructed for measuring them, and how the relationship is modeled using time-series and panel techniques. Finally, the results are presented and the findings discussed.

Background

R&D tax credits are a form of tax expenditure. A tax expenditure is an economic incentive wherein the government either does not collect taxes on a transaction or offers a direct reduction in tax liability (tax exemption and credits, respectively). Governments use tax expenditures to incentivize behavior policymakers believe will improve a state's economy (Brunori, 1997; Grady, 1987; Jensen, 2017; Leiser, 2017). State tax expenditures tend to support business-centric economic growth by encouraging job creation, industrial investment, and R&D (Donegan, Lester, & Lowe, 2018).

Minnesota adopted the first state R&D tax credit in 1982. The policy has since expanded to 37 states (Hearn, Lacy, & Warshaw, 2014; Wilson, 2005). Though the exact structure and rate of these credits vary by state, the credits generally allow firms to receive a discount on taxes owed as a percentage of incremental increases in annual R&D spending. Firms can receive both state and federal tax credits. When designing tax credits, most states use the federal R&D tax credit as a basis for determining what qualifies as R&D spending, with the added caveat that firms can only claim credit for R&D spending within the state. Firm expenditures on process improvement, elimination of uncertainty, development of new technology, and generation of knowledge are eligible for the federal credit. Activities such as reverse engineering, product improvement after commercialization, software development, and market research do not qualify as R&D spending (Chiang et al., 2012).

Extensive literature on R&D tax credits exists, making it one of the most well-studied tax incentives (Fichtner & Michel, 2015). Scholars have examined the conditions that lead to the adoption of these tax credits, their impact on private-sector R&D spending, their diffusion by state, and how the structure of the tax credit changes its effectiveness (Chiang et al., 2012; Finley et al., 2014; Hearn et al., 2014; Miller & Richard, 2010; Wu, 2008). The literature has investigated these issues at the international, national, and firm-level (Audretsch & Feldman, 1996; Duguet, 2012; Thomson, 2017; Wilson, 2009) but most efforts to understand R&D tax credits do not focus on the state/regional level.

Theory Development

A state incurs financial obligations in the form of expenditures, expenses, and debts to provide goods and services; a state is said to be fiscally healthy when it can meet these obligations without experiencing significant hardships (Higgins Jr., 1984; Wang, Dennis, & Tu, 2007). This paper defines fiscal health as, "the government's ability to adequately provide services that meet current and future obligations," a common definition in the literature (Hendrick, 2004; McDonald, 2017; Wang, Dennis, & Tu, 2007). Government fiscal health is a topic of frequent study in the public administration literature, particularly in the study of state and local government (Bahl, 1982; Clark, 1994; Dahlberg, 1966). Recently, the fiscal constraints imposed on governments by Tax and Expenditure Limits (TELs) have garnered considerable interest, because they limit a government's ability to carry debt, raise revenue, and meet the demand of expanding populations (Maher, Deller, Stallmann & Park, 2016).

The literature on economic-development tax expenditures focuses predominantly on their efficacy in encouraging economic growth (Goss & Philips, 1999; Lugar & Bae, 2005; Peters & Fisher, 2004). This focus neglects whether these tax credits are beneficial to governments that implement them, a common argument for these policies. Additionally, most studies into the efficacy of these economic-development policies reveal either mixed or negative results (Jensen et al., 2015). Furthermore, governments often fail to monitor the effects of the policies internally. While 95% of municipalities offer some form of tax expenditure incentive, only 55% use performance measures to track their implementation (ICMA, 2009). Moreover, the needs of a community are rarely used to calibrate the size of incentives.

While studies have separately discussed the impact of a state's institutional, economic, and political conditions on fiscal health, the relationship between a state's fiscal health and the offering of economic incentives has received limited attention (McDonald et al. 2019). The TEL literature provides some useful insight into studying economic incentives such as tax expenditures. TELs are legislative limits on the amount to which governments can raise taxes. They are enacted using similar justifications as for other economic incentives; a stable tax environment will encourage economic activity and incentivize firms to locate within an economy (Stallmann, Maher Deller, & Park 2017). Tax expenditure incentives behave like TELs by constraining the state's ability to raise income. For example, tax incentives in 2002 cost California $38 billion in foregone revenue (Lugar & Bae, 2005). Thus, incentives are limitations to future revenue that can be triggered by entities outside the government.

At a base level, incentives limit the revenues available for a government to collect while also requiring additional expenditures to meet the increased demand for public services that come with economic expansion (Buss, 2001). While R&D tax credits have specific benefits for economic growth, discussed below, the literature is divided on how long it can take for a firm to realize a return for investing in R&D (Griliches, 1981; Gurmu & Pérez-Sebastián, 2008; B. H. Hall et al., 1984). This lack of consensus leads to the following hypothesis:

H_1: *Increases in R&D tax credits result in short-term decreases in fiscal health.*

While most evidence on the efficacy of tax incentives and economic development is mixed, R&D has specific economic growth implications that mean it may be more effective than other forms of incentives (Jones, 1995; Stokey, 1995). R&D tax credits are the most common way for states to incentivize R&D spending by firms, and a number of studies have found they are successful in increasing R&D (Biggins et al., 2017; Wu, 2008). R&D spending directly improves firm performance through increasing the availability of technology, productivity, and innovation (Audretsch & Feldman, 1996; Audretsch & Keilbach, 2004b; Mansfield, 1972). More importantly, for economic development, R&D spending has positive externalities for state residents, because these firm-performance benefits spill over into the rest of an economy (Coe & Helpman, 1995; Klaassen et al., 2005). Public subsidies for R&D funding improve firm innovativeness

(Almus & Czarnitzki, 2003) and encourage a higher amount of spending in R&D (Lööf & Hesmati, 2004).

