Globalization and Inequality in Innovation: A Novel Perspective from U.S. R&D Tax Credits[1][2]

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Abstract

Many OECD countries, including the U.S., have adopted research and development (R&D) tax credits to encourage innovation, especially for those small and medium enterprises (SMEs) that do not have relatively abundant financial resources like their counterparts, the industry incumbents. But countries are different in the design of tax mechanisms. Moreover, studies have shown that smaller firms are important job generators and more innovative than larger firms (Klette and Kortum, 2004; Michaelidou et al., 2011). However, both U.S. and OECD data show that large firms dominate the R&D investments not only domestically but also globally. For example, the U.S. National Science Foundation reports that more than 80% of manufacturing R&D are undertaken by large firms and the OECD Science, Technology and Industry Scoreboard of 2015 reports that more than 60% of global R&D is done by only 250 companies. Moreover, compared with their large incumbents, SMEs are more vulnerable in the increasing global competition environment. Therefore, it is important to investigate whether in the U.S., the R&D tax credit stimulates SMEs to invest more in R&D, whether firms in different industries exhibit different R&D investment patterns, how the differences relate to the degree of their response to the R&D tax credit and the degree of their exposure to import competition. To our knowledge, there is no research answering those questions. This research aims to fill in the gap. Our study shows some interesting findings: First, after the newly enacted R&D tax credit in the U.S. in 2009, more SMEs are eligible and qualified for R&D tax credits and the value of our R&D inequality index declined dramatically after 2009. Second, when examining the index by industry in detail, we find that the R&D tax credits can favor either large firms or SMEs depending on the industry that we study. Third, our panel regression analysis indicates that import competition can negatively affect U.S. innovation but the negative effect can be mitigated as the degree of R&D inequality increases. Fourth, the degree of R&D inequality has a statistically positive relationship with U.S. innovation measured by U.S. capital stock of R&D assets. However, when measured by U.S patents, U.S. innovation has a statistically negative relationship with the degree of R&D inequality. That is, lowering R&D inequality can increase U.S. patenting.

[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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1. Introduction

OECD countries, instead of giving subsidies, have been increasingly adopting research and development (R&D) tax credits to encourage innovation, especially for those small and medium enterprises (SMEs) that do not have relatively abundant financial resources like their counterparts, the industry incumbents. Using U.K. data, Dechezlepretre et al. (2016) find that the R&D tax credit increases innovation activities, and that SMEs are more responsive to the tax credit (Dechezlepretre et al., 2016). The finding is encouraging in that some studies have shown that smaller firms are important job generators and may be more innovative than larger firms (Klette and Kortum, 2004; Michaelidou et al., 2011). Additionally, in the rising digital economy with the features of increasing returns to scale and rising cross-border online platforms, a few startups, such as Airbnb and Uber, have grown fast to become unicorns[4] for key service areas and the cheap cloud computing services have lowered the industry entry barriers and minimum operation scale for small firms (McAfee and Brynjolfsson, 2017; Varian, 2018). Moreover, countries are different in the design of R&D tax mechanisms and the resulting impacts may differ as well.

Moreover, both the U.S. and OECD data show that large firms dominate R&D investments not only domestically but also globally. For example, the U.S. National Science Foundation (NSF) reports that more than 80% of manufacturing R&D are undertaken by large firms and the OECD Science, Technology and Industry Scoreboard of 2015 reports that more than 60% of global R&D is done by only 250 companies. Furthermore, compared with their large incumbents, SMEs are more vulnerable in the age of globalization (Feinberg, 2016), except those SMEs with a higher degree of technological capabilities, which may be less vulnerable from import competition.

[4] Unicorns are companies that have reached $1 billion in valuation without tapping the stock markets. https://www.usnews.com/news/top-news/articles/2017-12-15/factbox-airbnb-spotify-among-unicorns-likely-to-list-in-2018

Therefore, it is important to investigate whether in the U.S., the R&D tax credit stimulates SMEs to invest more in R&D; whether firms in different industries exhibit different R&D investment patterns; and how the differences relate to the degree of their response to the R&D tax credit and the degree of their exposure to import competition. To our knowledge, there is no research answering those questions. This research aims to fill the gap.

