

The Impact of U.S. R&D Expenditures on U.S. Exports: Does R&D Tax Credit Policy Matter? ¹

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Abstract

R&D tax credits have generally led to increases in R&D investments, which in turn can explain the positive link between U.S. exports and productivity growth. Previous research has focused on the impact of R&D tax credit on domestic R&D investments rather than on U.S. exports. This paper examines the effect of the R&D tax credit policy on U.S. exports by industry during the period of 2006 to 2012. We consider two U.S. R&D tax credit provisions: regular research credit (RRC) and alternative simplified credit (ASC). They differ in the qualification requirements and stipulated rates. We empirically determine whether a firm file for RRC or ASC in each industry and year. Given these qualifications we estimate augmented for R&D firm-level total factor productivity (TFP). We construct the user cost of R&D by using heterogeneous industry-level R&D depreciation rates, federal and state R&D tax credits. We estimate predicted R&D expenditure based on the user cost of R&D, which we use as an instrument in estimating TFP. Finally, we estimate elasticities of U.S. exports with the respect to trade barriers controlling for firm-level heterogeneity by the R&D credit type. There are several key findings, which matter for policy implications. First, we identify main characteristics of firms favored in the ASC over RRC. Second, firms that choose to file for ASC are more productive than firms that choose to file for RRC both within and across industries. Consequently, the implied firm-level heterogeneity has differential impact of trade barriers on U.S. exports that depends on the type of R&D credit. This finding implies that an R&D tax credit policy should be industry-specific to strengthen the U.S. competitiveness internationally.

¹ The views expressed are those of the author and do not necessarily reflect those of the U.S. Department of Commerce, the Secretary of Commerce, the International Trade Administration (ITA), the Bureau of Economic Analysis (BEA), or the Under Secretary for International Trade.

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I. Introduction

Research and Development (R&D) tax credits are a prominent part of the industrial policy for many countries. The motivation for instituting the R&D subsidy is well micro founded and based on the idea that private investment in R&D is a public good with the presence of positive externalities. These externalities lead to underinvestment into R&D relative to what is socially optimal (Arrow (1962) and Jones and Williams (1999)). In the United States, the R&D subsidy began following the passage of 'The Economic Recovery Tax Act' in 1981 that contained a provision called the “Credit for Increasing Research Activities” (the Credit). The Credit was tailored to reverse the decline in U.S. research spending by providing an incentive that was premised on benefiting increases in (as opposed to total) year- over- year research spending. Since then, Congress has extended the credit repeatedly due to bipartisan support. However, policymakers and academics criticized this moving average base method because this mechanism allowed the marginal incentive effect in the first year significantly offset in the following years. In the Omnibus Budget Reconciliation Act of 1989, the US Congress amended R&D tax credit policy by redefining the base amount as a fixed-base percentage equal to the ratio of a firm’s research to its gross sales receipts for 1984-88, which is used to calculate the qualified incremental R&D expenditures to determine the amount of an R&D credit. The structural change of effects R&D tax credit provided mixed results empirical results (Swenson, 1992; Hall, 1993; Klassen, Pittman, and Reed 2004)

Following federal R&D tax credit provisions, U.S. states established similar credits. As of 2015, 34 states provided a tax credit for company-funded R&D with on average top-tier rate of roughly half of regular research credit (RRC) rate of 20%. While some research indicated that the structural change to R&D tax credit in 1989 decreased overall firm eligibility, the incentive effect of R&D tax credit remained unexplored and resulted in repeated improvement. Thereafter, US Congress enacted Alternative Simplified Credit (ASC) in 2009 to allow companies which cannot substantiate its claim for the regular R&D credit (RRC) to elect for an alternative calculation method.

Lower than RRC, the ASC provides a R&D credit of 14% of the QRE (Qualified Research Expenditure) in the current year that exceed 50% of the average QRE for the three preceding taxable years. The combined federal and state R&D tax credit rate system is fairly complex. To take advantage of an R&D tax credit provisions, a firm has to carefully determine the part of R&D expenditure that qualifies for a credit, the so-called qualified research expense (QRE), decide which R&D credit to file for, and calculate user cost of R&D capital. This user cost accounts for discounted by R&D credits federal and state corporate taxes liability for firm.

While there is substantial literature that explores the effect of R&D tax credit policy on R&D expenditure and intensity (the ratio of R&D expenditures to sales), much less is known to what extent this policy affects exports. Research has been done to explore the impact of R&D investment on the change in productivity to change in exports link. The exposure to trade will stimulate the more productive firms to enter the export market while the less productive firms continue with domestic production (Melitz, 2003). In this self-selection process, evidence has been found that exporting has a direct effect on further productivity improvement (Greenaway and Kneller, 2004). Recent empirical trade literature has explored the role of R&D investment as a potentially important factor of the productivity-export link. Lileeva and Trefler (2007) argue that exporting is associated with firm's R&D investment and technology innovation and adoption, which suggests productivity gains. Criscuolo, Haskel, and Slaughter (2005) point out that firms with global operation devote more resources to generate innovations and absorb and assimilate innovative knowledge worldwide. Aw, Roberts, and Xu (2009) note that R&D investment and exporting are interdependent factors, both of which have a positive, direct effect on productivity and that the high productivity reinforces a firm's self-selection into export market and R&D investment.

While many studies have been done on the impact of R&D investment on exports and productivity, in this paper we look beyond the R&D investment by studying the impact of the R&D tax credit policy (especially the newly-enacted ASC policy) on merchandize exports through the estimate of total factor productivity (TFP). We estimate that the R&D tax credit policy and change of policy provision would induce R&D investment through the policy impact on the user cost of R&D capital and increase productivity gains, and in turn, the

policy facilitates exports when more productive firms opt to export due to lessen impact of trade barriers on trade flows.

Specifically, we empirically analyze the effect of RRC and ASC R&D tax credit policies on the U.S. exports between 2006 and 2012. The intuition for the link between R&D tax credits and exports is fairly obvious from the stand point of the new trade models which were pioneered by Melitz (2003). From, the standard trade theory with heterogeneous firms, we know that only most relatively productive firms are profitable enough to select into exporting. Furthermore, as shown by Chaney (2008), firm-level heterogeneity distorts “gravity”, in the sense that in industries with larger and more productive firms trade barriers have relatively mild effect on trade flows. By identifying firm-level total factor productivity (TFP) distributions depending on the R&D tax credit, we quantify the firm-level heterogeneity effect on trade barriers *within* and *across* industries. The firm-level heterogeneity distortion is the channel through which R&D tax credit affects U.S. exports.

With a use of Compustat North America database, our empirical analysis proceeds in two stages. In the first stage, which we call a policy stage, we use various R&D tax credit conditions to probabilistically determine whether a firm choose to file for RRC or ASC with given firm-level balance sheet characteristics. Depending on the type of tax credit that a firm chooses to file for, we calculate the user cost of R&D capital. The user cost of R&D capital has both federal and state components of corporate tax rates and R&D tax credits. Furthermore, one of the innovations in our paper, is to calculate the user cost of R&D capital based on the newly estimated industry-level R&D depreciation rates (Li, 2015). The standard assumption adopts a constant rate, 15%, across industries (Wilson, 2007), which is against the conclusion from recent R&D research that the rate should be higher than 15% and varies across industries (Li and Hall, 2016). Hence, relative to the existing approaches, we have two additional sources of variation in the user cost of R&D capital. For a given US state and year, our measure varies by type of firm-level R&D tax credit, and by industry-level R&D depreciation rates. In the export performance (second) stage, we estimate gravity model of trade that accounts for firm-level heterogeneity by the R&D credit type. The degree of firm-level heterogeneity is estimated from firm-level R&D augmented TFP distributions by industry.

Recognizing endogeneity of R&D capital stock in estimating TFP, we follow Bloom et al. (2013) and use R&D tax credit policy as an instrument for the R&D stock.³ We estimate R&D expenditure cost using dynamic panel methods that take into account that current R&D investment decisions depend on the previous levels of R&D expenditure. Since, our user cost of R&D varies by the type of the tax credit, we are able to estimate elasticity of R&D expenditures with respect to ASC relative to RRC. In other words, we are able to calculate the direct effect of R&D tax credit policy for given corporate tax rates. The predicted R&D expenditures from estimating the cost of conducting R&D are converted into R&D stock using the perpetual inventory method. We extend Olley and Pakes, (OP) (1996) methodology to estimate R&D augmented TFP.

Our paper contributes to two strands of literature. First, the ample empirical evidence shows that R&D tax credits play a significant role in the R&D investment decisions. This argument, dated back to 1962, has been widely discussed and acknowledged that the R&D tax credit is positively associated with the R&D spending, which has positive impact on economic growth through technology spillover. Following Wilson (2007) we treat R&D as an input into a firm's production function. The price for this factor is the user cost after taxes. According to Rao, 2014, a 10% reduction in the user cost of R&D capital leads to an increase of R&D intensity in the short term and increase R&D spending in the long term. To accurately measure the R&D user cost, we improve Wilson's calculation by using federal corporate tax income brackets, which allows a more precise calculation of effective corporate tax rates.

