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Incentivizing Innovation:The Effects of Research and DevelopmentTax Credits on Corporate Behavior

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Author
Packer, Andrew

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Incentivizing Innovation:

The Effects of Research and Development Tax Credits on Corporate Behavior

Andrew Packer

Advisor: Ted Frech

Abstract:

With corporate income tax breaks and excise taxation consistently being used as methods of influencing company behavior, there has always been a desire to measure the size of the effect taxation has on corporate behavior. In this paper, I examine the effects of a change in research and development (R&D) tax policy on firm innovation, as measured by the quantity of US patent applications filed annually. Using a combination of panel data and linear regressions with year and company fixed effects, I look at the major differences in US patent application filings before and after the addition of the Alternative Simplified Credit (ASC) in 2009. The findings suggest that there is a positive effect of the ASC on patent applications, though it is quite negligible. Additionally, it appears that the effects of the ASC are negatively correlated with the size of the firm, but at an insignificant level.

1.0 Introduction:

For almost 40 years, the US Government has incentivized corporate research and development through R&D tax credits. These credits were created as part of the Economic Recovery Tax Act of 1981, and allow companies performing research and development related activities to claim a dollar for dollar offset of tax liabilities due to the credit.[1] Though used heavily in federal taxation, tax credits of this variety are not unique to the US national government; several cities, states, and foreign countries have enacted similar credits, with the

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[1] *Research & Development Tax Credits: Frequently Asked Questions." Frequently Asked Questions. Corporate Tax Incentives (CTI)," n.d. Web. 4 Nov. 2016.* http://www.ctillc.com/our-services/research-and-development-tax-credits/faq.

hope of both spurring local innovation and attracting research based firms to relocate R&D

activities to their respective governances.[2]

Research and development credits focus on a "cost capture" approach, where

businesses record expenses spent in departments performing R&D, and then use the

percentage of time spent performing R&D tasks to determine the expenditures to allocate to

R&D activities.[3] To determine what specifically qualifies as an R&D expenditure, the IRS

maintains a list of "Qualified Research Expenditures" (QREs), including items such as

documenting research, participating in technical meetings, developing internal software, and

designing new processes.[4] Naturally, the vast list of QREs creates ambiguity, both for

technology based firms and their tax contractors. To explore the complex application of the

R&D tax credit and its consequences on firm behavior, this paper examines whether the R&D

credit successfully incentivizes innovation at all.

In this study, I ask if R&D credits effectively spur firm innovation and, if they do, whether

the size of the firm relates to the level of firm response. Because the calculation of the federal

R&D credit is governed by such vague standards, its effects are hard to measure: How much

does the credit incentivize research? What qualifies as a QRE? How do firms need to

substantiate expenses? Does the temporary nature of the credit, the fact its renewal is

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[2] *Sanger, Tom. "R&D Tax Credit: New, Improved, and Permanent." CFO. CFO.com, 10 Mar. 2016. Web. 3 Nov. 2016. <http://ww2.cfo.com/tax/2016/03/rd-tax-credit-new-improved-permanent/>.*
[3] *Research Credit Technical Advisor Program. Briefing Paper on Taxpayer Approaches to Capturing Costs for the Research Credit. Tech. Internal Revenue Service, n.d. Web. 2 Dec. 2016. <https://www.irs.gov/pub/irs-utl/cost_capturing_approaches_2004-05-24.pdf>.*
[4] *Research & Development Tax Credits: Frequently Asked Questions." Frequently Asked Questions. Corporate Tax Incentives (CTI)".*

contingent on Congressional approval, play a role in a firm's willingness to invest in R&D?[5] To answer these questions, I apply a basic linear regression design to the Alternative Simplified Credit (ASC), an R&D tax policy change enacted in January of 2009.