To answer the questions, we use data from the world input-output dataset, the Compustat dataset, federal and state tax credits, and patent data from the United States Patents and Trademark Office (USPTO). The data cover the period of 1996 to 2011[5]. On the measurement of industry-level import competition by country and/or region, we adopt the Johnson and Noguera (2012)[6] approach to compute the value-added per export ratio. For example, the ratio from China to the U.S. will be the degree of import competition from China. We use the world input-output dataset[7] to calculate the industry-level value-added per export ratio. On the measurement of the degree of import competition per R&D dollar expenditure, we apply the Autor et al. (2013) method. In addition, we define an R&D inequality index to measure the inequality in the R&D tax credit. Lastly, we measure the U.S. innovation by two approaches, U.S. capital stock of R&D assets and U.S. patents.

Our study shows some interesting findings: First, after the newly enacted R&D tax credits in 2009, more SMEs are eligible and qualified for R&D tax credits and the value of our R&D inequality index declined dramatically after 2009. Second, when examining the index by industry in detail, we find the tax credit can favor either large companies or SMEs depending on the industry that we study. Third, when we use U.S. R&D capital to measure U.S. innovation, our panel

[5] The U.S. patent data cover the period of 1988 to 2011.
[6] http://econpapers.repec.org/article/eeeinecon/v_3a86_3ay_3a2012_3ai_3a2_3ap_3a224-236.htm

[7] http://www.wiod.org/publications/papers/wiod10.pdf

regression analysis indicates that import competition can negatively affects U.S. innovation, but the negative effect can be mitigated as the degree of R&D inequality increases. In addition, the degree of R&D inequality has a statistically positive relationship with U.S. innovation, a result that supports Harberger (1998) sun-rise and sun-set phenomenon – a small or modest set of firms can account for 100 percent of productivity growth in an industry. Fourth, when we use U.S. patents to measure U.S. innovation, our panel regression analysis still indicates that import competition can negatively affect U.S. innovation, but the negative effect can be mitigated as the degree of R&D inequality increases. However, the mitigation effect is not statistically significant. In addition, the degree of R&D inequality has a statistically negative relationship with U.S. innovation. That is, lowering R&D inequality increases patenting.

The rest of paper is organized as follows. Section 2 lays out the methodology. Section 3 specifies the data. Section 4 shows the empirical analysis. Section 5 concludes.

2. Methodology

Dechezlepretre et al. (2016) use U.K. data and find that R&D tax credits increase innovation activities and SMEs are more responsive to the credits (Dechezlepretre et al., 2016). Moreover, studies have shown that smaller firms are important job generators and may be more innovative than larger firms (Klette and Kortum, 2004; Michaelidou et al., 2011). Unlike the U.K. where a firm's R&D tax credit is calculated based on total R&D spending, the U.S. designs a different R&D tax credit based on a firm's incremental R&D spending. Therefore, under this kind of tax mechanism, we would like to examine whether in the U.S., SMEs are also more responsive to the R&D tax credit and whether the degree of responsiveness varies across industries. We design a R&D inequality index to measure the relative responsiveness between large firms and SMEs.

Moreover, studies in OECD countries show that import competition positively affect innovation rates (Bloom et al., 2016) and trade literature has shown that more productive firms can be better protected from import competition. Given those findings, we would like to examine whether industries with higher degrees of R&D inequality have lower innovation output, which implies that these industries are less competitive in the open trade environment.

2.1 The VAX ratio: Measurement of the Degree of Import Competition

The Derivation of the Value Added Per Export (VAX) Ratio

In this section, we briefly describe the derivation of the VAX ratio as introduced by Johnson and Noguera (2012). Here, we define *i* as the source country, *j* as the destination country, *s* as the source industry, *s'* as the destination industry, and *t* as the year. The market clearing condition in value terms is:

$$y_{it}(s) = \sum_{j} f_{ijt}(s) + \sum_{j} \sum_{s'} m_{ijt}(s, s')$$

where $y_{it}(s)$ is the value of total output in industry *s* of country *i*, $f_{ijt}(s)$ is the value of final goods shipped from country *i* to country *j* in industry *s* , and $m_{ijt}(s, s')$ is the value of intermediate goods from industry *s* used in industry *s'*. Following Johnson and Noguera note, we define the exports $x_{ijt}(s)$ as the total number of final goods and intermediate goods exported to country *j*. Then, the market clearing condition states that total output is divided between gross exports (sum of $x_{ijt}(s)$, domestic final use $f_{ijt}(s)$ and domestic intermediate use (sum of $m_{iit}(s, s')$).