Second, significant amount of work has researched the effectiveness of the federal R&D tax credit, the regular R&D tax credit (RRC), among which are Wilson's (2007) and others. Initially, some researchers questioned the effectiveness of R&D tax credit policy by looking into the budget loss comparing to R&D spending induced by this tax credit policy (Corde, 1989). Others added the leak of technology into the equation to study the effectiveness of R&D tax credit (Mansfield, 1986). More recent research combined the two countervailing spillovers – the technology spillovers and a negative business stealing effects – together and concluded that technology spillovers quantitatively dominate the impact of R&D on economic growth (Bloom, 2013). Another recent study shows that a 10% reduction

³ This analysis is presently incomplete and will serve as a robustness check for our findings.

in the user cost of R&D capital leads to an increase of R&D intensity in the short term and increase R&D spending in the long term (Rao, 2015) The recent introduction of ASC into the R&D tax credit mechanism has brought challenges to the existing RRC. A significant portion of the eligible R&D firms opt to file for ASC. The availability of ASC has been factored in at firm-level decision regarding their R&D spending. Yet, current R&D tax credit research, focusing only on the RRC, has not given sufficient consideration and study on the newly-enacted ASC. This paper contributes to the classic R&D tax credit and empirical trade literature by considering how two available R&D tax credit provisions affect firms' decisions to invest in R&D and its subsequent impact on their export participation. To the best of our knowledge this is the first study to quantify these links.

This paper is organized as follows. In the next section we discuss our data sources and provide descriptive statistics; section III is devoted to the policy stage of our estimation; section IV presents estimates of R&D tax credits on U.S. exports and discusses policy implications; and section V concludes

II. Data

A. Data and Sample Selection

Our estimation strategy involves two stages. In the first stage, we determine how introduction of Alternative Simplified Credit (ASC) in 2009 affected R&D expenditures of firms who chose to file for ASC relative to firms filing for Regular R&D tax credit (RRC). We use R&D tax credit policy as an instrument for endogenous R&D expenditure in the production function to estimate total factor productivity (TFP). In the second stage, we estimate an international trade model to shed light on how R&D tax credit policy affects U.S. exports through its effect on firms' productivity.

For the first stage estimation we collect a sample of all listed firms on the Compustat Industrial North America between 2006 and 2012. Our year range covers three years before ASC went into effect and three years after to set up difference-in-difference type regression analysis.⁴ Compustat data is notoriously difficult to directly use in the estimation due to inconsistent coverage, missing data for some firms and duplicate data for others. After cleaning

⁴ Under IRS provision, ASC is allowed to carry back three years.

data from duplicates; selecting firms with reported R&D expenditure in at least one year in our sample; and dropping the highest and lowest 1 percent of the observations for each firm-year to remove the effects of outliers, our sample is an unbalanced panel that consists of 11,882 firm-year observations representing 3,007 firms.

In order to determine whether a firm is “eligible” and “qualified” to receive an R&D tax credit, we need to obtain the value for Qualified Research Expenditure (QRE). QRE is available from the IRS Statistics of Income database, which we do not have access for. For a firm to be “eligible” to receive an R&D tax credit, its QRE in a given year must be greater than a base year spending amount. We use formula (1) established by Congress after 1989 to calculate the base spending amount for each year t in our sample period.

$$Base_t = \max \left[\left\{ \left(\frac{1}{4} \sum_{t=1}^4 Sales_{t-k} \right) \times \min \left(0.16, \frac{\sum_{j=2006}^{2012} Sales_j}{\sum_{j=2006}^{2012} QRE_j} \right) \right\}, 0.50 \times QRE_t \right] \quad (1)$$

In formula (1) *Sales* represents value of total sales for each firm-year reported in Compustat. Following the related literature, we assume that QRE equals 50% of the reported R&D expense. As discussed by Gupta et al. (2011), to be “qualified”, a firm must only be eligible, but also have a sufficient tax liability against which to use the credit. We use Gupta’s et al. (2011) conditions to determine whether a firm is “qualified” to receive an R&D tax credit.

In order to conduct our calculation for user cost of R&D capital, we collect data of state R&D tax credit rate. Since Minnesota became the first state to enact a R&D tax incentive in 1981, nearly all states have enacted some kind of incentive for R&D. They also have modified, expanded the incentive, and sometimes repealed and sunset it. Most states offer some version of an R&D tax credit to supplement the federal R&D tax credit incentive except the District of Columbia and six states: Alabama, Arkansas, Hawaii, Nevada, Wyoming, and Missouri, whose R&D tax credit sunset in 2005. In most cases the state credit is generally patterned after the Federal R&D tax credit in that it uses the same definitions such as qualified research expenses, base amount, and is incremental and nonrefundable in nature. For example, a majority of states use the federal definition of qualified research expense (QRE) from the internal Revenue code, Section 41, with a modification to include only expenses incurred within the state.

We survey the specifics of the R&D tax credits of the 50 states and the District of Columbia.⁵ The information for each state has been gathered primarily from websites of state governments and from state tax codes. For some states with no sufficient online information, we have initiated phone and email conversations with state officials for the data collection. Attempts and great efforts have been made to verify the information for each state, especially those of R&D tax credit differing from the typical QRE model. By direct communication with state tax and/or economic development officials, we correct a number of mistakes of the lists of state R&D tax credit currently available in this arena. For example, after consulting New York state officials, we realize that R&D tax credit of New York City has been widely used in relevant research and replace it by the correct New York state R&D tax credit. In very few cases, we make references to other reports. The R&D tax credit references we collected reflect the current practice of each state at the time of this paper.

However, states' tax credit mechanisms vary greatly in their design. Our understanding of this mechanism across states would be limited if the attention is only paid to the tax credit rate. In very few states, R&D credit is non-incremental in nature, for example in Kentucky. A few states allow taxpayers to claim some percentage of their federal credit, for example, in Nebraska. A number of states offer small businesses R&D tax credit with higher percentage of the research expense, such as Connecticut and North Carolina. Some states make some portion of their credit refundable, like Iowa. A few states choose to depart from the typical QRE model of business tax incentives. Different from most states' R&D tax incentive, Mississippi offers a \$1000 tax credit per employee hired by R&D companies from corporate income tax for the first five years. Sales tax exemptions are another type of incentive departing from the typical QRE model. Tennessee extends tax credits to machinery, apparatus and equipment, etc. if it is purchased primarily for the purpose of R&D. Complicated as this R&D tax credit mechanism gets, we carefully select state R&D tax credit rate, including the effective rate, lower bracket rate, and higher bracket rate for the calculation for user cost of R&D stock.

Also for the purpose of calculating user cost of R&D capital, we select and compile state corporate income tax rates for the period of 2006 to 2015 from the data base of the Tax Foundation. Since many states have multiple statutory tax rates, the stepwise increase of which

⁵ The complete table with R&D tax credit provision for each state is available upon request from the authors.

depends on the corporate income, we follow the way of data selection by Wilson (2009) using the top marginal tax rate. In doing so, we collect state corporate income tax rate of the highest bracket from 2006 to 2014 and compile it with the state corporate income tax rates of the highest bracket of 2015 to complete the calculation of user cost of R&D stock.

B. Descriptive Statistics

Based on the described criteria for eligibility and qualification for R&D tax credit, we find that in our sample of the total of 11,862 firm-years 8,746 (73.7%) are eligible for any R&D tax credit; and among eligible 8,746 firm-years, 5,502 (62.9 %) are qualified for any R&D tax credit. Furthermore, using our methodology for determining whether a firm chooses to file for RRC or ASC, we find that among eligible firm-years 67.4% filed for RRC, and 32.5% filed for ASC.

In Table D1 and D2 we report the descriptive statistics for characteristics of firms that chose to file for RRC and ASC respectively in our sample. Since Compustat contains data on publicly traded firms, it is not surprising that largest share of firms (33.1%) are eligible and qualified (E&Q) for RRC. Among the firms that chose to file for RRC, those that are E&Q have on average spend significantly more on R&D, have significantly larger revenues and sales, and have significantly higher tax liability relative to firms who are not eligible and not qualified (NE&NQ). Comparing these statistics to ones for firms choosing to file for ASC, we find that that the latter group of firms has notably higher R&D expenditure and significantly lower R&D intensity compared to firms that choose to file for RRC. Since R&D intensity is defined as a ratio of R&D expenditures to sales, this difference indicates that firms that choose to file for ASC undertake considerably larger R&D expenditure relative to sales. This finding is important for two reasons. First, it validates the intent of filing for ASC. Second, more importantly, it gives us confidence in our approach in determining which R&D tax credit a firm choose to file in a given year.

In Table D3 we report top 10 share of eligible (E) and E&Q firms filing for RRC and ASC by state. First, find that eligibility and qualification of firms for an R&D tax credit is heterogeneous by states. Even though we report only top 10 states by share only very few states had no firms filing for R&D tax credits. Second, the share of firms that choose to file for RRC is

significantly higher compared to that of for ASC. For the top three states, all of the eligible firms chose to file for RRC, but slightly more than 30% filed for ASC.

In Tables D4 and D5 we report shares of E and E&Q firms choosing to file for RRC and ASC 4-digit NAICS industries. Similar, to variation in shares by states, we find industry heterogeneity in filing for R&D tax credits. Firms that choose to file for RRC are in relatively less R&D intensive industries. For example, the average R&D intensity in fifth ranked Cement and Concrete products manufacturing for firms filing for RRC is 0.005, while the average R&D intensity similarly ranked Chemical Products and Preparation for firms choosing to file for ASC is 0.378. This result suggests that there may be a differential impact of R&D tax credits on exports by industry provided that our hypothesized channel in firm-level heterogeneous changes in productivity induced in part through these credits. Furthermore, this analysis gives another way to look at validity of our R&D tax credit firm-level selection methodology that we turn to in the next section.