Prior to 2009, R&D credits were claimed largely through the Regular Research Credit (RRC). The RRC "uses a base period that can reach back as far as 1984, with disparate results that can reward some taxpayers with a windfall and deny a credit to others."[6] What's more, administrative obstacles and the requirement for firms using the deduction to have high levels of taxable income make the RRC impractical for many technologically focused companies. To combat this, Congress introduced the ASC in 2007, with full implementation completed on January 1, 2009. Among other benefits, the ASC removes gross receipts from the credit calculation and lowers the credit threshold.[7] Because this shift in policy makes the credit more accessible to firms, I use the date of full implementation of the ASC, January 1, 2009, as my measurement threshold. Using the ASC policy change, US patent application and R&D spending data from the National Science Foundation, and year fixed effects, I am able to construct a model that ultimately shows a slight increase in patent applications and firm innovation after January 1, 2009, the day the ASC was fully implemented.

2.0 Literature Review

Much has already been studied regarding the effects of taxation on firm behavior, including the specific effects of R&D credits on innovative behavior. However, though

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[5] *Karnis, Daniel. "Navigating the R&D Tax Credit." Journal of Accountancy. Journal of Accountancy, 01 Mar. 2010. Web. 4 Nov. 2016. <http://www.journalofaccountancy.com/issues/2010/mar/20092122.html>.*
[6] *Ibid.*
[7] *Ibid.*

examined through a variety of lenses and techniques, the incentivizing power of tax credits on firm behavior is still largely in question, particularly with regards to the effects of size on the adaptation of policy. I hope to examine that relationship by extending on the research already put forward in the field.

Many studies have focused on the differences in effects of tax policy due to company size. Agrawal et al. (2014) examined the question of firm size differentials using tax credits and R&D expenditures to examine the disparities between small and large firms in Canada.[8] Once again exploring a threshold shift via a regression discontinuity model, the study found that a 15% increase in the maximum credit allowed increased average R&D spending by 15%.[9] The study also calculated an after-tax elasticity of R&D for all firms of -1.5.[10] Interestingly enough, small firms included in the model had on average a smaller responsiveness to the increase in credit limits. This was expected to be a result of the fixed adjustment costs for establishing a new system.

Additional research on the effectiveness of R&D incentives comes from Bronzini and Iachini in 2014, who observed the effects of government subsidies on R&D activity by firm size.[11] The study focused on northern Italy, examining the differences in R&D spending habits between subsidized and unsubsidized firms. Firms submitted R&D proposals to the government, who then decided which groups to subsidize. In contrast to the aforementioned

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[8] *Agrawal, Ajay, Carlos Rosell, and Timothy Simcoe. "Do Tax Credits Affect R&D by Small Firms? Evidence from Canada." NBER Working Paper Series (2014): n. pag. NBER. Web. 4 Nov. 2016.*
[9] Ibid.
[10] Ibid.
[11] Bronzini, Raffaello and Eleonora Iachini. 2014. "Are Incentives for R&D Effective? Evidence from a Regression Discontinuity Approach." *American Economic Journal: Economic Policy*, 6(4): 100-134.

study out of Canada, Bronzini and Iachini found that the subsidy only had a significant effect on smaller firms, who directly increased R&D expenditures by the amount of subsidy they received.[12]

A study by Dechezlepretre et al. (2016) examined the effects of R&D tax credits on innovation using a change in tax policy from the UK.[13] By exploiting a filing threshold shift from 2006 using a regression discontinuity design, the study was able to observe the causal impact of R&D tax incentives on innovation. They found that R&D expenditures in the period from 2006 to 2011 were 10% greater in the aggregate with the credit than they would have been without.[14] Additionally, the credit stimulated new R&D spending, with a ratio of new R&D expenditures to relocating current expenditures to R&D activities of 1.7:1.[15]

The research discussing patent application levels by firm size has been furthered by Anthony Breitzman in part with the United States Small Business Administration. Breitzman's research explores the varying trends in firm innovation during the 2007-2009 recession, by size of the firm.[16] By observing roughly 1300 firms of varying size, as measured through sales and employees, the study analyzes the effects of economic downturns on innovation, a useful control for a study in tax credits. According to the analysis, though all firms experienced some level of patent filing downturn, large firms did not shift until 2009, while small firms

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[12] Ibid.