Stacking the market clearing conditions by country, we have both total output, $y_{it}(s)$ and final goods $f_{ijt}(s)$ as S x 1 vectors, while the intermediate goods, $m_{ijt}(s, s')$ are an S x S matrix. Then, we define $A_{ijt}(s, s')$ as the proportion of intermediate inputs used in total output where

$A_{ijt}(s,s') \equiv \frac{m_{ijt}(s,s')}{y_{jt}(s')}$. This allows us to rewrite the market clearing conditions as an S x N matrix where:

$$y_t = A_t y_t + f_t$$

where $A_t = \begin{pmatrix} A_{11t} & \cdots & A_{1Nt} \\ \vdots & \ddots & \vdots \\ A_{N1t} & \cdots & A_{NNt} \end{pmatrix}$, $y_t = \begin{pmatrix} y_{1t} \\ \vdots \\ y_{Nt} \end{pmatrix}$, and $f_t = \begin{pmatrix} \sum_j f_{1jt} \\ \vdots \\ \sum_j f_{Njt} \end{pmatrix}$.

Next, we solve for the total output and rewrite the total output vector as:

$$y_t = (I - A_t)^{-1} f_t.$$

Define the ratio of total intermediate inputs in country *I* as the total amount of inputs collected from all other industries and countries divided by the total output in country *i* so that the ratio $r_{it}(s)$ is defined as

$$r_{it}(s)=1-\sum_j \sum_{s'} A_{jit}(s', s).$$

Then we multiply this ratio by the individual elements of the total output vector to obtain the measure of value-added trade from country *i* to country *j*,

$$va_{ijt}(s) = r_{it}(s) y_{ijt}(s).$$

As Johnson and Noguera (2012) note, the framework above provides details of a circular process of production where inputs and outputs are continuously transferred from one country-industry to another, which implies an infinite number of production stages. Using a two-stage sequential production process, Johnson and Noguera (2012) construct values of gross exports and value-added exports using the input output tables with the following components:

$$\bar{x}_{ij} = f_{ij} + A_{ij} f_{jj} + A_{ij} f_{ji} + \sum_k A_{ij} f_{jk}, \text{ and}$$

$$\overline{va}_{ij} = f_{ij} + A_{ij} f_{jj} + A_{ii} f_{ij} - \sum_k A_{ki} f_{ij} + \sum_{k \neq i,j} A_{ik} f_{kj}.$$

We can then define the approximate VAX ratio as:

$$\overline{VAX}_{ij} = \frac{\overline{va}_{ij}}{\bar{x}_{ij}}.$$

2.2 Methodology for the Measurement of R&D Inequality

Studies have used different kinds of measurements for firm size, such as the number of employees, annual sales, and the value of assets, etc. In the U.S., the Small Business Administration (SBA) establishes small business size standards on an industry-by-industry basis,[8] but in general, a small business has fewer than 250 employees, a medium-sized business has fewer than 500 employees, a large-sized business has fewer than 1000 employees, and an enterprise is considered to be more than 1000.

To estimate the value of R&D inequality index, we first classify firms into SMEs and large firms. We divide sales in four quantiles. We then calculate the mean value of maximum sales in each quantile. Firms with sales less than the mean are classified as SMEs and the rest are large firms. The methodology allows us to compare sales quantiles that sufficiently account for sales of all firms in the sample by industry. In addition, the cutoff sales levels are similar to those of small and medium sized firms, and large firms in current definition of firm sizes by SBA. In order to calculate the value of R&D inequality index, we use the sample of firms that meet both eligibility and qualification requirements. To receive R&D tax credit, a firm must have qualified research expenditures - that establishes eligibility. Furthermore, a firm also must have tax liability to write it off through the credit - that establishes qualification. The R&D inequality index is defined as:

$$\boldsymbol{RDI = 1 - \frac{(number\ of\ SMEs\ eligible\ \&\ qualified)/(total\ number\ of\ SMEs)}{(number\ of large\ firms\ eligible\ \&\ qualified)/(total\ number\ of\ large\ firms)}}$$

[8] According to Section 3 of the Small Business Act of 1953 (15 U.S.C. 632), the Small Business Administrator shall ensure that the size standard varies from industry to industry to the extent necessary to reflect the differing characteristics of the various industries and consider other factors deemed to be relevant by the Administrator. The Small Business Jobs Act of 2010 follows this definition.