There are certainly reasons to suspect R&D tax credits have positive economic development implications, but those benefits may take years to manifest. There is no clear consensus on how long it may take for a firm to receive a return from engaging in R&D, and even defining or measuring this return is problematic (Mankin, 2007). If the success of R&D is measured in terms of patenting, then firms that increase R&D spending see primarily contemporaneous benefits, but defining the success in terms of increases in productivity that may take years to manifest is a much longer-term process (Almus & Czarnitzki, 2003; Gurmu & Pérez-Sebastián, 2008; B. H. Hall et al., 1984). This implies the spillover effects of R&D may occur in both the short and long term. If R&D tax credits have positive economic-development benefits in the long run, then a government should have an increased tax base (Bartik, 1992; Mansfield, 1972; Segerstrom, 1991).

An improved tax base is not sufficient to improve a state's fiscal condition, as the expenditure may be constraining the state's ability to collect revenue (McDonald et al. 2019). However, the structure of the R&D tax credit may somewhat mitigate the extent to which the credit constrains a state's fiscal condition. R&D tax credits provide a subsidy to firms that increase their levels of R&D spending. This limits the extent to which the credit constrains government revenue. Not only is the local economy benefiting from overall levels of R&D spending, but the firms must continue to accelerate R&D spending for the credit to adversely affect the state's fiscal health. Such an adverse effect is unlikely, as firms tend to make a relatively smooth investment in R&D over the long run, because R&D is associated with high adjustment costs of labor due to the high cost of hiring and firing highly skilled workers with firm-specific knowledge (G. Becker, 1994; B. H. Hall et al., 1984; Lach & Schankerman, 1989). This leads to the following hypothesis being posited:

H_2: Increases in R&D tax credits have a positive long-term impact on a state's fiscal health.

Data & Methods

Data

To determine the short- and long-term implications of R&D tax credits on the fiscal health of a state, a panel is built using repeated measures of state governments. The study period spans 2001–2015 and encompasses all 50 states, and all dollar amounts are expressed in terms of 2015 dollars. Table 1 presents the summary statistics of each of the following variables.

Table 1: Descriptive Statistics

		Variables			
Variable	Obs	Mean	Std. Dev.	Min	Max
Operating Ratio	750	1.04	0.16	0.24	1.61
%Δ Revenue	700	0.06	0.31	-0.67	4.5
Cash Ratio	750	4.58	3.04	1.07	35.97
R&D Ratio Cred	683	0.01	0.02	0	0.33
County Numbers	750	60.67	45.69	0	254
Special Districts	750	733.2	696.11	14	3249
Annual Budget	750	0.61	0.49	0	1
Party Control	750	1.25	1.17	0	3
GDP Per Capita	750	48980.33	9471.89	30564	79894
ln(GDP Per Capita)	750	10.78	0.19	10.33	11.29
Unemployment	750	0.06	0.02	0.02	0.14
Female Ratio	750	0.51	0.01	0.48	0.52
Minority Ratio	750	0.18	0.12	0.02	0.7
Elderly Ratio	750	0.13	0.02	0.06	0.19
Youth Ratio	750	0.24	0.02	0.19	0.32

One of the difficulties with measuring fiscal health is the way it is defined varies with the perspective of the party performing a study (Maher & Nollenberger, 2009; McDonald, 2018). As a result, this paper draws on several measures of fiscal health. Wang et al. (2007) consider fiscal health in terms of four broad categories: budget solvency, service solvency, cash solvency, and long-run solvency. Budget solvency refers to an organization's ability to generate sufficient revenues to fund its current or desired service levels. This paper uses an organization's operating ratio (total revenue divided by total expenditures) as a measure of budget solvency. Service solvency concerns an organization's ability to provide and sustain a service level that citizens require and desire. To measure service solvency, a government's percent change in total revenue (%Δ revenue) is calculated. A government's cash solvency is a government's cash liquidity and management and is demonstrated by the ability to generate sufficient financial resources to pay its current liabilities. Cash solvency is operationalized in this paper as a government's cash ratio (cash and investments divided by current debt liabilities). The final category, long-run solvency, concerns bond obligations and future resources with a maturation timeframe that this paper cannot study. Data on state-government expenditures and revenues are obtained from the U.S. Census Bureau's Census of Government (U.S. Census Bureau, 2019).

The key independent variable of interest is a state's R&D tax credit ratio. This variable is the ratio of R&D tax credits claimed by corporations within a state to the amount of R&D spending performed by corporations in that state. This measure is the proportion of R&D spending a state subsidizes. Data on the amount of R&D tax credits claimed comes from state tax expenditure reports and is a measure of the total dollar amount of tax credits claimed by companies within a given year. This method of measuring tax credits circumvents one of the difficulties of studying state tax policy—that every state has a different tax structure—because it measures the extent to which the credit was actually utilized, as opposed to effects relating to the structure of the credit. Data on the amount of R&D spending performed by corporations within a state comes from NSF's BRDIS (*Business R&D and Innovation Survey*, 2018).

Many control variables on other factors thought to affect a state's fiscal health conditions are also included. The control variables are broadly separated into the following categories: economic, structural, political, and demographic. The variables related to a state's economic condition are the state's economic output and unemployment levels. Economic output is measured as a state's gross state product (GSP). The data on economic output comes from the U.S. Bureau of Economic

Analysis's Regional Economic Accounts and is measured on a per-capita basis. Unemployment is measured as the annual average percentage of a state's labor force that is unemployed and is obtained from the U.S. Bureau of Labor Statistics.

The second set of control variables relate to a structural condition of the state that may impact fiscal health. The presence and types of government that exist within a state may influence a state's financial behavior; this is captured using the number of counties and special districts (towns & cities) as reported by the U.S. Census Bureau. Additionally, the periodicity of the state's budget process is measured. This is captured as a binary variable where 1 is assigned to states that have an annual budget process and a 0 where the budget process is bi-annual.