[13] *Dechezlepretre, Antoine, Elias Einio, Ralf Martin, Kieu-Trang Nguyen, and John Van Reenen. "DO TAX INCENTIVES FOR RESEARCH INCREASE FIRM INNOVATION? AN RD DESIGN FOR R&D." NBER Working Paper Series 30.1 (2016): n. pag. NBER. Web. 4 Nov. 2016.*

[14] *Ibid.*

[15] *Ibid.*

[16] Breitzman, Anthony, PhD. *Patent Trends Among Large and Small Firms during the 2007-2009 Recession*. Rep. N.p.: SBA Office of Advocacy, May 2013. Print. (3)

experienced a more immediate and severe downturn.[17] This was largely expected to be the

result of the need for smaller firms to cut R&D expenses more quickly than larger firms if the

need were to arise, in order to remain profitable.[18]

The idea that smaller firms are less innovative than their larger counterparts is echoed

in the words of Professor of Entrepreneurial Studies at Case Western Reserve University, Scott

Shane: Due to lower levels of funding in innovation, inferior yield on patent applications, and

their lower level of likelihood to develop new technologies and processes, small businesses are

at an inherent disadvantage in the race to invent and patent.[19] Though this affects the level of

R&D output by firms based on size, it does not address the effects of policy on each firm size

grouping relative to itself, something my research strives to address.

Studies have also been performed to examine what the optimal taxation policy for

increasing firm innovation entails. Ufuk Akcigit, Douglas Hanley, and Stefanie Stantcheva with

the University of Chicago Human Capital and Economic Opportunity Global Working Group

perform a series of regressions using a model with firm level data and patent data to discover

what can better optimize R&D tax policy.[20] Through studying final goods producers and

intermediate goods producer's reliance on R&D as a method of supplying a demand for

innovation, Akcigit et al. (2016) find that subsidizing R&D via a "parsimonious R&D subsidy

function" or by creating a prize mechanism, optimize R&D output as opposed to the generic

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[17] *Ibid.*

[18] *Ibid.*

[19] Shane, Scott. "Small Business May Be Less Innovative Than You Think." *Small Business Trends*. Small Business Trends, 02 Mar. 2015. Web. 12 Jan. 2017.

[20] Akcigit, Ufuk, Douglas Hanley, and Stefanie Stantcheva. *Optimal Taxation and R&D Policies*. University of Chicago Human Capital and Economic Opportunity Global Working Group, 28 Nov. 2016. Web

linear R&D subsidy or profit taxation.[21] Though my research does not delve into the optimization of R&D tax policy, I do address the relative effectiveness of linear R&D subsidies similar to those addressed in this study.

Much like Dechezlepretre et al.(2016), my research examines a shift in tax policy that creates more accessible deductions for R&D related activities. Like their Regression Discontinuity model used on the UK policy shift, as well as the Agrawal et al. (2014) model for Canadian R&D tax policy, I examine the filing periods before and after the implementation of the ASC in January of 2009 to quantify the effects of policy on R&D productivity, using US patents as a proxy. The concept of using patent applications as an indicator of innovation is very much a common practice, used heavily in the Dechezlepretre et al. (2016) study from above.[22]

Using methods embraced by prior research on foreign tax policy shifts, I create a model that examines a recent tax policy shift in the United States. Though research has been performed on similar domestic policies, the focus on the 2009 ASC filing change is significant as it occurred during a recession which negatively correlated with patent applications for all firms, regardless of size.[23] By utilizing a model similar to previous studies to delve into a filing change in the middle of a recession, my research expands on the already vast collection of tax policy studies in an attempt to provide more evidence of the significant effects of taxation on firm behavior.

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[21] *Ibid, 1*
[22] Dechezlepretre, Antoine, Elias Einio, Ralf Martin, Kieu-Trang Nguyen, and John Van Reenen, (11)
[23] Breitzman, Anthony, PhD, (3)

3.0 Empirical Methodology

I will address the following questions: Did the Alternative Simplified Credit for Research and Development tax deductions effectively increase firm innovation? Does this effect change by size of the firm studied? Does the origin of a firm play a role in the level of tax credits claimed? Based on previous research and my own understanding of the role of policy, my prediction would be that the ASC effectively increased firm innovation for all firms, but with a greater magnitude for small firms than large, and nationally based firms more than foreign ones. This would make sense given the increased accessibility of R&D credits should benefit smaller firms in general over large firms already capable of claiming R&D deductions.