C. Industry-level R&D Depreciation Rates

Given the fact that most industries have R&D depreciation rates higher than 15% and the rate should vary across industries, U.S. Bureau of Economic Analysis has published industry-level R&D depreciation rates for all high-tech industries (Li, 2012, Li, 2015, Li and Hall, 2016). In this research, contrary to existing research on R&D tax credit, we calculate user cost of R&D capital stock based on industry-level R&D depreciation rates. Table xx list the industry-level R&D depreciation rates (Li, 2012, 2015) that we use for each industry.

III. First Stage: R&D Credit Policy

A. Background

In 1981, the Economic Recovery Tax Act established Section 41, which allows a non-refundable research and development regular R&D tax credit (RRC) designed to benefit taxpayers incurring research activities. Expenses for salaries and wages, supplies, and contract research conducted on the taxpayer's behalf are considered when calculating the R&D credit. Such expenditures are known as qualified research expenditures ("QRE".) Current IRS

enforcement policies have forced tax departments and R&D functions to focus on whether they have the documentation needed to determine, as well as to sustain, R&D tax credits. This is due, in part, to the fact that the research credit is an incremental credit computed on the increase of research spending over the amount the company would be expected to spend on research (called the “base amount”). Determining the base amount for the traditional credit requires companies to substantiate the amount of research spending during the years from 1984 – 1988, or for the initial years of operation (if not in existence during 1984-88).

Recognizing the difficulty taxpayers faced in substantiating research spending occurring 10 – 20 years ago, led to the enactment of the Alternative Simplified Credit (ASC) which eliminates the need to substantiate research spending occurring many years ago. On June 10, 2011 the IRS issued final regulations relating to the ASC. The final regulations generally adopt the proposed regulations issued in 2008, with minor revisions that came into effect in 2009. The ASC provides companies the opportunity to claim a credit without having to compute the historical base amount by simply quantifying their QRE for the current tax year and the previous three tax years. The base amount is 50% of the average prior three years of qualifying R&D expenditures. Taxpayers then get a credit equal to 12% (7.8% after the Section 280C(c) reduced credit adjustment) of the excess R&D spending over this base amount. This credit amount increases to 14% (net 9.1%) for tax years ending in 2009. So unless a taxpayer's R&D spending is down significantly, they would virtually be assured of getting a credit under the ASC, but may not be able to get over the traditional base amount. The specific conditions to elect filing for ASC instead of RRC are summarized in Table A1.

B. Estimation

With two available R&D tax credit provisions (RRC and ASC) the accurate measurement of the user cost of R&D requires determining which provision a company filed for. Importantly, once the ASC is elected for the tax year it is irrevocable, but only for that tax year, i.e., a taxpayer could not elect the ASC and then elect an amended return reporting the regular credit for the same tax year. In our data, we do not observe which credit type a firm filed for. Accordingly, we use ASC conditions in Table 1 to probabilistically determine the likelihood of filing for either ASC or RRC. We extend Gupta et al. (2011) and estimate the logistic specification (2).

$$\begin{aligned}
STATUS_{it} = & \beta_0 + \beta_1 \ln(RGDP)_t + \beta_2 \ln(SalesGrowth)_{it} + \beta_3 \ln(RDGrowth)_{it} \\
& + \beta_4 \ln(Size)_{it} + \beta_5 \ln(MRT)_{it} + \beta_6 ASC_t + \beta_7 ASC_Cond_{it} \\
& + \beta_8 (ASC_t \times \ln(Size)_{it}) + \beta_9 (ASC_t \times ASC_Cond_{it}) + \varphi_j + \varepsilon_{it}
\end{aligned} \tag{2}$$

In specification (2) *STATUS* takes the value of one if a firm (*i*)-year (*t*) is either eligible or qualified for the R&D tax credit zero otherwise; *RGDP* is real GDP in year (*t*); *SalesGrowth* is annual sales growth, defined as the change in sales divided by prior sales; *RDGrowth* is annual R&D expense growth, defined as the change in R&D expenditure divided by prior R&D expenditure; *Size* is firm size, measured as total assets; *MRT* is one-year lagged, after-financing marginal tax rate; *ASC* takes the value of one if a firm files for an R&D credit after 2009 and zero otherwise; *ASC_Cond* takes value of one if one of the ASC filing conditions holds and zero otherwise; the interactions between ASC with *Size*, and ASC with ASC Condition are capturing differential effect ASC introduction had on firms of various size, and ASC filing conditions respectively; φ is 4-digit NAICS industry *j* fixed effect; ε is an idiosyncratic error term.

Let $\hat{\rho}_{it}$ be the predicted probability of eligibility or qualification for each firm-year observation using the Logit estimates from (1), and let $\hat{\rho}_x$ be marginal post ASC introduction eligibility/qualification industry *z* probability evaluated at averages of observed variables in (2) such that one of the ASC filing conditions hold⁶. Then a firm *i* is predicted to file for ASC in year *t* if $\hat{\rho}_{it} > \hat{\rho}_x$, and it files for RRC otherwise.⁷

We report the estimation results for the specification (2) in Table R1 for the unbalanced sample.⁸ In columns [1] and [4] we report eligibility and qualification probabilities without ASC filing condition respectively. We find that the coefficient on ASC is positive, but not significant for eligibility, and negative and significant for qualification. Using the odds ratios these estimates indicate that post-ASC eligibility for an R&D credit (ASC or RRC) are 1.1 times pre-ASC estimated odds. Similarly, these odds are 0.9 times for qualified firms. We then interact ASC with firm size. The interaction coefficient is negative and significant, indicating that post-

⁶ In general, this marginal probability estimation yields four outcomes: pre ASC introduction – ASC filing condition does not hold; post ASC introduction – ASC filing condition does not hold; pre ASC introduction – ASC filing condition holds; post ASC introduction – ASC filing condition holds. We are interested in the latter combination.

⁷ Even though ASC was passed in 2009, IRS allowed an eligible/qualified firm to back file for ASC up to 4 years.

⁸ The results for balanced sample, which includes firms with observations in each year in our sample, gives similar results.

ASC eligibility for an R&D credit (ASC or RRC) are 0.02 times pre-ASC estimated odds for larger firms. This result indicates that while introduction of ASC had no overall effect on eligibility, it met intended goal of increasing eligibility for relatively smaller firms. We illustrate the marginal effect of the change in firms' size with the respect to the eligibility probability in Figure 1. The probability of qualification post-ASC increases with firm size, but significantly so only for relatively large firms as illustrated in Figure 2.

Since we do not specifically know the qualification conditions to apply for ASC, we focus on eligibility to probabilistically determine whether a firm chose to file for ASC or RRC. Consider the first ASC filing condition. This condition implies that firm's sales grow faster than R&D spending growth. Accordingly, we assign ASC_Cond to take value of one if a firm's sales grow faster than R&D expenditures and zero otherwise. We re-estimate specification 1, where we interact ASC introduction with the first ASC filing condition. We find that post-ASC eligibility odds for firms that meet this ASC filing condition is 1.5 times pre-ASC estimated odds for these firms. This result indicates that ASC introduction raised eligibility of an R&D credit for firms which are presumably ineligible for RRC. Similarly, we find that odds of post-ASC qualification are also higher for firms that meet this ASC filing condition, but they are not significant.⁹

The second ASC filing condition implies that the firms are more likely to apply for ASC when R&D spending growth is positive. We first confirm that firms with positive R&D growth have higher odds of eligibility and qualification for an R&D credit in columns [3] and [6] of Table R1 respectively. These eligibility and qualification odds for an R&D credit are 3.6 times, and 1.1 times higher for these firms respectively. Next, we estimate whether these odds are higher post-ASC introduction. The coefficient on the interaction term ASC×ASC_Cond is negative and significant for the eligibility regression. This result is surprising, as it implies that post-ASC eligibility for an R&D credit are 0.5 times pre-ASC estimated odds for firms with positive year-over-year R&D growth. In other words, introduction of ASC did not raise filing eligibility of R&D credit firms with increasing year-over-year R&D expenditures.

We estimate the likelihood of a firm to applying for ASC as opposed to RRC using the decision rule based on the two ASC filing conditions discussed above. Using these conditions, we find that the fraction of firms filing for ASC are 64.2% and 47.3% respectively. Since ex-ante

⁹ We verified that these results hold for the balanced sample as well.

there is no baseline we can compare our results against, we rely on private tax consulting firms that find that the former share represents a realistic estimate of the share of firms filing for ASC in the United States. Accordingly, we select first ASC filing condition to be most likely predictor of fraction of firms choosing to select ASC in favor of RRC.