Note that RDI ratio below zero implies that SMEs have a higher percentage of eligibility and qualification for R&D tax credit than large firms. If the ratio is higher than 0, the situation is the opposite, and SMEs have a smaller percentage of eligibility and qualification for R&D tax credit than large firms. If the RDI ratio is equal to zero, there is no inequality. Therefore, the increase in the value of the index indicates that the R&D tax credit increasingly favors large firms.

2.3 Methodology for the Matching of Patent Data

Because our empirical model will relate a measure of innovation to the industry level measures of import competition, R&D inequality and firm-level characteristics from Compustat, we first follow the methodology developed by Autor et al. (2017) to web-match organization names in the USPTO database with firm names in the Compustat. This methodology allows obtaining counts of patents filed by each matched firm in a given year corresponding to SIC (NAICS) primary industry of the firm as given in Compustat. After merging the USPTO data with Compustat, we still had 687 not matched firms. We developed an additional algorithm to mine the patent data from https://patents.justia.com to further improve the matching rate. This refined methodology allows us to reduce the number of unmatched firms using Autor et al. (2017) methodology by 22%. Furthermore, to control for the possibility that trends in patenting can vary both by industry and technology, we use the cross-walk between patent classes and SIC-4 industry codes (Hall, Jaffe, and Trajtenberg (2001)) to categorize patents into six main technology fields based on their primary technology class: Chemical; Computers and Communications; Drugs and Medical; Electrical and Electronics; Mechanical; and Others. This classification allows calculating the fraction of patents filed by each matched firm in a given year in each of these six categories. Finally, following the broad industry classification in Autor et.al (2014), we categorize each firm's SIC-4 code into 13 sectors such that the identification is based on the time variation of a firm's primary industry in the growth of the degree of import competition per R&D dollar expenditure, R&D inequality, and patenting.

3. Data

3.1 Data Sources

There are four main data sources: world input-output dataset, Compustat dataset, federal and state tax credits data, and USPTO patent data.

3.1.1 World input-output dataset – industry-level degree of import competition

On the measurement of industry-level import competition, we adopt the Johnson and Noguera (2012)[9] approach by computing the value-added per export ratio. For example, the ratio from China to the U.S. will be the degree of import competition from China. We use the world input-output dataset[10] to calculate the industry-level value-added per export ratio from the rest of the world.

3.1.2 Compustat

We collect a sample of all listed firms on the Compustat Industrial North America between 1996 and 2012. Our year range covers at least three years before Alternative Simplified Credit (ASC) went into effect and three years thereafter in order to set up difference-in-difference type regression analysis.[11] Compustat data is notoriously difficult to be directly used in the estimation due to inconsistent coverage, missing data for some firms, and duplicate data for others. After cleaning 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-

[9] http://econpapers.repec.org/article/eeeinecon/v_3a86_3ay_3a2012_3ai_3a2_3ap_3a224-236.htm

[10] http://www.wiod.org/publications/papers/wiod10.pdf

[11] Under IRS provision, ASC is allowed to carry back three years.

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 Internal Revenue Service (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 not only be eligible, but also have a sufficient tax liability, against which it can 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.

Based on the described criteria for eligibility and qualification for R&D tax credit, we find that in our sample of the total of 11,882 firm-years 8,746 (73.7%) are eligible for any R&D tax credit; and among the eligible 8,746 firm-years, 5,502 (62.9 %) are qualified for any R&D tax credit.

3.1.3 Federal and state R&D tax credits

In order to conduct our calculation for the 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 investments. They also have modified, expanded the incentive, and sometimes repealed and sunset it. Most states offer some version of 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 (QRE), base amount, and is incremental and nonrefundable in nature. For example, a majority of states use the federal definition of qualified research expense 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. The information for each state has been gathered primarily from the 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 US $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 investments. 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 of the user cost of R&D capital.

Also for the purpose of calculating the 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 and the stepwise increase of which depends on corporate income, we follow the way of data selection in Wilson (2009) where he used 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 the user cost of R&D capital.