The methodology I use to answer the previously posed questions focus on three separate regression models that each utilize the date of the ASC enactment to create a dummy for post-ASC patent application trends. All three models make two basic assumptions: The date the ASC became available for use, January 1, 2009 is always used as an independent dummy variable to examine the change in tax policy, and patent application or R&D expenditures are consistently used as the dependent variables for measuring innovation. The use of the ASC date as an independent variable makes sense, as my hypothesis is that this specific change in filing policy would significantly influence the level of patents applied for. Patent applications are a reliable proxy for measuring firm innovation because, generally speaking, there tends to be an immediate increase in applications as a result of an increase in research expenditures while patent grants tend to take a significant amount of time to be approved.[24]

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[24] Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg. "MARKET VALUE AND PATENT CITATIONS: A FIRST LOOK." *Working Paper Series*. National Bureau of Economic Research, June 2000. Web. 12 Jan. 2017. (1)

Model 1

Model 1 involves measuring aggregate data for patent filings over an extended period of time to measure the consequences of the ASC shift in 2009. Because this model is in the aggregate, it provides only big picture trend information rather than specific firm size and firm level results. Model 1 is as follows:

(i) *Patent $_t$=α + β₁ASC$_t$ + β₂Unemployment$_t$ +β₃Trend $_t$+ε $_t$*

Patent in the above equation is the dependent variable representing aggregate patent applications in any given year. *ASC* is a dummy variable that is equivalent to 1 for 2009 and forward, or 0 for all years prior to 2009. To properly account for economic trends, *Unemployment* provides the unemployment rate overtime. *Trend* is a time trend variable, while the residual is given by ε.

Model 2

In my second model, I use essentially the same equation as Model 1, but with firm level patent panel data, in order to observe the effects of the ASC policy shift on innovation for firms in general. The key equation is as follows:

(ii) *Patent$_{i,t}$=α + β₁ASC$_t$ + β₂Unemployment$_t$ +β₃Trend$_{i,t}$+μ$_{i,t}$+ε$_{i,t}$*

Patent represents patent applications by a specific firm in any given year. *ASC, Unemployment,* and *Trend* remain the same as in Model 1. Firm specific fixed effects such as management quality, adverse effects, cash flow cycles, and more are provided by μ. To address the fact that

the error term in time series regressions are serially correlated, I use OLS and the Newey-West

standard error, in line with Lazarus, Lewis, Stock, and Watson.[25]

Model 3

The third model works with firm sizes in a crude time series model to provide some insight into

the varying level of effects of policy change due to firm size. Though I will touch on this further

in the *Data* section of my paper, I was not able to access firm-specific data correlated with size

and thus this model only provides a crude analysis of size effects. Nevertheless, Model 3 is

given by:

(iii) $R\&D_{i,t}=\alpha + \beta_1 ASC_t + \beta_2 Unemployment_t + \beta_3 Trend_{i,t} + \beta_4 Meansize_{i,t} + \mu_{i,t} + \varepsilon_{i,t}$

In the above equation, *R&D* is research and development expenditures by firm size adjusted to

2004 real terms. *ASC, Unemployment, Trend,* and μ remain the same as in prior models.

Meansize is the average number of employees in a given grouping, as provided in the dataset

described later. *Meansize* is a dummy for each size grouping in the dataset. As in Model 2, I

apply the OLS with Newey-West Standard Errors to address the serial correlation of the error

term.

4.0 Data

Each model I run uses a different dataset. Model 1 takes aggregate patent data from the

U.S. Patent Statistics Chart: Calendar Years 1963-2015, provided by the Patent Technology

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[25] Lazarus, Eben, Daniel J. Lewis, James H. Stock, and Mark W. Watson. "HAR Inference: Recommendations for Practice." *National Bureau of Economic Research*. Department of Economics and the Woodrow Wilson School, Princeton University, 19 Apr. 2016. Web. (6)

Monitoring Team at the US Patent and Trademark Office.[26] Updated on an annual basis, this

survey monitors all patent grants and applications in a given year, sorted by patent type (utility,

plant, or design) and origin of filing group (domestic versus foreign). The benefit of having

foreign and domestic based firms is that it allows one to examine the difference in the effect of

the ASC for each group. Because this data comes from the U.S. Patent and Trademark Office,

the organization responsible for reviewing and granting patents, it is highly reliable. Each of the

53 annual observations, 1963-2015, are displayed in Figure 4.1, as well as summarized in Table

4.1.