C. User Cost of R&D Capital

Standard economic theory assumes that R&D is an input into a firm's production function. The price of R&D can be measured using the classical Hall and Jorgensen (1967) formula for the user cost of R&D capital (per dollar of investment). Following Wilson (2009), we incorporate federal and state level R&D credits and tax levels into this formula. We also account for a specific R&D credit type that a firm in our sample is most likely to file for (i.e. RRC or ASC). The R&D user cost formula is given in (3).

$$\rho_{it}^{cr} = \frac{1 - s(k_{st}^e + k_{ft}^{ecr}) - z_t(\tau_{st}^e + \tau_{ft}^e)}{1 - (\tau_{st}^e + \tau_{ft}^e)} [r_t + \delta_z] \quad (3)$$

In formula (3) the user cost for R&D for a firm (i)-year (t) depends on k_{st}^e and k_{ft}^{ecr} which are state R&D effective credit rates specific to state s and federal rate f that, in turn depends on type of the R&D credit $I_{cr}(i) = \begin{cases} 1 & \text{if } i \text{ files for ASC} \\ 0 & \text{if } i \text{ files for RRC} \end{cases}$ filed by a firm (i); τ_{st}^e and τ_{ft}^e are effective state s and federal f effective corporate tax rates; s is the share of R&D that qualifies for preferential tax treatment or QRE which we assume to be equal $s = 0.5$.¹⁰; z_t is the present value of depreciation allowances for R&D expenditures, which we assume to be equal to $z_t = 0.525$ ¹¹; r_t is long-run average rate of return, which following the related literature we assume to equal to 0.024; and δ_z is the depreciation rate of R&D capital, which we use the rates based on the published BEA high-tech industry R&D depreciation rates and the rates for non-high-tech industries from Li (2015).

In the United States the effective federal corporate tax rates is lower than actual statutory rate because the taxes a firm pay to its state are deductible from its federal tax liability. In our data, we observe firms with significant dispersion in income levels. This implies that firms' tax

¹⁰ This share is consistent with evidence from IRS Statistics in Income

¹¹ The depreciation value is taken from Wilson (2009)

liability may fall in various income tax brackets, which we considered in calculating the effective corporate federal tax rate more precisely. Furthermore, as discussed by Wilson (2009), the effective corporate state tax rates vary based on their partial or full deductibility from federal tax liability. If a state has multiple statutory tax rates, we use top marginal tax rate. Similarly, the state effective R&D tax credit rate depends on whether credit applies to all R&D expenditures (non-incremental credit) or only R&D expenditures above a designated base level (incremental credit); whether credit is “recaptured” (part of the credit itself is considered taxable); whether a state has a multi-tiered schedule of R&D tax credit rates. We adopt Wilson’s (2009) assumptions in calculating effective state R&D tax credit. At the federal level, the effective R&D tax rate depends for a firm depends on whether it chooses to file for RRC, which is incremental since it was introduced in 1981 or ASC, which we described earlier. The rate for the former is 20%, while the rates for the latter have increased from 12% between 2006 and 2008 to 14% after 2009. For firms with no prior history of R&D expenditure, ASC rate is 6% for a year during which they conducted R&D.

Our contribution to the literature that considers user cost of R&D capital effects on R&D expenditure is two-fold. First, unlike earlier studies which adopt a constant R&D depreciation rate for all industries, we calculate the user cost based on industry-level R&D depreciation rates. As shown in Table A1, these rates are heterogeneous and most are higher than 15%. This implies that the common assumption of this rate to equal 0.15 can often result in underestimating the user cost of R&D capital for most industries. Second, the approach with two different R&D tax credit types for a given total corporate tax liability allows us to isolate the impact of R&D tax credits on R&D expenditures. According to the user cost of R&D formula (3) the higher total R&D credit results in lower user cost of R&D. More precisely, consider the marginal change of R&D expenditures with respect to user of R&D for two R&D credit types as shown in (4).

$$\frac{\partial RD^{ASC}}{\partial \rho^{ASC}} = \varepsilon^{ASC} \frac{RD}{\rho^{ASC}}; \frac{\partial RD^{RRC}}{\partial \rho^{RRC}} = \varepsilon^{RRC} \frac{RD}{\rho^{RRC}} \quad (4)$$

In expressions (4) ε^{ASC} is the elasticity of R&D expenditure with the respect to user cost of R&D, which we estimate in the next sub-section. Taking ratio of the marginal changes and user costs (see formula (3)) for each R&D credit type we obtain an expression (5).

$$\frac{\frac{\partial RD^{ASC}}{\partial \rho^{ASC}}}{\frac{\partial RD^{RRC}}{\partial \rho^{RRC}}} = \frac{\varepsilon^{ASC}}{\varepsilon^{RRC}} * \frac{\rho^{RRC}}{\rho^{ASC}} \cong \frac{\varepsilon^{ASC} tk^{RRC}}{\varepsilon^{RRC} tk^{ASC}} \cong \ln(\varepsilon^{ASC} tk^{RRC}) - \ln(\varepsilon^{RRC} tk^{ASC}) \quad (5)$$

In the expression (5) $tk^{RRC} = k_{st}^e + k_{ft}^{eRRC}$ and $tk^{ASC} = k_{st}^e + k_{ft}^{eASC}$ are total effective R&D credit rates. According to the expression (5) the relative marginal change in R&D expenditure for each R&D credit type approximately equals to the log difference in R&D user cost elasticities inflated by the of total effective R&D credit rates.

D. R&D Augmented TFP Estimation

A. Set-up

We investigate whether R&D tax credit policy increases total factor productivity (TFP) by estimating firm level production function (6), which takes into account that the current R&D investment decisions depend on the past R&D expenditures net of depreciation.

$$Y_{it} = f_t(L_{it}, K_{it}, R_t) + \varphi_{it} + \epsilon_{it} \quad (6)$$

In the production function (5) a firm's i -year t output Y_{it} , is determined by the labor L_{it} , capital stock K_{it} , stock of R&D capital R_t in period t , unobserved and to be estimated TFP φ_{it} and idiosyncratic error term ϵ_{it} . Together φ_{it} and ϵ_{it} forms the Hick's neutral productivity shock v_{it} . The goal of empirically estimating production function (6) is to identify the joint distribution of productivity $\varphi_{it} + \epsilon_{it} = Y_{it} - f_t(L_{it}, K_{it}, R_{it})$

We extend Olley and Pakes, (OP) (1996) methodology to estimate R&D augmented TFP. The related approaches by Levinsohn and Petrin, (2003) and Ghandi et. al (2013) are not suitable given the limitations of the Compustat in the lack of data on materials and intermediate inputs. Following OP approach, we assume that at the beginning of each period $t + 1$ a firm decides whether to continue production or exit based on the realized productivity φ_{it} in period t . Labor L_{it} is the only variable input, while physical capital K_{it} , and R&D capital R_{it} are fixed in period t , and their values are affected by the distribution of φ_{it} in the period t . In other words, the expected productivity is a function of current productivity, physical and R&D capital stocks $E[\varphi_{it+1} | \varphi_{it}, K_{it}, R_{it}]$. Since the realized productivity is observed by the firm before it makes variable factor input decisions, the estimated elasticities would be biased due to the simultaneity between output and these variable inputs. Furthermore, not accounting for the exit of non-productive firms, gives rise to the selection bias.

To address these biases, and following OP, we estimate production function (6) in three stages. First, to control for simultaneity, we assume the inverse of investment decision rule is given in (7).

$$\varphi_{it} = I^{-1}(I_{it}, K_{it}, R_{it}, a_{it}) = h(I_{it}, K_{it}, R_{it}, a_{it}) \quad (7)$$

In (7), function $h(\blacksquare)$ is strictly increasing in I_{it} and a_{it} it the age of capital. We calculate the average age of capital by dividing the accumulated depreciation by current depreciation.¹² Following, Imrohorglu and Tuzel (2013), we smooth age by taking 3-year moving average. Substituting (7) into production function (6) gives the specification (8). This specification accounts for the simultaneity bias because we account the approximated productivity given the observed fixed factors of production at time t . Consequently, the labor elasticity β_l is consistently estimated.

$$y_{it} = \beta_l l_{it} + \phi(i_{it}, k_{it}, r_{it}, a_{it}) + \eta_{it} \quad (8)$$

In specification (8) all variables are expressed in natural logs; $\phi(i_{it}, k_{it}, r_{it}, a_{it}) = \beta_0 + \beta_k k_{it} + \beta_{rd} r_{it} + \beta_a a_{it} + h(i_{it}, k_{it}, r_{it}, a_{it})$, where $\phi(\blacksquare)$ is a second order polynomial series in investments, capital, R&D, and age.¹³ Second, to control for selection of firms into continuing serving the market, we estimate the probability that a firm i that was active in our sample in year t remains as such in year $t + 1$ conditional on the second order polynomial approximation series in investment, capital, R&D, and age. Third, with the predicted probability (\hat{P}_{it}) of firms' survival we use nonlinear least squares to estimate the elasticities of capital (β_k) and R&D (β_{rd}) in specification (9).

$$y_{it} - \hat{\beta}_l l_{it} = \beta_k k_{it} + \beta_{rd} r_{it} + g(\hat{\phi}_{t-1} - \beta_k k_{it-1} - \beta_{rd} r_{it-1}, \hat{P}_{it}) + \eta_{it} \quad (9)$$

Similar to the earlier steps, $g(\blacksquare)$ is approximated by the second order polynomial in $\hat{\phi}_{t-1} - \beta_k k_{it-1} - \beta_{rd} r_{it-1}$ and \hat{P}_{it} .

¹² In Compustat the accumulated depreciation is measured using a variable DPACT; the current depreciation is DP.

¹³ Approximating with a higher order polynomial instead does not significantly change the results.