3.1.4 U.S. Patent Data

Our data cover the sample of organizations that filed for the utility patents between 1988 and 2011. The sample period coincides with the introduction of the Alternative Simplified Tax Credit (ASC) in 2009. This sample contains over 3 million filed applications that are distinguished by the kind of the filing (whether it is initial filing or re-examination), grant dates, technology classes and citation count for each patent.[12] As discussed in detail by Autor et al. (2017), although patent data contains a wealth of information, it is notoriously difficult to use for empirical analysis. First, for competitive non-disclosure reasons, the unit of observation in the patent data is an organization, not a firm. Organization can be any entity including individual filings, universities, research institution etc. Second, each patent application is characterized by technology class, which does not directly map into an industry under either NAICS or SIC classification. Accordingly, it is unclear ex-ante whether an invention to be patented falls in the same primary industry as the filing organization. For example, if a pharmaceutical firm developed and filed a patent application for a computer automation system to fill the bottles with pills, this patent will be assigned to Class 703 (Data Processing: Structural Design Modeling, Simulation, and Emulation). The information of technology class in patent may not be able to tell us the industry sector that the inventor belong to.

Table 1 presents the match rates between firms in Compustat and organizations that applied for patents by the broad industry classification as respective patent counts. Our overall match rate for the entire sample is 92% on average, although among firms in Textile and Apparel this rate drops to only 48%. Given the fact that most firms in our sample are in Chemicals, Petroleum and Rubber sectors, we feel confident with our patent matching approach. Further decomposing our sample into pre and post ASC sub-samples, we find consistently high match rates with patent applications and firms. Note that most patents were filed in pre-ASC period.

[12] USPTO technology classes can be found at https://www.uspto.gov/web/patents/classification/selectnumwithtitle.htm

Table 1: Summary of Patent Applications to Firm Matching by Sector

Sectors	Underlying Patents Counts	Pre-ASC (1988 -2009) Match Share	Pre-ASC (1988 -2009) Patent Counts	Post-ASC (2009-2011) Match Share	Post-ASC (2009-2011) Patent Counts	Entire Sample (1988-2011) Match Share	Entire Sample (1988-2011) Patent Counts
Chem., Petrol, Rubber	30,461	97.80%	33,558	98.30%	8,238	97.9%	41,796
Computers, Electronics	64,540	100%	951	.	0	100.0%	951
Machinery, Equipment	20,902	100%	20,057	100%	342	100.0%	20,400
Transportation	1,353	100%	14,302	100%	4,109	100.0%	18,441
Paper, Print	1,439	80.8%	4,368	78.8%	794	80.2%	5,162
Metal, Metal Products	7,398	100%	1,014	100%	305	100.0%	1,319
Food, Tobacco	655	100%	959	100%	293	100.0%	1,252
Clay, Stone, Glass	10,280	98.4%	701	97.1%	287	98.1%	988
Wood, Furniture	414	100%	1,803	100%	587	100.0%	2,390
Textile, Apparel, Leather	5215	50.4%	207	33.30%	35	48.3%	242
Non-Manufacturing		.	0	.	0	.	0

3.2 R&D Tax Credits in Key Countries

Business R&D is a vital input to innovation, which is an increasingly important factor in the competitiveness of firms and of countries as well as the main driver of long-term growth in productivity and higher standards of living. Because the possible spillover effects, firms may not be able to capture the full benefits of their R&D investments and hence may opt for an under-investment level. To provide a remedy for this market failure, various governments are trying to address the issue of financial constraints for business R&D. The oldest and more widely used solution is property rights, such as patents, trademarks, copyrights, but they cannot entirely compensate for the lack of incentive to invest in R&D because the enforcement these property rights are often not strong enough to defend the returns on R&D investments.

A second solution is to increase the private return to R&D by reducing its costs. It has two approaches: direct government subsidy and tax incentive. Direct government subsidies to business innovation in the form of competitive grants or subsidized or guaranteed loans remain important. It represents the bulk of public financial support to basic, science research, and others in all OECD countries. It is also the preferred instrument of policies to promote R&D in certain sectors, for example technological arenas. Nevertheless, the use of indirect schemes such as tax credits has tended to increase. Fiscal measures to promote R&D and innovation, specifically R&D tax credit, are now being widely discussed in many OECD countries due to its unique advantages over subsidies.

The R&D tax credit allows less interference in the market so that decision makers in the private sector keeps their autonomy in devising R&D strategies to react to the market signals. The R&D tax incentive provides more readily predictable and more stable than subsidies or grants that require periodical review and appropriations. Moreover, the tax incentive requires less layers of bureaucracy and less detailed specifications for receiving subsidies or grants. Upon the advantages of R&D tax credits, many countries seek to promote R&D investment in the economy by granting this kind of preferential tax treatment to eligible R&D expenditures incurred by firms. Over the last decade, several OECD countries have increased their reliance on R&D tax incentives. In 2016, 29 of the 35 OECD countries provide R&D tax incentives. We next take a look at trends in actual R&D tax incentives, in particular SME innovation incentives in some countries.