Figure 4.1: Annual Aggregate Patent Filings

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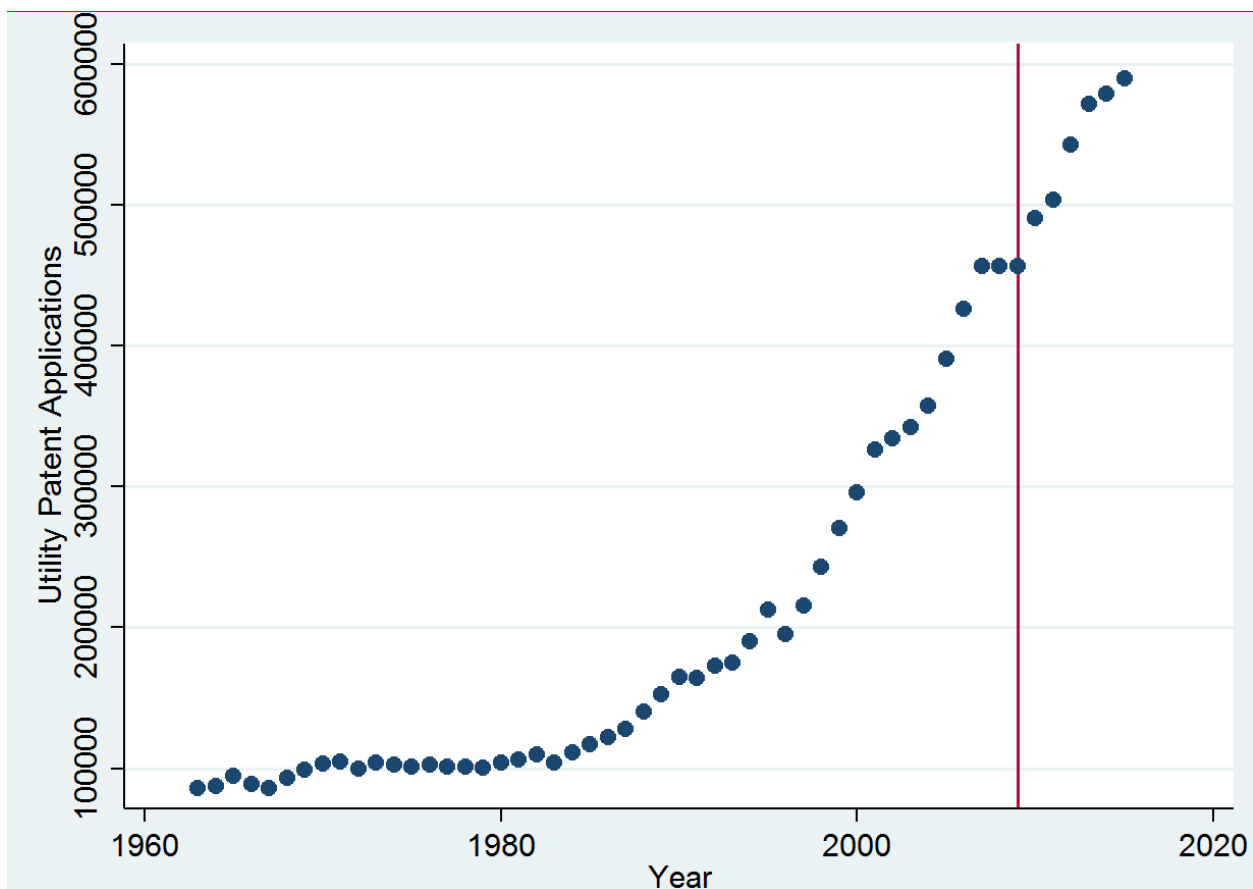
[26] Patent Technology Monitoring Team. *U.S. Patent Statistics Chart Calendar Years 1963-2015*. Rep. N.p.: U.S. Patent and Trademark Office, 2016. Print.