Finally, the estimated augmented for R&D TFP is given in expression (10).

$$\widehat{TFP}_{it} = \exp(y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_{rd} r d_{it}) \quad (10)$$

B. Potential Endogeneity of R&D Investment

We are concerned that the unobserved productivity shock may simultaneously impact output and R&D expenditure in the production function (6). In this case $E[v_{it}, R_{it-1}] \neq 0$, and OLS is inconsistent. Furthermore, since current R&D investment decisions depend on the past R&D expenditures R&D expenditures are characterized with a dynamic model, and usual within fixed effects estimators are biased. Accordingly, we apply dynamic panel difference generalized method of moments (GMM) estimator that uses R&D user cost as an instrument for R&D specific supply side shock to consistently estimate R&D expenditure specification in (11). We then use the policy predicted R&D expenditure as input into the production function (6) by applying perpetual inventory method to obtain R&D capital stock.

$$r_{it} = \beta_0 + \beta_1 r_{it-1} + \beta_2 \rho_{it}^{cr} + \gamma F_{it} + \varphi_j + \zeta_t + \epsilon_{it} \quad (11)$$

In specification (11) each variable is natural logs, R&D expenditure and state s GDP deflated by GDP deflator; F_{it} is a vector of firm specific balance sheet characteristics that include internal funds, leverage, Tobin's Q , and sales; φ is 4-digit NAICS industry j fixed effect; ζ is the year t fixed effect; and ϵ is an idiosyncratic error term.¹⁴

We report the estimates for specification (11) in Table R2. In column [1] we estimate (11) with OLS to establish the baseline. As we discussed OLS estimates are biased and inconsistent because of autoregressive change in R&D expenditure. As expected, we find that previous R&D expenditure positively affect the current level of R&D, higher user cost of R&D negatively affects R&D, and higher firm sales are positively associated with R&D expenditures. In column [2] we estimate (6) using Arellano and Bond (1991) difference two-step GMM estimator that was further developed by Arellano and Bover (1995), and Blundell and Bond (1998). We find that the R&D process is AR(1), and Sargan test for over identifying restrictions

¹⁴ See Gupta et al. (2011) on how firm level variables F_{it} are calculated using Compustat

implies that our instruments are valid. The previous R&D expenditure positively affects current R&D, but its magnitude is roughly half that of OLS estimate. It matches the same estimate found by Wilson (2009). The user cost of R&D estimate implies that all else equal 1% increase in R&D user cost reduces R&D expenditure by 2.6%. This estimate is substantially higher than a finding by Wilson (2009).¹⁵ However, Wilson (2009) does not estimate the relationship between R&D expenditure and user cost of R&D at the firm level, nor he differentiate depreciation rates of R&D capital between industries. Interestingly, state GDP has no significant effect on the change in R&D expenditure. The effect of firm sales on R&D expenditure is positive and almost double in magnitude as compared to the OLS estimate.

To shed light on how a specific R&D tax credit policy affects R&D expenditure, we separately estimate (6) for firms that apply for ASC and RRC according to our ASC filing conditions. In column [3], we report GMM estimates for firms that choose to apply for ASC. Recall that ASC was introduced for firms without long history of R&D expenditure, which allows eliminating calculation of the base QRE. Reassuring with this policy provision, we find that previous R&D history of R&D expenditure has no effect on the current R&D expenditure for this set of firms. The user cost of R&D elasticity is roughly -2.1. Turning to firms that choose to file for RRC in column [4], we find that for these firms previous R&D expenditure significantly affects current R&D expenditure. Importantly, the user cost of R&D elasticity is -1.5, which is in the range of user cost elasticities estimated by Wilson (2009), who only considers RRC. Based on the expression (4), we calculate that for a marginal firm filing for RRC the relative user cost of R&D capital is 2% lower than for a firm filing for ASC. Finally, we generate predicted R&D expenditures for each firm that are induced by R&D tax credit policy through its effect on the user cost of R&D. As discussed by Bloom et. al. (2013), a potential concern is that R&D tax credit may be endogenous is not borne out in data. Moreover, since state-level R&D tax credits have been growing at differential rates and levels across states, these state-by-year differences in generosity are seemingly uncorrelated with lagged economic or political variables.

C. R&D Tax Credit Policy and TFP

Our preliminary results on the effects of R&D tax credit policy showed that firms choosing to file RRC are in relatively less R&D intensive industries as compared to firms that file for ASC.

¹⁵ Wilson (2009) finds that the internal user cost elasticity of -1.21

We hypothesized that there may be a differential impact of R&D tax credits on exports by industry provided that our hypothesized channel in firm-level heterogeneous changes in productivity induced in part through these credits. To estimate whether there is a differential impact of RRC and ASC R&D tax credits on TFP, in specification (12) we extend specification (9) to include an interaction term with R&D capital and the R&D credit type that a firm i choose to file for in year t .

$$y_{it} - \hat{\beta}_l l_{it} = \beta_k k_{it} + \beta_{rd} rd_{it} + \beta_{rd_{cr}} rd_{it} * ASC_{it} + g(\hat{\phi}_{t-1} - \beta_k k_{it-1} - \beta_{rd} rd_{it-1} - \beta_{rd_{cr}} rd_{it-1} * ASC_{it-1}, \hat{P}_{it}) + \eta_{it} \quad (12)$$

In specification (12) ASC_{it} takes value of 1 if a firm i choose to file for ASC in year t and zero otherwise; and the rest of the variables are as defined before, with second order polynomial series expansion $\phi(\blacksquare)$ including the R&D tax credit interaction term. Accordingly, the estimated TFP for firms choosing to file for RRC and ASC is given in expression (13).

$$\widehat{TFP}_{it} = \begin{cases} \exp(y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_{rd} rd_{it}) & \text{if } ASC = 0 \\ \exp(y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_{rd} rd_{it} - \hat{\beta}_{rd_{cr}} rd_{it} * ASC_{it}) & \text{if } ASC = 1 \end{cases} \quad (13)$$

Table R3 reports the estimates for elasticities of labor ($\hat{\beta}_l$), physical capital ($\hat{\beta}_k$), and R&D capital ($\hat{\beta}_{rd}$) after estimating 3-step OP model for 2011.¹⁶ Since we estimate the model using non-linear least squares, we are able to obtain these elasticities for each year in our sample. In column [3] we report elasticities from the full specification with R&D tax credit interaction term. In line with literature, we find that labor and capital elasticities of 0.8 and 0.3 respectively. The R&D elasticity is 0.06. This estimate represents a lower bound, as our estimation does not take into account spillover effects of R&D. For firms that choose to file for ASC R&D elasticity increases by 0.01 on average between 2007 and 2011.

¹⁶ Estimates for other years are similar.

Second Stage: Export Performance

A. Empirical Specifications

In this section we develop an empirical model of trade to test whether R&D tax credit policy affects U.S. exports. We hypothesize that R&D tax credits affect exports through its effect on productivity. Since R&D investment is a dynamic decision we expect that R&D tax credit provides enough incentive for a firm increase future R&D and thereby increase its productivity. In turn, based on the trade theory with heterogeneous firms (Melitz (2003)), more productive firms are more likely to become exporters. Among exporters, relatively more productive firms are able to export more, as they face relatively lower effects of trade barriers. Given these ideas, we predict that there are heterogeneous effects of R&D tax credits on export volumes within and between industries.

To test this prediction, we set up the gravity model of trade that follows Chaney (2008). We test whether R&D tax credits “distort” gravity through its differential impact of TFP distributions by industries. Formally, we assume that TFP (x) shocks in industry j are distributed as Pareto with cumulative distribution function (CDF) that is given in (14).

$$F_j(x) = 1 - x^{-\alpha_j}; dF_j(x) = -\alpha_j x^{-\alpha_j-1} \text{ for } x \geq 1 \quad (14)$$

The inverse of the shape parameter α_j measures the degree of heterogeneity with $\alpha_j > 2$ and $\alpha_j > \sigma_j - 1$, where σ_j is elasticity of substitution between varieties in the industry j . Industries with high α are more homogeneous, in the sense that the output is concentrated among small and least productive firms.

We use rank-size regressions to estimate the shape parameters α_j for each 2-digit NAICS industry j .¹⁷ Considering distribution of sales, the probability that firm i has a value of sales above a firm of a certain size falls with a rank. Thus, the firm that ranked first in terms of value of its sales will be in the tail of the distribution. It follows that there exists negative relationship

¹⁷ While we estimate our trade model at the 4-digit NAICS level of disaggregation, we do not have enough firm-level observations within each 4-digit NAICS industry to have sufficient predictive power for the rank-size regressions. Consequently, we estimate these regressions at 2-digit NAICS level.

between rank and sales. Furthermore, the trade theory with heterogeneous firms predicts that more productive firms capture larger demand, by charging lower prices and through access to more markets. Consequently, there is exists negative relationship between sales rank and TFP. Since most productive firms have access to multiple foreign markets, there may be a difficulty in measuring the firm size. However, in the case of the United States being large and relatively closed economy, the firm size is almost entirely determined by the sales in the domestic market. Accordingly, we rank U.S. firm sales (i to N) with largest firm first in each 2-digit NAICS industry j and estimate the specification (15).

$$\ln\left[\left(\text{Rank}_i^j - \frac{1}{2}\right)/N_j\right] = \beta_0 - \beta_j \widehat{TFP}_{it}^{j,RDC} + \zeta_t + \epsilon_j \quad \text{with } RDC \in \{RRC, ASC\} \quad (15)$$

In specification (15) β_j is the estimate of the shape parameter for the TFP distribution of firms in the industry j that choose to file for either RRC or ASC R&D credits; the estimated TFP values (\widehat{TFP}_{it}) are obtained from the expression (11); and ζ_t denotes time fixed effects that account for unobserved within industry shocks in each year t . In the industries, where firm size has lower variance ($\widehat{\beta}_j$ is larger, and degree of heterogeneity is lower), trade barriers should have larger negative impact on bilateral trade flows.