Party control of a state's government is used as a political control variable. Party control is calculated by considering which party controls a state's governor's office, state senate, and state house. Each state receives a score of 0 to 3, depending on how many parts of the state's government are controlled by the Democratic party. Thus, a 0 means the Republican party has total control of the state government, and a 3 means the Democratic party has total control of the state government. For example, Colorado scored a 2 in 2015 because of its Democratic governor and state house but Republican-controlled senate. In the event an Independent serves as a state's Governor or partisan control of the legislature is tied, the state receives 0.5 for that segment of government. In 2015, Alaska had a Republican-controlled house and senate but an Independent governor and thus received a score of 0.5. Data from this variable comes from Ballotepedia.com[1].

[1] Nebreska is the only state with a unicameral legislature. This would present a problem, but the governor's office and the state senate have been held by the Republican party since the 1990s.

The final set of control variables refers to the demographic conditions of a state's population. These are female ratio, minority ratio, ratio over 65, and ratio under 17. Female ratio is the female share of a state's total population. Minority ratio is the ratio of non-white individuals to the total population. Ratio over 65 and ratio under 17 both refer to their respective shares of the total population. The Center for Disease Control's WONDER database provides data on state demographics.

Methods

The analysis of the study progresses in two phases. First, the relationship is modeled in the short term using contemporaneous data in a panel with state fixed effects. The second phase estimates the long-term impact of R&D tax credits by using a distributed lag model which also includes state fixed effects.

First, it is necessary to identify a model that can capture the short-term impact of R&D tax credits. This relationship is modeled using year fixed effects. The benefit of using a fixed effects model is it controls for all omitted state variables. However, there are some limitations to this analytical strategy, discussed below. The following equation is used to analyze the short-term effects of the credit on a state's fiscal health:

$$Y_{st} = \beta_0 + \beta_1 R\&D_{st} + \beta_2 E_{st} + \beta_3 G_{st} + \beta_4 P_{st} + \beta_5 D_{st} + \delta_s + t + Y_{st-1} + \varepsilon_{st}$$

In the equation, *Y* refers to the measures of fiscal health for the *s-th* state in the *t-th* year. R&D refers to the R&D tax credit variable. *E* refers to a vector of economic control variables, while *G*, *P*, and *D* refer to all governmental, political, and demographic control variables. δ_s represents the state fixed effects and *t* refers to a linear time trend. Y_{st-1} is included to control for auto-regression in the dependent variable. This model is estimated using robust standard errors.

The second phase of analysis leverages a distributed lag model to estimate the long-term impact of R&D tax credits. A distributed lag model is used to isolate the impact of individual year effects of an independent variable on the dependent variable. This is performed by using the same control variables as before but introducing time lags of the key independent variable. The distributed lag model is estimated using the following equation:

$$Y_{st} = \beta_0 + \beta_1 R\&D_{st} + \beta_2 R\&D_{st-1} + \cdots + \beta_5 R\&D_{st-4} + \beta_j X_{jst} + \delta_s + t + Y_{st-1} + \varepsilon_{st}$$

In the equation, X_{jst} is a vector of the control variables discussed above. The model above uses four years of lags, which is determined using information criteria[2]. One of the difficulties with interpreting a distributed lag model is understanding the overall effects of the tax credit as opposed to the effects from a given lag. Estimating the cumulative dynamic multiplier allows for examining the effect of the tax credit in each and all previous years (Stock & Watson, 2007). The following can be used to calculate the cumulative dynamic multiplier of a distributed lag model:

$$Y = \delta_0 + \delta_1 \Delta R\&D_{st} + \cdots + \delta_3 \Delta R\&D_{st-3} + \delta_5 R\&D_{st-4} + \beta_j X_{jst} + \delta_s + t + Y_{st-1} + \varepsilon_{st}$$

Each of the coefficients $\delta_1 - \delta_5$ are equal to the summation of the relevant coefficient from the distributed lag model. For instance, $\delta_3 = \beta_1 + \beta_2 + \beta_3$. $\Delta R\&D_{st}$

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[2]The model's information criteria are evaluated by calculating the AIC and BIC for each set of lagged variables. The model with the AIC and BIC is the preferred model.

refers to $R\&D_{st} - R\&D_{st-1}$. It should be noted δ_5 is referred to as the long-term cumulative multiplier and estimates the cumulative effect of the tax credit over all the years represented in the model.

Results

Using the data and statistical approaches discussed above, the relationship between R&D tax credits and state fiscal health is estimated in both the short term and long term. Overall, the models seem to perform well when estimating each of the measures of fiscal health, as demonstrated by the R^2 for each estimate, though the percent change models explain the least amount of variance. Additionally, many of the commonly accepted drivers of state fiscal conditions are significant and point in the direction suggested by the literature.

Short Term

The results of the short-term models are presented in Table 2. According to Column 1, the R&D tax credit ratio is negatively and significantly associated with a state's operating ratio (β = –1.34). According to Column 2, a state's percent change of total revenue is negatively related to the R&D tax credits (β = –1.84). A state's cash ratio is negatively and significantly associated with the R&D tax credits (Column 3) (β = –2.68). These results give compelling evidence in support of H1: *Increases in R&D tax credits results in short-term decreases in fiscal health.* The large magnitude of these results should also be noted as it has important implications for the second hypothesis.

The control variables, when they are significant, are consistent with theory. It should be noted the magnitude of the results for some of the coefficients is rather large and potentially problematic. Both the dependent variable and most of the independent variables are ratios; these variables have a relatively small amount of variation compared to the size of the coefficients. Therefore, care should be taken when interpreting the results.