Table 4.1: Summary Statistics for Model 1

Variable	Mean	Standard Deviation	Min	Max
US Patent Applications	123,700.20	75,298.28	59,390	288,335
Foreign Patent Applications	96,798.68	81,863.94	284	301,075
Utility Patent Applications	225,847.80	159,485.90	85,697	589,410
Total Patent Applications	241,157.60	169,417.10	95	1,406
Observations	53			

As you can see in Figure 4.1, there is a significant jump in patent applications following the stagnation created by the recession from 2007-2009. Though there are similar jumps in patent application behavior, 2009-2010 is the largest increase on the graph, with an additional 34,120 patents compared to the 2006-2007 increase of 30,187. Though not definitively related to the ASC, this jump at least shows that there is potential for the ASC to have some consequence on patent applications.

Although comprehensive and reliable, the survey is only in the aggregate, which severely limits the usefulness of the data. Without firm specific observations, I cannot directly observe the effects of a policy shift as they shift depending on firm characteristics.

Model 2 uses another report provided by the U.S. Patent and Trademark Office's Patent Technology Monitoring Team- The *All Technologies (Utility Patents) Report*.[27] This report provides firm-level information for firms that have over 1,000 Patents, organized by the year of

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[27] Patent Technology Monitoring Team. *All Technologies (Utility Patents) Report*. Rep. N.p.: U.S. Patent and Trademark Office, 2016. Print.

patent grant, and, more importantly for this paper, the year of patent application. The report

includes data from 1991 to 2015, with years 1991-2001 aggregated in a "Pre-2002" number.

Much like Model 1's data, because this information is published by the very organization

responsible for accurately maintaining records of all relevant patent and trademark data, it can

be considered highly reliable information. The summary statistics for all 450 firm level

observations is provided in Table 4.2.

Table 4.2: Model 2 Data

Variable	Mean	Standard Deviation	Min	Max
Patent Applications	352.99	3,862.96	0	94,789
Year	8.50	4.03	2	15
Observations	6,272			

Like Model 1, *Patent Applications* represents total utility patent applications per year by

a specific firm. *Year* is part of the cross-sectional data that acts as the time variable, measured

annually from 2002 (2) to 2015 (15). *Firm* is the ID variable assigned to each firm-level

observation.

Though incredibly useful due to the firm-level nature of the report, this data still leaves

more to be desired. In the given data set, firms are noted only by the number of patent

applications/grants provided and given, respectively, in a specific year. There is no information

regarding firm specific qualities, specifically for my research, size. Regardless of this setback,

having firm level data allows for me to address firm fixed effects in my model, which can

hopefully build on Model 1's aggregate output to provide some more insight into the effects of the ASC on patent output.

Unlike Models 1 and 2, Model 3 uses an entirely different set of data provided by the National Science Foundation's *Business Research and Development and Innovation Survey* (BRDIS) and is predecessor, the *Survey of Industrial Research and Development* (SIRD).[28] The survey is conducted by the Census Bureau in part with the National Center for Science and Engineering Statistics. Data is collected by taking a national sample of companies in a variety of industries. I use data covering 2004 to 2013 that records R&D expenditures by firm size and industry. Because all expenditure values are not adjusted to inflation, I adjusted all data to Q1, 2004 using the FRED GDP Implicit Price Deflator. Summary statistics for Model 3 are provided in Table 4.3.

Table 4.3: Model 3 Summary Statistics

Variable	Mean	Standard Deviation	Min	Max
Total	115.14	181.57	1.98	841.53
Mean Size	5,331.98	8,367.85	7	25,000
Size	2.03	0.87	1	3
Observations	102			

In Model 3, rather than measuring patent applications as a proxy for innovation, *Total* represents actual R&D expenditures adjusted to real terms for the beginning of this dataset, Q1

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[28] *National Science Foundation. Business Research and Development and Innovation Survey (BRDIS). Web. 12 Nov. 2016.*

2004. *MeanSize* measures the averages in firm size categories; Small firms with 1-9 employees have a value of 4.5, 10-14 has a value of 12, and so on. *Size* is a variable measuring firm size fixed effects, with a value between 1 and 3 assigned to each firm size grouping based on number of employees. Small firms (<200) have a value of 1, mid-sized firms (200<=employees<1000) have a value of 2, and large firms (1000+) have a value of 3. Each size group and year gives a total of 100 observations for this panel data set.