With the estimated shape parameters of the TFP distributions by industries and R&D tax credit types, we test whether the degree of firm level heterogeneity affects the sensitivity of trade flows with the respect to trade barriers using specification (16). Each industry is comprised of firms that choose to file for either RRC or ASC R&D tax credits in any given year. Our methodology identifies such firms within each industry, and allows estimating TFP distribution shape parameters for them. Consequently, we are able to estimate marginal effects of the firm heterogeneity sensitivity between and within industries.

$$\ln(X_{cjt}) = Y_{jt} + Y_1 B_{ct} + Y_2 (B_{ct} \times \delta_j) + \epsilon_{cjt} \quad (16)$$

In the gravity specification (14), X_{cjt} is exports from United States to a country c by industry j in year t ; Y_{jt} is the vector of industry j and year t fixed effects; B_{ct} is the vector of trade barriers that includes distance, market size (as measured by real GDP in PPP terms), common language,

and border; $B_{ct} \times \delta_j$ is the interaction between the vector of trade barriers and the degree of firm-level heterogeneity in each industry j ; and ϵ_{cjt} is the error term that is assumed to be normally distributed and orthogonal to the explanatory variables in the model. The degree of firm-level heterogeneity δ_j by industry j is estimated using (15). The large δ_j corresponds to a more homogeneous industry which corresponds to thinner tail of the TFP distribution. The industry and time fixed effects control for relative price on trade flows by industry and unobserved yearly trade shocks respectively. The robust standard errors are clustered by country-industry pairs to allow for shocks that affecting trade flows differ by each country within each industry.

In line with standard trade theory, we expect that firm-level heterogeneity dampens the effect of trade barriers on trade flows, such that industries where the output is concentrated among few and most productive/larger firms. The converse should hold for industries with less concentrated output of firms. Finally, we expect that the firm-level heterogeneity to have similar effect on trade flows within industries.

B. Results.

We report the estimated shape parameters and corresponding measures of industry heterogeneity (the inverse of the shape parameters) in Table R4. Comparing our estimated parameters for two R&D credit types, we find that in industries where firms choose to file for RRC, the degree of heterogeneity is relatively lower than that for industries where firms choose to file for ASC. In other words, it appears that firms filing for ASC are more productive in these industries. Furthermore, the TFP distribution of firms that choose to file for RRC second order stochastically dominates (SSD) that for firms that choose to file for ASC.¹⁸ Recall, that our descriptive statistics showed that firms in relatively more R&D intensive industries choose to file for ASC. Since R&D investment is associated with substantial risk taking, this result is consistent with substantial strand of literature that studies the relationship between managerial

¹⁸ A distribution with CDF $F(x)$ second order stochastically dominates (SSD) a distribution with CDF $G(x)$ if $F_2(x) \leq G_2(x)$ for $\forall x [0, +\infty]$, where $F_0(x) = f(x) \dots F_2(x) = \int_0^x F_1(x) dx$. In the context of two TFP Pareto distributions we are considering, the SSD condition is satisfied when $1/(\widehat{\alpha}_{RRC} + 1) \leq 1/(\widehat{\alpha}_{ASC} + 1)$, where $\widehat{\alpha}_{RRC}$ and $\widehat{\alpha}_{ASC}$ are estimated shape parameter for Pareto distribution respectively.

incentives and R&D investment in firms.¹⁹ This result also suggests that higher R&D tax credit rate (20%) under RRC is given to relatively small and most productive fraction of firms that likely don't benefit from these provisions as compared to less productive firms that only qualify for ASC rate of 14%.

We use U.S. bilateral exports data between 2006 and 2012 to estimate the gravity specification (16). In Table R5 we report the estimated elasticities of U.S. exports with respect to the vector of trade barriers in specification (14). In column (1) we estimate this model without controlling for firm-level heterogeneity. Consistent, with standard empirical trade literature we find that U.S. exports fall with distance, rise with market size, common language and border. In columns (2) and (3) we introduce an interaction between trade barriers and firm-level heterogeneity parameters for each industry. Consistent with our prediction, we find that on average for firms filing for ASC the effect of market size (as measured by GDP) and common language is dampened, while these effects are non-significantly magnified for firms filing for RRC. Conversely, and somewhat surprising, the distance and border elasticities are non-significantly dampened for industries where firms file for RRC, and are magnified for firms filing for ASC.

To gain better understanding of how implied firm-level heterogeneity dampens the effect of variable trade barriers on U.S. exports by industry, we estimate marginal effects over each industry in our sample. We report this estimates in Table R6. We find non-uniform marginal effects of firm-level heterogeneity distortions within and across industries induced by TFP under RRC and ASC. For example, *within* Computer and Electronic Products (NAICS 334) the distance reduces U.S. exports by 0.6% and by 0.7% for firms that file for ASC and RRC respectively. For firms that files for RRC *across* industries distance reduces U.S. exports between 0.7 and 1 percent. For firms that files for ASC *across* industries distance reduces U.S. exports between 0.6 and 1 percent Therefore, our analysis suggests the need for a variable R&D tax credit rate for firms even within industries insofar this credit boosts productivity and consequently dampening negative effect of trade barriers on trade flows.

¹⁹ For example, Hoskisson et al. (1993) finds negative relationship between managerial risk aversion and R&D intensity.

IV. Concluding Remarks

This paper develops an empirical methodology to analyze the impact of R&D tax credits on U.S. merchandise exports. We consider two U.S. R&D tax credit provisions: regular research credit (RRC) and alternative simplified credit (ASC). They differ in the qualification requirements and stipulated rates. We empirically determine whether a firm files for RRC or ASC in a given industry and year. Given these qualifications we estimate TFP for each firm. We hypothesize that R&D tax credit acts as a demand shifter that induces R&D investment. In turn, R&D investment increases firm-level productivity. Based on the trade theory with firm-level heterogeneity, larger/more productive firms export in higher volume/more destinations as they face a relatively dampened effect of trade barriers. While the impact of the firm-level heterogeneity on trade barriers has been studied in the trade literature *across* industries, our contribution is the analysis of the firm-level heterogeneity effect on trade barriers *within* industries.

Our findings largely match our hypothesized channel of the impact of R&D tax credits on the U.S. exports. First, we find firms that choose to file for ASC are relatively more heterogeneous than firms that file for RRC both within and across industries. Second, firms that file for ASC are relatively riskier in R&D investment despite receiving a lower R&D tax credit rate. Third, the effect of trade barriers on U.S. exports is dampened relatively more for firms filing for ASC as compared to firms that file for RRC within industries. It also varies across industries that vary by the credit type. These findings indicate that the current policy of providing the same R&D tax credit rate to a firm regardless of the industry may provide insufficient incentive in boosting TFP through the additional R&D investment. While, there are still additional robustness checks remain to be conducted to strengthen the validity of our results, it is our preliminary conclusion that a more targeted R&D tax credit policy may additionally raise U.S. exports by increasing firm competitiveness through lowering trade barrier costs.

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Appendix

Table A1 – ASC Filing Conditions

Condition	Notes
<p>1. R&D spending relative to gross receipts has not kept pace with the ratio set in the "base period" that governs eligibility for the regular credit.</p>	<p>(1) a company's sales increase significantly in the intervening years (2) a company enters into an additional line of business that generates additional gross receipts but performs little R&D (3) a company spends less to perform the same amount of R&D because it becomes more efficient in its R&D processes.</p>
<p>2. The effective rate is higher for those with increasing R&D spending from year to year, and lower for those with declining R&D spending (even though the latter holds higher total R&D spending)</p>	
<p>3. A start-up firm with no R&D expenses in the three preceding years or one of these three years</p>	<p>The R&D credit rate is 6%</p>
<p>4. High base amount under the RRC</p>	
<p>5. Incomplete records to determine the startup base period (from the mid-1980s)</p>	
<p>6. A complex history of organizational activity (mergers, acquisitions and dispositions)</p>	

Table A2: Depreciation Rates of R&D Assets for 35 Industries

Industry	NAICS Group or single NAICS	δ_{RD} [%]
1 Agriculture, Hunting, Forestry and Fishing	1111, 1112, 1113, 1114, 1119	N/A ²⁰
2 Mining and Quarrying	2111, 2121, 2122, 2123, 2131	N/A
3 Food, Beverages and Tobacco	3111, 3112, 3113, 3114, 3115, 3116, 3117, 3118, 3119, 3122	N/A
4 Textiles and Textile Products	3131, 3132, 3133, 3141, 3149	N/A
5 Leather, Leather and Footwear	3161, 3162, 3169	N/A
6 Wood and Products of Wood and Cork	3211, 3212, 3219	N/A
	3371, 3372, 3379	64
7 Pulp, Paper, Paper, Printing and Publishing	3221, 3222	N/A
	3231	N/A
	5111	N/A
8 Coke, Refined Petroleum and Nuclear Fuel	3241	N/A
9 Chemicals and Chemical Products	3251, 3252, 3253, 3255, 3256, 3259	70
	3254	10
10 Rubber and Plastics	3261, 3262	N/A
11 Other Non-Metallic Mineral	3271, 3272, 3273, 3274, 3279	N/A

²⁰ N/A indicates no R&D stock, no data or data are insufficient for calculating the R&D stock and OC stock. If you have R&D investments data for those industries, we can temporarily use 15%.