Table 2: Short Term Models

	Operating Ratio (1)	%Δ Revenue (2)	Cash Ratio (3)
R&D Ratio Cred	-1.34 ***	-1.84 ***	-2.68 *
	(0.34)	(0.48)	(1.12)
County Numbers	4.10E-02 *	-3.58E-02	0.35 ***
	(1.94E-02)	(3.49E-02)	(6.51E-02)
Special Districts	-4.61E-05	-1.20E-04 *	4.78E-05
	(5.24E-05)	(4.74E-05)	(2.92E-04)
Annual Budget	6.96E-02 ***	0.14 ***	0.13
	(1.75E-02)	(1.77E-02)	(0.25)
Gov Party	-1.38E-02 *	3.61E-03	-1.88E-02
	(7.04E-03)	(1.37E-02)	(2.60E-02)
GDP Per Capita	2.46E-02	0.40 +	-2.66
	(0.15)	(0.23)	(3.05)
Unemployment	-5.25 ***	4.75 ***	-12.04 **
	(0.66)	(0.77)	(3.89)
Female Ratio	23.95 **	1.42	-45.01
	(8.40)	(7.51)	(44.61)
Minority Ratio	-0.91	-1.05	10.69 *
	(2.01)	(1.89)	(4.84)
Elderly Ratio	-11.92 ***	1.09	-8.62
	(2.70)	(2.53)	(16.64)
Youth Ratio	-9.65 ***	7.11E-02	12.83
	(2.57)	(2.02)	(9.58)
Year	2.37E-02 **	-1.48E-02 +	0.10
	(7.53E-03)	(8.43E-03)	(6.60E-02)
$Y_t - 1$	-9.50E-02 *	-0.21 ***	0.96 ***
	(3.93E-02)	(1.14E-02)	(0.09)
State FE	Y	Y	Y
Obs	647	610	647
R^2	0.23	0.12	0.81
Adj. R^2	0.15	0.018	0.79

Note: *·p<0.1; *p<0.05; **p<0.01; **p<0.001*

$Y_t - 1$ *refers to auto-regressive term*

Long Term

Having estimated the short-term model, the study proceeds to estimate the long-term effect of R&D tax credits on fiscal health. Analyzing the long-term effects takes place in two steps, the distributed lag model followed by the cumulative dynamic multiplier model. As is the case with the short-term model, these models perform reasonably. The estimation of the control variables displays a similar relationship to those of the short-term model, and the R^2 of the long-term models are consistently higher than their short-term counterparts.

The results of the distributed lag models are presented in Table 3. Column 1 shows R&D tax credits are significant and negatively related to the state's operating ratio in years *t* and *t-1*. However, this relationship changes in years *t-2* and *t-3* so the tax credit variable is positively related to a state's operating ratio. Then in year *t-4*, the association is again negative.

Table 3: Distributed Lag Models

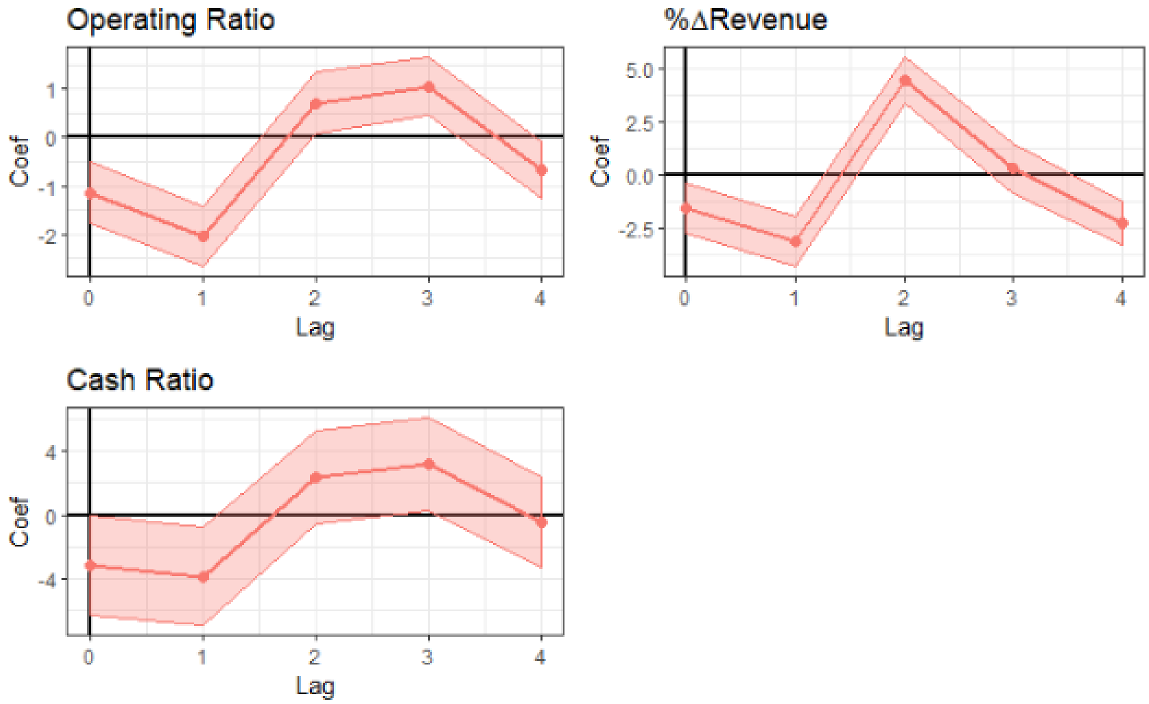
	Operating Ratio (1)	%Δ Revenue (2)	Cash Ratio (3)
R&D Ratio Cred$_t$	-1.14 ***	-1.57 ***	-3.12 *
	(0.24)	(0.30)	(1.37)
R&D Ratio Cred$_{t-1}$	-2.04 ***	-3.13 ***	-3.83 **
	(0.34)	(0.61)	(1.33)
R&D Ratio Cred$_{t-2}$	0.71 **	4.44 ***	2.32 *
	(0.22)	(0.83)	(0.96)
R&D Ratio Cred$_{t-3}$	1.06 ***	0.31	3.19 **
	(0.18)	(0.29)	(0.99)
R&D Ratio Cred$_{t-4}$	-0.68 *	-2.26 ***	-0.46
	(0.30)	(0.36)	(0.75)
County Numbers	-5.34E-03	-2.13E-02	0.19 *
	(1.40E-02)	(3.47E-02)	(8.79E-02)
Special Districts	-4.14E-05	-1.84E-04 +	9.72E-05
	(6.56E-05)	(9.40E-05)	(2.61E-04)
Annual Budget	4.15E-02 **	5.65E-02 *	-0.15
	(1.56E-02)	(2.27E-02)	(0.26)
Gov Party	-1.26E-02 +	6.16E-03	-0.02
	(7.60E-03)	(9.77E-03)	(0.04)
GDP Per Capita	0.11	0.43	-4.01
	(0.24)	(0.28)	(3.84)
Unemployment	-4.37 ***	4.01 ***	-11.17 *
	(0.72)	(0.83)	(4.61)
Female Ratio	15.87	19.31 +	-81.96
	(14.11)	(10.10)	(68.92)
Minority Ratio	-1.87	-3.06 +	4.61
	(3.12)	(1.75)	(7.93)
Elderly Ratio	-5.63	-6.68 *	-1.26
	(3.98)	(3.30)	(24.00)
Youth Ratio	-6.67 *	-3.07	20.20
	(2.98)	(2.84)	(14.33)
Year	9.44E-03	1.68E-02 +	9.85E-02
	(1.22E-02)	(9.63E-03)	(9.37E-02)
Y_{t-1}	-0.10 *	-0.18 ***	1.02 ***
	(4.59E-02)	(5.11E-02)	(7.82E-02)
State FE	Y	Y	Y
Obs	474	474	474
R^2	0.31	0.32	0.82
Adj. R^2	0.20	0.21	0.79