The largest issue with this dataset is, simply put, how crude the information is. This data set is unbalanced because firms can move from size grouping to size grouping on an annual basis, meaning that R&D expenditures by any one given firm cannot be assumed to remain the same year to year. Despite this, the information itself can be assumed reliable. As an output of the Census Bureau and the National Science Foundation there is merit to the information. However, with all surveys, errors by those taking the survey are not to be ruled out.

In all models, I control for economic trends via the unemployment rate. The unemployment rate data is taken from the Bureau of Labor Statistics *Labor Force Statistics from Current Population Survey* data, which is updated on a daily basis.[29]

The biggest issue with all my data, as touched on above, is the lack of specific firm level information. Several organizations, including the US Patent and Trademark office and National Science Foundation collect firm-level data, but release only aggregate information to the public. An additional issue stems from the type of company performing this level of R&D work. Any company who is private need not disclose R&D expenditure numbers on any publicly available

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[29] Bureau of Labor Statistics. Labor Force Statistics From Current Population Survey-Unemployment Rate. 2017. Raw data. BLS, Washington D.C.

financials they do in fact provide. For public companies, R&D expenditures are really only disclosed on financial statements if the expenditures are material in relation to assets and income from operations.[30] Ultimately, this data shortcoming leads to a focus on aggregate effects of tax policy shifts, with some recommendations as to how to address firm-level results going forward.

5.0 Results

Results and relevant discussions are given by model and relevant alterations as follows.

Model 1: Aggregate Data

The key equation used in Model 1 is a standard linear regression with Newey-West standard errors. Table 5.1 shows the relevant output for the initial, unedited model.

Table 5.1: Utility Patent Applications (In Thousands of Applications)

Alternative Simplified Credit (Dummy)	202.15 (20.46)
Unemployment	-1,918.45 (285.67)
Time Trend	7.18 (0.61)
Constant	122.38 (17.79)
Observations	53
R-Squared	0.9313

Notes: The above table is given in thousands of patent applications. Newey West Standard errors are given in parentheses. Results are significant at the 1% level (p<0.01)

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[30] "R&D Expenditures." Message to the author. 20 Jan. 2017. E-mail. In response to request for assistance in finding relevant data. From Todd Hines, Asst. Economics, Finance, and Data Librarian at Princeton University.

In this initial model, the existence of the ASC has a large, significant effect on the number of patent applications filed, with about 202,000 patent applications filed in years with the ASC as compared to years without. Additionally, unemployment acts as we would expect, significantly decreasing patent applications as unemployment increases. To extrapolate on this model, I tested whether foreign based patent applications are influenced to a different degree than domestically originating applications, summarized in Table 5.2.

Table 5.2: The Effects of the ASC Policy Change on Foreign and Domestic Patent Applications (In Thousands)

	Foreign (1)	Domestic (2)
ASC effects	66.03	94.23
	(22.42)	(12.76)
Observations	53	53
R-Squared	0.7575	0.9071

Notes: The above table is given in thousands of patent applications. Newey West Standard errors are given in parentheses. Results are significant at the 1% level (p<0.01)

It appears that, with some significance, the ASC tax policy shift does in fact have a different effect on foreign based applications than on domestic ones. This is an interesting discovery, perhaps due to the location of the R&D expenditures (performed abroad or on US soil). Because domestic firms obviously spend more on R&D on U.S. soil, they are eligible for more deductions than their foreign counterparts performing a majority of research overseas.

Model 2: Large Firm Panel Data

The second model, broken down in Table 5.3, should also show a significant increase in patent applications as a result of the ASC policy shift. However, this model had little to no relevance with my hypothesis, most likely due to the model itself.