12 Basic Metals and Fabricated Metal	3311, 3312, 3313, 3314, 3315	N/A
	3321, 3322, 3323, 3324, 3325, 3326, 3327, 3328, 3329	56
13 Machinery, Nec	3331, 3332, 3333, 3334, 3335, 3336, 3339	54
14 Electrical and Optical Equipment	3341	41
	3344	27
	3342	31
	3343, 3344, 3345, 3346	26
	3351, 3352, 3353, 3359	55
15 Transport Equipment	3361,3362	28
	3363A	23
	3364	21
	3366A	34
	3369	N/A
16 Manufacturing, Nec; Recycling	3391, 3399	55
17 Electricity, Gas and Water Supply	2211, 2212, 2213	N/A
18 Construction	2361, 2362, 2371, 2372, 2373, 2379, 2381, 2382, 2383, 2389	47
19 Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	4411, 4412, 4413	N/A
20 Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	4231, 4232, 4233, 4234, 4235, 4236, 4237, 4238, 4239, 4241, 4242, 4243, 4244, 4245, 4246, 4247, 4248, 4249,4251	N/A
21 Retail Trade, Except of Motor Vehicles and	4421, 4422,	N/A

Motorcycles; Repair of Household Goods	4431, 4441, 4442, 4451, 4452, 4453, 4461, 4471, 4481, 4482, 4483	
22 Hotels and Restaurants	7211	N/A
	7223	N/A
23-25 Inland, Water, and AirTransport, and other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	4811, 4812, 4821, 4831, 4832, 4841, 4842, 4851, 4852, 4853, 4854, 4855, 4859, 4861, 4862, 4869, 4871, 4872, 4879, 4881, 4882, 4883, 4884, 4885, 4889	N/A
27 Post and Telecommunications	5111, 5112, 5121, 5122, 5151, 5152, 5171, 5172, 5174, 5179, 5182, 5191	78
28 Financial Intermediation	5221, 5222, 5223	N/A
	5231, 5232, 5239	N/A
	5241, 5242	N/A
	5251, 5259	N/A
29 Real Estate Activities	5311, 5312, 5313	N/A
30 Renting of M&Eq and Other Business Activities	5112	24
	5182	36
	5321, 5322, 5323, 5324, 5331	N/A
	5411	N/A
	5415	39
	5411, 5412, 5413, 5414, 5415, 5416, 5417, 5418,	16

	5419	
	5611, 5612, 5613, 5614, 5615, 5616, 5617, 5619	N/A
31 Public Admin and Defense; Compulsory Social Security		N/A
32 Education		N/A
33 Health and Social Work	6211, 6212, 6213, 6214, 6215, 6216, 6219	N/A
	6221, 6222, 6223 6231, 6232, 6233, 6239	N/A
34 Other Community, Social and Personal Services	5121, 5122	25
	5621, 5622, 5629	N/A
	7111, 7112, 7113, 7114, 7115	N/A
	7131, 7132, 7139	N/A
35 Private Households with Employed Persons		N/A

Source: Li (2012, 2015)

Table D1 - Descriptive Statistics for Firms Choosing to File for RRC

Firm Characteristics	Statistic	Eligible & Qualified	Eligible & Non-Qualified	Non Eligible & Non-Qualified
R&D Expense	Mean	22.20	18.34	14.95
	Std Dev	54.46	44.52	33.27
	Median	1.90	2.67	3.05
R&D Intensity	Mean	6.80	12.14	0.82
	Std Dev	208.14	98.39	8.37
	Median	0.02	0.10	0.12
Revenue	Mean	1222.45	465.11	270.95
	Std Dev	3206.97	1389.70	1009.63
	Median	238.19	27.30	29.71
Leverage	Mean	0.68	1.53	1.01
	Std Dev	3.49	8.67	4.28
	Median	0.11	0.16	0.04
Tobin's Q	Mean	5.54	11.10	5.46
	Std Dev	26.47	47.08	19.90
	Median	2.80	3.27	2.09
Sales	Mean	1271.12	523.67	268.30
	Std Dev	3170.89	1654.86	1000.50
	Median	272.80	34.77	29.69
Size	Mean	4.67	3.37	2.99
	Std Dev	2.00	2.33	2.14
	Median	4.87	3.58	3.05
Marginal Tax Rate	Mean	0.24	0.13	0.10
	Std Dev	0.11	0.11	0.10
	Median	0.29	0.09	0.05
Firm-Years	Total	3,931	1,967	466
	Share (%)	33.13	16.58	3.93

Table D2 - Descriptive Statistics for Firms Choosing to File for ASC

Firm Characteristics	Statistic	Eligible & Qualified	Eligible & Non-Qualified	Non Eligible & Non-Qualified
R&D Expense	Mean	35.78	21.83	10.03
	Std Dev	67.86	39.05	23.54
	Median	10.93	7.69	1.72
R&D Intensity	Mean	0.91	5.02	0.15
	Std Dev	8.16	43.94	0.46
	Median	0.08	0.29	0.07
Revenue	Mean	921.01	231.00	230.74
	Std Dev	2480.18	966.19	848.59
	Median	168.08	20.49	31.63
Leverage	Mean	0.43	0.81	1.07
	Std Dev	1.62	3.42	8.58
	Median	0.09	0.04	0.05
Tobin's Q	Mean	6.56	8.96	5.78
	Std Dev	73.19	31.03	13.68
	Median	2.96	3.57	2.61
Sales	Mean	939.34	236.44	226.45
	Std Dev	2516.46	987.13	836.61
	Median	164.53	20.51	31.44
Size	Mean	4.64	3.21	2.82
	Std Dev	1.99	2.13	2.16
	Median	4.80	3.50	2.93
Marginal Tax Rate	Mean	0.21	0.10	0.09
	Std Dev	0.12	0.10	0.10
	Median	0.25	0.06	0.05
Firm-Years	Total	1571	1277	712
	Share (%)	13.24	10.77	6.00

Table D3 - Share of Firms Filing for an R&D Tax Credit by State (Top 10)

R&D Credit Condition	RRC		ASC	
	State	Share (%)	State	Share (%)
Eligible (Top 10)	Alaska	100.00%	Maryland	31.94%
	West Virginia	100.00%	Rhode Island	31.82%
	Wyoming	100.00%	Oregon	31.30%
	Kentucky	87.27%	Massachusetts	30.18%
	Louisiana	77.27%	South Dakota	29.41%
	Tennessee	76.43%	Connecticut	29.24%
	District of Columbia	73.33%	North Carolina	28.16%
	Vermont	70.00%	California	27.78%
	Oklahoma	68.18%	New Jersey	27.74%
	Idaho	65.38%	Washington	26.56%
Eligible & Qualified (Top 10)	Kentucky	78.18%	Rhode Island	27.27%
	Vermont	70.00%	South Dakota	23.53%
	Oklahoma	63.64%	Nebraska	21.74%
	Tennessee	60.51%	Vermont	20.00%
	Louisiana	54.55%	Oregon	19.85%
	Alabama	54.05%	Connecticut	18.64%
	Idaho	53.85%	Maryland	18.52%
	West Virginia	50.00%	Minnesota	17.26%
	District of Columbia	46.67%	Montana	16.67%
	Rhode Island	43.18%	Massachusetts	16.37%

Table D4 - Share of Manufacturing Firms Filling for RRC by Industry

R&D Credit Condition	RRC		
	Industry	Naics4	Share (%)
Eligible (Top 10)	Fiber, Yarn, and Thread Mills	3131	100.00%
	Cut and Sew Apparel	3152	100.00%
	Lime and Gypsum Products	3274	100.00%
	Leather and Allied Products	3169	75.00%
	Cement and Concrete Products	3273	75.00%
	Fruit and Vegetable Preserving	3114	64.00%
	Household Appliances	3352	62.50%
	Footwear	3162	61.54%
	Sugar and Confectionery Products	3113	60.00%
	Animal Slaughtering	3116	60.00%
Eligible & Qualified (Top 10)	Lime and Gypsum Products	3274	100.00%
	Cut and Sew Apparel	3152	75.00%
	Leather and Allied Product	3169	75.00%
	Sugar and Confectionery Products	3113	60.00%
	Footwear	3162	50.00%
	Cement and Concrete Products	3273	50.00%
	Household Appliances	3352	50.00%
	Furniture Related Products	3379	50.00%
	Fruit and Vegetable Preserving	3114	44.00%
	Motor Vehicle Body and Trailer	3362	42.11%

Notes: Industries with less than 2 firms are excluded.