Note: *$^{\cdot}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{**}p<0.001$*

Y_t-1 refers to auto-regressive term

The second model predicts the percent change of a state's total revenue. In years *t* and *t-1*, R&D tax credits are negative and significantly related to the percent change of total revenue. In year *t-2* the R&D tax credits are positively related to a state's total revenue. In year *t-3* it is not significant but again negative in year *t-4*. In the model predicting a state's cash ratio, the R&D credit variable is negatively related to a state's fiscal condition in years *t* and *t-1* and positively related to fiscal health in *t-2* and *t-3*. There is no significant relationship between the R&D tax credit and a state's cash ratio in *t-4*. The relationship between R&D tax credits and the dependent variable in year *t* and *t-1* is consistent with the results of the short-term model. Then, across all three models, the R&D tax credit is positively associated with the fiscal health variable in the next two years before returning to a negative or non-significant relationship in *t-4*. Figure 1 plots the results of the distributed lag model with respect to the relationship of R&D tax credits to fiscal health in each of these years.

Figure 3: Distributed Lag Models



The above results suggest there is insufficient evidence to support the second hypothesis; however, it is unclear whether the R&D tax credit variable has a net positive or negative relationship on a state's fiscal health. One of the difficulties of analyzing time series data with multiple lags is understanding the cumulative impact of an independent variable on the dependent variable. It is particularly difficult when the magnitude of the relationship reverses direction between years, as is the case with the results above. The cumulative dynamic multiplier model can clarify these results and is presented in Table 4.