Table 5.3: Firm-Level Patent Applications

Alternative Simplified Credit (Dummy)	-480.11
	(442.32)
Unemployment	10,547.21
	(6,427.04)
Time Trend	10.86
	(42.44)
Constant	-183.01
	(500.31)
Observations	6,272

Notes: The above table is given in thousands of patent applications. Newey West Standard errors are given in parentheses. Results are not significant (p>0.20 for all variables)

As the above results show, the results of model two are not statistically significant at all, and are thus negligible. Nevertheless, it is worth including them here in order to complete the picture of research performed as part of this discussion.

Model 3: Size Grouping Panel Data

To exam the effects of firm size on R&D expenditures, I run the OLS model with and without size dummies, as shown below in Table 5.4. While the ASC seems to be insignificant, each size dummy does show a trend between R&D spending and firm size.

Table 5.4: R&D Expenditures by firm size

	OLS Model (1)	OLS Dummy Model (2)
Alternative Simplified Credit (Dummy)	9.19 (36.19)	-18.83 (11.64)
10-14		70.69 (34.54)
15-24		-245.71 (34.97)
25-49		-346.97 (34.54)
50-99		-396.07 (34.54)
100-249		-439.28 (34.97)
250-499		-451.49 (34.54)
500-999		-452.82 (34.54)
1,000-4,999		-464.07 (34.54)
5,000-9,999		-464.71 (34.54)
10,000-24,999		-463.37 (34.54)
Constant	110.28 (26.33)	476.61 (31.04)
Observations	102	102
R-Squared	0.0006	0.9105

Notes: The above table is given in thousands of patent applications. Newey West Standard errors are given in parentheses. Results are significant at the 1% level (p<0.01)

Interestingly enough, as the size of a given firm increases, R&D expenditures decrease. Obviously, due to the insignificant nature of this model, it appears that the passing of the ASC had little to no effect on R&D expenditures at all.

6.0 Discussion

When looked at as a whole, the results of each Model suggest that the January 2009 enactment of the Alternative Simplified Credit, although meant to spur firm innovation, had little to no effect on patent application levels and R&D spending. These results are significant for several reasons. First and foremost, even though tax credit legislation is edited and revised on a very frequent basis and the intention is always to alter behavior, not every single policy shift has the desired outcomes on firm spending habits and resource investment. Secondly, though the effects of the ASC itself are null in the second two models, the size variables in Model 3 do suggest that, size is in fact negatively correlated with R&D spending as a result of the ASC. This is an interesting conclusion that is most likely reached in this scenario due to the crude nature of the data. In some ways this would make sense, when combined with the results of the ASC and size interaction variable. Though the ASC itself has little to no effect on all firms, the effect it has on small firms is greater than that of large firms.

In the aggregate data from Model 1, there does appear to be a significant effect of the ASC on patent applications. Though taken from aggregate data, this result does seem promising, as it shows that, on a large scale trend (from 1963-2015) the recent enactment of the ASC did positively correlate to an increase in patent applications. However, looking at patent trends independent of the ASC, it seems as if, barring any recessions, patent applications

are on an upward trend in general. Given the technology driven state of society, it's to be expected that years after 2009 would have larger levels of patent applications than any year prior.

With regards to the origin of patent applications, Model 1's varying results for domestic and foreign patent applications are incredibly interesting. Though anyone doing business in the US, of domestic or foreign origin, is required to file taxes, it seems that the ASC policy shift still has a greater effect on domestic companies than foreign ones. This most likely is due to the location of the R&D work performed. As previously discussed, the purpose of R&D tax credits are to incentivize innovation and research within specific regions or, in this case, within the United States. Because R&D expenditures must be performed within a specific jurisdiction, domestic companies are inherently able to claim more of the credit than foreign firms, who are most likely performing a larger portion of their research abroad.

In order to better understand the nature of tax policy and its effects on innovation, there are several improvements and additional studies that can be performed on top of the models I used above. First and foremost, the effectiveness of every model used would increase significantly with firm-level data, including size, sales, and percentage of assets/net income R&D expenditures are. This information, combined with the previously mentioned fixed effects used in these models, should in theory produce far more useful results for this research. Throughout this entire process, it has been the lack of firm-specific observations that have led to skewing the results and preventing any legitimate conclusions regarding the effect of size on the benefits of the ASC.

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