Table D5 - Share of Manufacturing Firms Filing for ASC by Industry

R&D Credit Condition	ASC		Share (%)
	Industry	Naics4	
Eligible (Top 10)	Cut and Sew Apparel	3122	44.44%
	Bakeries and Tortilla	3118	42.86%
	Steel Products	3312	42.86%
	Boiler, Tank, and Shipping Container	3324	42.86%
	Chemical Product and Preparation	3259	41.67%
	Alumina and Aluminum Production	3313	40.00%
	Reproducing Magnetic and Optical Media	3346	40.00%
	Pharmaceutical and Medicine	3254	38.91%
	Other Food	3119	37.50%
	Railroad Rolling Stock	3365	35.71%
Eligible & Qualified (Top 10)	Bakeries and Tortilla	3118	42.86%
	Alumina and Aluminum Production	3313	40.00%
	Boiler, Tank, and Shipping Container	3324	35.71%
	Cut and Sew Apparel	3122	33.33%
	Animal Slaughtering and Processing	3116	30.00%
	Textile Furnishings Mills	3141	28.57%
	Steel Products	3312	28.57%
	Spring and Wire Products	3326	28.57%
	Railroad Rolling Stock	3365	28.57%
Iron and Steel Mills	3311	27.27%	

Notes: Industries with less than 2 firms are excluded.

Table R1 - Policy Stage Logistic Estimates For Full Sample

	Eligible			Qualified		
	[1]	[2]	[3]	[4]	[5]	[6]
Real GDP	-1.457 (1.342)	-1.551 (1.334)	-2.983** (1.339)	-5.728*** (1.881)	-5.873*** (1.883)	-6.181*** (1.888)
Sales Growth	0.189*** (0.0718)	0.308*** (0.116)	0.169*** (0.0622)	-0.0002 (0.001)	-0.0001 (0.0007)	-0.0003 (0.0007)
R&D Growth	0.482*** (0.117)	0.313*** (0.0890)	0.195*** (0.0495)	0.0123 (0.0133)	0.00626 (0.0101)	0.00806 (0.0104)
Size	0.0827*** (0.0209)	0.0897*** (0.0209)	0.0425** (0.0213)	0.0824*** (0.0225)	0.0863*** (0.0227)	0.0820*** (0.0227)
Tax Rate	0.548** (0.257)	0.393 (0.257)	0.301 (0.261)	6.367*** (0.334)	6.272*** (0.337)	6.330*** (0.336)
ASC	-0.978*** (0.103)	-1.229*** (0.119)	-0.714*** (0.110)	-2.390*** (0.543)	-0.548*** (0.143)	-0.591*** (0.146)
	[0.292]	[0.293]	[0.489]	[0.092]	[0.578]	[0.554]
Tax Credit Condition 1		-0.746*** (0.103)			-0.174** (0.0796)	
		[0.477]			[0.840]	
Tax Credit Condition 2			1.282*** (0.0891)			0.0410 (0.0854)
			[3.602]			[1.041]
ASCxSize	-0.0775*** (0.0231)	-0.0774*** (0.0232)	-0.0453* (0.0239)	0.134*** (0.0306)	0.133*** (0.0303)	0.129*** (0.0305)
	[0.925]	[0.925]		[1.144]	[1.142]	[1.137]
ASCxTax Credit Condition 1		0.381*** (0.101)			0.0279 (0.123)	
		[1.464]			[1.028]	
ASCxTax Credit Condition 2			-0.747*** (0.104)			0.140 (0.129)
			[0.473]			[1.150]
Industry Fixed Effects (NAICS 4)	Yes	Yes	Yes	Yes	Yes	Yes
Wald χ^2	1023.76***	1089.17***	1242.23***	1556.16***	1224.28***	1226.1***
Pseudo R-Squared	0.125	0.133	0.147	0.191	0.192	0.191
Number of Observations	9,307	9,307	9,307	6,086	6,086	6,086
Underlying Observations	14,705	14,705	14,705	11,471	11,471	11,471

Notes: Robust standard errors are in parenthesis; odds ratios in square brackets

Table R2 -R&D User Cost Estimates

Variables	[1] Full OLS	[2] Full GMM	[3] ASC GMM	[4] RRC GMM
R&D Expenditure Lagged	0.901*** (0.008)	0.452** (0.233)	-0.540 (0.340)	0.275* (0.170)
R&D User Cost	-2.220*** (0.453)	-2.663** (1.245)	-2.073* (1.285)	-1.487* (0.844)
Internal Funds	-0.0003*** (0.0001)	-0.0004 (0.0004)	-0.001 (0.002)	-0.0002 (0.0002)
Leverage	-0.003 (0.002)	0.007 (0.005)	0.004 (0.005)	0.005* (0.003)
Tobin's Q	-0.0007 (0.0005)	-0.0003 (0.0007)	0.0003 (0.001)	-0.001 (0.0009)
Marginal Tax Rate Lagged	0.257 (0.067)	0.308* (0.163)	1.156*** (0.319)	-0.008 (0.172)
Sales	0.079*** (0.007)	0.139*** (0.035)	0.250*** (0.063)	0.112*** (0.039)
Industry Fixed Effects (NAICS 4)	Yes	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.918			
Wald χ^2		257.97***	82.53***	190.16***
Arellano-Bond test for AR(1)		-2.23	0.87	-2.11*
Arellano-Bond test for AR(2)				-1.60
Sargan Test χ^2		11.24	16.36	19.67
Number of Observations	7,182	3,094	1,599	1,495
Number of Underlying Observations	11,862	11,862	11,862	11,862

Notes: All variables are measured in natural logs.

Dependent variable is natural log of R&D expenditures in all specifications

Robust standard errors are in parenthesis clustered by a firm identifier

Table R3 -Production Function Estimates

Variables	[1] 2011	[2] 2011	[3] 2011
Labor	0.794*** (0.026)	0.789*** (0.026)	0.788*** (0.026)
Capital	0.275*** (0.035)	0.231*** (0.054)	0.236*** (0.050)
R&D		0.068 (0.048)	0.056 (0.047)
R&D Tax Credit (ASC)			0.012** (0.006)
Exit	-0.051 (0.585)	-0.181 (0.572)	-0.260 (0.575)
Averages	(2007-2011)	(2007-2011)	(2007-2011)
Labor	0.797	0.793	0.793
Capital	0.305	0.267	0.272
R&D		0.045	0.031
R&D Tax Credit (ASC)			0.013
Effect of R&D Tax Credit (ASC)			0.044
Industry Fixed Effects (NAICS 4)x Year Effects	Yes	Yes	Yes
R-Squared (second stage)	0.917	0.912	0.912
R-Squared (third stage)	0.504	0.517	0.514
Number of Observations (second stage)	1,303	1,303	1,303
Number of Observations (third stage)	890	890	890

Notes: All variables are measured in natural logs.

Dependent variable is natural log of value added in the second stage

Robust standard errors are in parenthesis

Significance: *** (1%); ** (5%)

Table R4 - Estimated Shape Parameters and Heterogeneity Measures

NAICS	RRC		ASC	
	Shape Parameter	Implied Heterogeneity	Shape Parameter	Implied Heterogeneity
32	0.324	3.086	0.066	15.152
33	0.306***	3.268	0.220***	4.545
51	0.356**	2.809	0.084	11.905
54	0.322	3.106	0.158	6.329
Average		3.067		9.482

Notes: number of observations for each estimation varies depending on the observable number of firms in each industry and credit type

Time fixed effects are included.

Significance: *** (1%); ** (5%)

Table R5 - Gravity Distortion Estimates Induced by Firm Heterogeneity

Variables	[1] Benchmark	[2] RRC	[3] ASC
Distance (in logs)	-0.741* (0.083)	-0.735** (0.083)	-0.736*** (0.083)
Distance* δ_j		0.701 (0.645)	-0.040** (0.016)
Real GDP (in logs)	0.365*** (0.017)	0.365*** (0.018)	0.365*** (0.017)
GDP* δ_j		-0.061 (0.143)	0.010*** (0.003)
Language	1.113*** (0.119)	1.113*** (0.119)	1.116*** (0.119)
Language* δ_j		-0.677 (0.934)	0.040* (0.024)
Border	3.985*** (0.252)	3.995*** (0.408)	3.998*** (0.255)
Border* δ_j		1.328 (2.214)	-0.096** (0.048)
Fixed Effects			
Industry (NAICS 4)	Yes	Yes	Yes
Year	Yes	Yes	Yes
R-Squared (overall)	0.283	0.284	0.285
Number of Underlying Observations	21,340	21,340	21,340

Notes: Dependent variable is natural log of Exports in all specifications

δ_j is the inverse of the shape parameter estimated using rank-size TFP regressions

Robust standard errors are in parenthesis clustered by the importer-industry pairs

Significance: ***(1%); **(5%); *(10%)

Table R6 - Marginal Effects of Variable Trade Barriers on Exports by Industry

Industry	No Credit		RRC		ASC	
	Distance	GDP	Distance	GDP	Distance	GDP
325- Chemical Manufacturing	-0.741*** (0.083)	0.366*** (0.017)	-0.802** (0.098)	0.371*** (0.020)	-0.982*** (0.129)	0.427*** (0.025)
334 - Computer and Electronic Products	-0.741*** (0.083)	0.366*** (0.017)	-0.675*** (0.105)	0.360*** (0.023)	-0.562*** (0.112)	0.320*** (0.024)
336 - Transportation Equipment	-0.741*** (0.083)	0.366*** (0.017)	-0.675*** (0.105)	0.360*** (0.023)	-0.562*** (0.112)	0.320*** (0.024)
511 - Publishing Industries	-0.741*** (0.083)	0.366*** (0.017)	-0.997*** (0.246)	0.388*** (0.053)	-0.854** (0.096)	0.394*** (0.018)

Notes: Standard errors are calculated using delta method

Significance: *(5%); ***(1%)