Table 4: Cumulative Multiplier

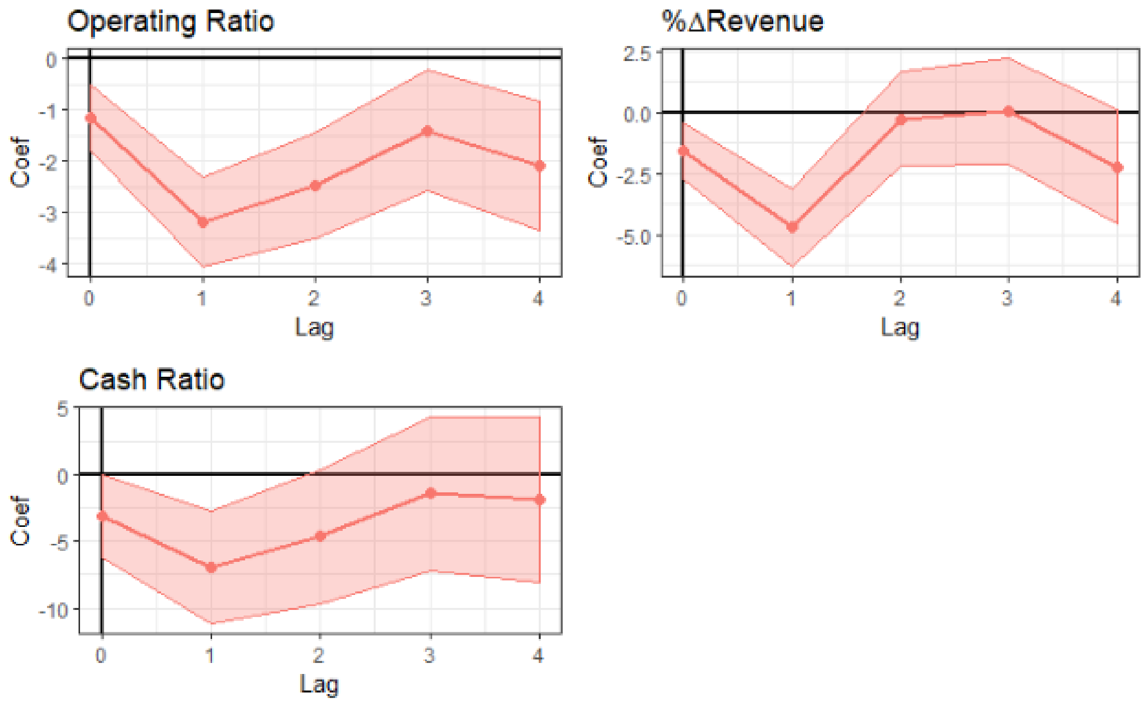
	Operating Ratio (1)	%Δ Revenue (2)	Cash Ratio (3)
Δ R&D Ratio $Cred_t$	-1.14 ***	-1.57 ***	-3.12 *
	(0.24)	(0.30)	(1.37)
Δ R&D Ratio $Cred_{t-1}$	-3.18 ***	-4.70 ***	-6.95 **
	(0.55)	(0.82)	(2.46)
Δ R&D Ratio $Cred_{t-2}$	-2.47 ***	-0.26	-4.63 $^{+}$
	(0.61)	(0.66)	(2.73)
Δ R&D Ratio $Cred_{t-3}$	-1.41 *	0.05	-1.44
	(0.58)	(0.74)	(2.96)
R&D Ratio $Cred_{t-4}$	-2.08 ***	-2.21 **	-1.91
	(0.48)	(0.71)	(3.22)
County Numbers	-5.34E-03	-2.13E-02	0.19 *
	(1.40E-02)	(3.47E-02)	(8.79E-02)
Special Districts	-4.14E-05	-1.84E-04 $^{+}$	9.72E-05
	(6.56E-05)	(9.40E-05)	(2.61E-04)
Annual Budget	4.15E-02 **	5.65E-02 *	-0.15
	(1.56E-02)	(2.27E-02)	(0.26)
Gov Party	-1.26E-02 $^{+}$	6.16E-03	-0.02
	(7.60E-03)	(9.77E-03)	(0.04)
GDP Per Capita	0.11	0.43	-4.01
	(0.24)	(0.28)	(3.84)
Unemployment	-4.37 ***	4.01 ***	-11.17 *
	(0.72)	(0.83)	(4.61)
Female Ratio	15.87	19.31 $^{+}$	-81.96
	(14.11)	(10.10)	(68.92)
Minority Ratio	-1.87	-3.06 $^{+}$	4.61
	(3.12)	(1.75)	(7.93)
Elderly Ratio	-5.63	-6.68 *	-1.26
	(3.98)	(3.30)	(24.00)
Youth Ratio	-6.67 *	-3.07	20.20
	(2.98)	(2.84)	(14.33)
Year	9.44E-03	1.68E-02 $^{+}$	9.85E-02
	(1.22E-02)	(9.63E-03)	(9.37E-02)
Y_{t-1}	-0.10 *	-0.18 ***	1.02 ***
	(4.59E-02)	(5.11E-02)	(7.82E-02)
State FE	Y	Y	Y
Obs	474	474	474
R^2	0.31	0.32	0.82
Adj. R^2	0.20	0.21	0.79

Note: *·p<0.1; *p<0.05; **p<0.01; **p<0.001*

Y_t-1 *refers to auto-regressive term*

In the case of the operating ratio, the cumulative impact of the R&D tax credit variable is negatively related to fiscal health for all years. The long-term dynamic multiplier (R&D credit ratio *t-4)* is significant and negative. These results suggest the cumulative effect of R&D tax credits is detrimental to a state's operating ratio. When considering the long-term effects of R&D tax credits on total revenue, it appears the cumulative effect is negative. However, in *t-2* and *t-3* it does not have a cumulative effect on fiscal health. Interestingly, the negative relationship between R&D tax credits and the cash ratio variable is negative only in the first years and then has a relationship that is not significantly different than 0. These results suggest there is not enough evidence to support H_2*: Increases in R&D tax credits have a positive long-term impact on a state's fiscal health*. In fact, the results of the operation ratio and the total revenue models suggests the opposite may be true. Figure 2 plots the cumulative dynamic multiplier and the measure of fiscal health.

Figure 2: Cumulative Multiplier



Robustness Tests

While the above results are significant, it is important to understand the sensitivity of these results before discussing their implications. To that end, robustness tests are conducted to address concerns the R&D tax credit ratio variable is responding to changes in the overall level of R&D spending but not to changes in the amount of R&D tax credits claimed. To address this concern, a measure is included of the amount of federal funding of R&D a state received. Federal R&D is highly correlated to corporate R&D spending (0.74), so it should control for changes in R&D spending. Including this term shows no significant differences in the short-term models or the cumulative dynamic multiplier. Though there are some minor differences in the distributed lag model, this suggests the model is responding to changes in the tax credit as well as changes in R&D spending.

Discussion & Conclusion

The results of the short-term model and the early years of the distributed lag model offer compelling evidence R&D tax credits are associated with decreasing levels of state fiscal health. This result parallels the findings of McDonald et al. (2017). Given the decrease associated with the tax credit and percent change of total revenue, it is likely decreases in fiscal health are due in part to decreases in revenue. This matches the theoretical explanation proffered earlier, that in the short term credits are essentially forgone revenue.

The results of the long-term model suggest over the course of the study, R&D tax credits are detrimentally associated with state fiscal health. However, due to the limitations discussed below and the exploratory nature of the paper, it is not possible to discuss the causality of these results. It is possible these results are a function of the amount of time it takes for firms and therefore the economy to see a return from R&D. Over a long enough time horizon, R&D tax credits may improve a state's fiscal health. Additionally, the results of the model could be biased by the possibility states with more generous R&D tax credits offer more tax expenditures generally. Future research could extract the raw data from tax expenditure reports to construct a measure of a state's overall level of tax expenditures, which could account for this bias.

This paper's primary contribution is the attempt to connect R&D tax credits to fiscal health and is part of a nascent body of literature studying tax incentives and fiscal health. The findings provide evidence against the efficacy of tax incentives as an investment for governments. Furthermore, the paper highlights the benefits of using state tax expenditure reports as a source of data on state fiscal and tax policies, which provides scholars an opportunity to leverage variation in a tax incentive’s size and scope when evaluating its effectiveness.

States have two fundamental problems with offering firm-based tax incentives. First, there is the risk a government is incentivizing behavior a firm would have engaged in even without the tax credit (Bozeman & Link, 1984). Even though R&D tax credits are effective in increasing the level of R&D a firm performs, it is unclear if this increase in R&D results in breakthroughs or just an increase in slack for R&D activities (Mankin, 2007). Essentially, an R&D tax credit lowers the marginal cost for firms to perform R&D, but it is unclear if the marginal increases in R&D spending result in new products or innovation. R&D is an inherently uncertain and random process, and there is likely not a direct linear relationship between spending and innovation (Mankin, 2007; Segerstrom, 1991).

The second issue with firm-based tax incentives offered by states is both capital and firms are free to move between states. Federal law prohibits state governments from erecting barriers to control the flow of capital and investment between states (Niemi et al., 1995). Therefore, knowledge created from R&D credits can be easily transferred out of a state. The danger is firms are not responding to the credit by generating new R&D but are instead responding by relocating R&D between states. Wilson (2009) finds firms respond to more generous R&D credits by moving R&D into states at approximately the same rate they pull R&D from neighboring states, implying state R&D tax credits do not increase the national level of R&D.

This study has several limitations that should be addressed. The structure of the panel means for every additional year of lag used, the model loses fifty observations. Therefore, four years of lags results in the loss of nearly a third of the observations. It is conceivable four years of lags is insufficient to capture the overall impact of these tax credits. Uncertainty around how long it takes for individual firms to receive returns from innovation corresponds with uncertainty around how long it takes for innovation to affect a state's tax base (Gurmu & Pérez-Sebastián, 2008; B. H. Hall et al., 1984; Mankin, 2007). While the results of the information criteria find the model with four years' worth of lags is preferred, this test may have been misleading due to missing observations from increasing the number of lags.

This study is also limited by its use of aggregate measures that fail to capture decision-making by individuals and firms. This is particularly restrictive for economic-development studies, because it eliminates the ability to determine if firms are receiving benefits from these incentives without actually modifying their behavior. The study may also suffer from omitted variable bias. States with high levels of R&D tax credits also may be offering other generous tax credits. Outside of R&D tax credits acting as a proxy for other credits, the use of fixed effects should help mitigate this limitation. However, the use of the fixed effects model introduces different limitations. First, the model estimates only within-state effects and not the between-state effects of these tax credits. Second, the results are not generalizable to states that never adopted an R&D tax credit.

When considering the practical implications of the study, it is important to remember these results are not causal. Policymakers should use caution when acting on these findings. State governments could leverage their access to tax returns and microlevel data to test these findings. Additionally, R&D tax credits have implications beyond the state's fiscal position. This study suggests states should rigorously evaluate the effects of R&D tax credits, as they should with all incentives, so they can have the best understanding of the cost and benefit of the credits. If the results of the study hold, then states should consider economic-development policy that does not subsidize an activity that firms can transfer out of the state.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

Review of the literature on different economic-development theories and strategies inspired pursuit of this dissertation. Most economic-development policies receive a rather bleak treatment in the literature, meaning the vast majority of benefits are captured by the firms that engage in the program rather than the government or community that offers them (Currid-Halkett & Stolarick, 2011; Fichtner & Michel, 2015; Porter, 2003; D. J. Wilson, 2009). The literature tends to be more optimistic toward R&D tax credits because of evidence of the credit's efficacy in boosting R&D spending and because endogenous growth theory has proven to be relatively successful. In addition, government-subsidized R&D is responsible for much of the technological advances that, for better or worse, define the modern age, including the internet, global positioning satellites, shale gas fracking, and the human genome project, to name a few (Singer, 2014).

The goal of the dissertation is to move past the typical assumption that R&D spending is the most important outcome of the credit and instead attempt to connect R&D tax credits to outcomes that theory predicts would be associated with the credit. The first two papers appear to be successful in this regard, as they connect the R&D tax credit to the movement of PhDs and innovation. However, these papers find the tax credit's effect is relatively small compared to the outcome they were predicting. Detecting these second- and third-order effects from the tax credit is empirically challenging. Plus, the tax credit itself offers only a marginal discount on the cost of R&D. Therefore, it is unsurprising the effects of the tax credit are rather small.

The third paper finds R&D tax credits have a sizable and negative association with a state's fiscal health. In the short term, that result is expected and hypothesized. However, the fact the negative and sizable relationship holds in the long-term is surprising. Before offering recommendations for policy or avenues for future research, it is worth discussing some of the insights gained about R&D tax credits while preparing this dissertation.

Economic Development

One insight offered by this dissertation concerns R&D tax credits' implications for economic development. The first two papers examine two outcomes that are theoretically associated with R&D tax credits. The first paper examines whether R&D tax credits have an impact on the state's highly skilled labor force, specifically those with PhDs. The paper discusses the economic development implications associated with these highly skilled laborers but does not directly test the impact of these workers or the tax credits on a state's economy.

The second paper examines the effect of R&D tax credits on innovative activity occurring within the state. Innovation also has important implications for economic development, and unlike the previous paper, it does consider R&D tax credits' impact on a state's economy. While this paper finds R&D tax credits do not have a significant impact on economic growth, this relationship is only in the short term, and the paper uses a model designed to be conservative in its estimation. Additionally, the economy is only treated as a control variable in this paper. The third paper considers R&D tax credits' short-term and long-term impact on state fiscal health, with the underlying assumption that the tax credit has improved a state's economy and thus should improve the state's fiscal condition.

The economy is treated as a control variable in all three papers, but it is also an important part of the story for R&D tax credits. Future work should consider more deeply the tax credits' connection to the economy, as scholars continue to try to inform policymakers on the best way to implement tax policy that can drive economic behavior.

R&D in the Literature

During development of this dissertation, review of the literature around R&D tax credits revealed three gaps in the literature. First, most studies only look at the efficacy of the tax credits in terms of R&D spending. Second, all R&D spending is treated as equal. Finally, there are shortcomings in how current economic theory treats R&D in the literature. While the dissertation addresses the first, the second and third gaps deserve more scrutiny.

Many studies that explore the effects of R&D spending on a variety of outcomes consider R&D spending as a monolith wherein all R&D spending is equally impactful. For instance, pharmaceutical companies can claim R&D credits for both developing new drugs and for modifying existing drugs (*Patents and Regulatory Exclusivities*, 2015)[3]. A long-standing criticism of patents from the patenting literature is the disparate economic effects of patents (Acs et al., 2002; Griliches, 1981). R&D spending should be considered in a similar light. Becker (2015) offers the concern that R&D tax credits are creating slack in a firm's production of R&D by allowing for more funding for administrative tasks and extra supplies for experimentation without the guarantee this extra funding leads to innovations or new worker hires.

The other gap in the R&D tax credit literature concerns how the economic theory treats R&D. In broad strokes, R&D is treated as an input in a firm's Cobb-Douglas production function along with labor and capital (Wilson, 2009). This approach assumes firms can derive the optimal amount of resources to spend on R&D. It also implies the marginal benefit and marginal cost of R&D can be derived from a firm's production function, and these marginal curves are smooth, meaning it is possible to predict the effect marginal increases in R&D has on a firm's output. The problem with this approach is R&D is a messy stochastic process where researchers explore many different avenues before making a breakthrough, and it is uncertain whether a given breakthrough will result in a monetizable innovation. Therefore, it might be wiser to consider the production benefits of R&D more like a jagged or step function and less like a smooth function. In other words, a firm's R&D spending has to reach some threshold before a breakthrough can occur. The implications of this for R&D tax credits is the credit offers a marginal cost reduction of increased R&D, but the rate of the tax credit for most states is

[3] Technically, the government does require modification of existing drugs be sufficient for the application for a new patent; however, pharmaceutical companies can do so after relatively minor adjustments.

likely too small for R&D to be pushed to the next threshold to allow a breakthrough to occur. It is a stretch to believe large- or medium-sized firms will only achieve a breakthrough because of a single-digit discount on the cost of R&D.

Recommendations

It is premature to definitively declare R&D tax credits ineffective, because the paper has considerable limits, and the study does find small positive effects of the R&D tax credit on the outcome variables of interest. However, state governments need to evaluate the efficacy of their R&D tax credits and may want to consider alternative policies for encouraging R&D related economic growth. Early work on Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) matching policies shows some encouraging results. Lanahan and Feldman (2017) find state matching of SBIR and STTR awards result in companies experiencing more success. Another avenue to consider is for states to implement policies that target specific R&D projects or types of R&D, rather than a general credit for all R&D. For instance, North Carolina offers a more generous tax credit for R&D investment into biotech companies as part of its efforts to build a biotech cluster in the state. The political challenges of transitioning to a targeted subsidy from a general subsidy, and the difficulty of correctly targeting the subsidy, should not be understated.

In addition to directly funding research projects, investing in R&D infrastructure may be a strategy that proves fruitful for states. Specifically, investment in high-tech education, technology-transfer programs that move research from universities to market, and the development of technology or start-up incubators may all show promise. The goal of these policies should be to encourage R&D and innovation that would not have occurred in the absence of the policy or to accelerate their development.

Further research is needed to gain a deeper understanding of the efficacy of these tax credits. That research likely needs to explore firm- or industry-level data. Firm-level data would allow a researcher to get a better understanding of how a firm is directly responding to the credit. Ideally, these research efforts would employ a quasi-experimental design and employ treatment and control groups. This would allow a researcher to create a counterfactual that could approximate what a firm would have done without the state tax credit. Alternatively, researchers could pursue industry-level effects of the R&D tax credit. The Upjohn Institute has created a database of tax incentives by industry that might prove a useful starting place for the tax credit. The advantage of this approach is it could identify which industries benefit the most from the tax credit and which industries benefit the least. This research would be useful in helping states better target their tax credits.

Another question raised by this dissertation concerns the lag between R&D tax credits implementation and the effect the credits have on the economy. In the case of the third paper, it is entirely possible the negative findings can be attributed to not allowing enough time to pass to capture the effectiveness of the tax credits. While there is evidence companies capture the benefit of R&D spending contemporaneously (Thomson, 2017), it may take several years for the credit to influence second- and third-order outcomes like fiscal health. To that end, it may prove useful to use structural stability analysis to attempt to determine how long after a tax credit is implemented before there is a structural shift in a time series predicting the outcome variables. This approach requires more years of data and developing a strategy to account for each state adopting the tax credit at different times (Bai, 2010).

Finally, it might be useful to investigate the extent to which firm size influences the R&D tax credit's effectiveness. The tax credit marginally lessens the cost of increased R&D activities. For a medium- or large-sized firm, it is easy to imagine this discount is not sufficient to push the firm to pursue new avenues of research. However, small and developing firms may receive a more substantial benefit from the credit, not because it opens new research avenues, but because it gives the firms more flexibility as they develop. Georgia allows new firms to use their research tax credit to pay partner firms for services like human resources or payroll.

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