Countries differ in the extent to which they rely on tax measures to support R&D, and those that do, design tax relief measures in substantially different ways. Some countries implement R&D tax credits, which allow firms to deduct a certain percentage of their R&D expenditures from their tax liabilities, as in Canada, France, Japan, and the United States. Others employ tax concession, which permit firms to deduct eligible R&D expenditures against their taxable income. Belgium, for example, allows taxpayers to deduct 80% of their qualifying patent income from their taxable income. Each of these approaches reduces the effective cost of conducting R&D aiming to increases its supply.

Many OECD countries have introduced two main types of tax incentives for R&D: volume-based and incremental-based tax incentives. The United States has opted for incremental-based mechanism, providing an incentive proportional to the increase in R&D outlays in a given year compared to the average real volume of spending during a reference period. Most countries (such as Australia, Canada, the United Kingdom, etc.) utilize the volume-based tax incentives, which is proportional to the volume of R&D performed. A few countries use both approaches – Japan offers a combination of an incremental formula and volume-based tax credits.

Despite the difference in the R&D tax incentive mechanisms, they give various solutions to the same problem: How to ensure that companies that have no tax liabilities, particularly those with temporarily loss-making in a cyclical downturn, or newly established firms, are not excluded from the benefits of the tax incentive (or reduction) scheme. The most widely used solution is to allow tax-credits to be carried forward (for instance, Australia, Austria, Canada, France, the United Kingdom, and the United States) or to be refunded (for example, Austria, Canada, France, and the United States).[13] If a country does not offer tax incentives to R&D (i.e. Germany), would the firms located in this country operate and compete at a disadvantage? There is no straightforward answer to this question. The impact of R&D tax incentives on firms' competitiveness cannot be isolated from that of the other components in the national systems of government support to R&D and innovation, including the tax-system as a whole.

Among those countries with R&D tax credits, tax incentive mechanisms differ from one country to another in many of their details, including: the definition of a minimum volume of eligible R&D expenditures (for example, all costs of "Research and Experimental Development," in the United States); the ceiling (fixed amount of percentage) imposed on tax benefits; whether a two-tier system exists, involving both central /federal and regional/provincial/state tax incentives, as in the United States, Canada or in China; whether they give differential treatment according to firm-size, region or technology.

After the pioneer works of Schumpeter highlighted the importance of SMEs in innovation, his hypothesis regarding SMEs has been revisited in many contributions to the literature, and the contribution of corporate R&D within SMEs discussed heatedly. In 2007, a group of experts advising the Commission on the European Industrial Research and Innovation Monitoring System (EIRIMS) highlighted the need to investigate corporate R&D in SMEs, as a preliminary step for tailoring research and innovation policies specifically addressed to European SMEs.

[13] Another solution, adopted by the Netherlands is to apply the tax-rebate not to the tax on profit but to that on wages.

Within this context, many OECD countries have moved to implement preferential R&D tax incentives for SMEs. In Australia, a refundable tax credit of 45% of eligible R&D expenditure is available for SMEs (i.e., companies with gross receipts of less than AUD 20M that are not controlled by exempt entities) comparing 40% tax credit for all other eligible entities. France allows SMEs to request an immediate refund of unutilized credits when the credit is not utilized within the three-year period while large taxpayer is entitled to a refund in three years. In the United Kingdom, SMEs qualify for the following expenditure-based tax incentives at 230% while large companies qualify for 30% of its eligible R&D costs. Unused tax credits are refundable only for SMEs. Japan's SMEs qualify for R&D tax credit at 12% of the total R&D expenditure, yet large companies at 8-10% of the total R&D expenditure.

Table 2: R&D Tax Credits in Key Countries

	Tax incentive	Type of instrument	Eligible expenditures	Rates	Refundable	Carry-over	Thresholds/Ceiling
Australia	Tax credit	Volume-based	Current, depreciation	SME: 45% Others: 40%	SME: Yes Others: No	Indefinite	Threshold: SMEs with gross receipts of less than AUD 20M that are not controlled (>50%) by exempt entities Ceiling: AUD100M
Austria	Tax credit	Volume-based	Current and capital	14%(12% until 2017)	Yes	Yes, indefinite	Ceiling: €1M for subcontracted R&D expenses.
Belgium	Increased investment deduction or tax credit for R&D	Volume-based	Qualifiying fixed assets (including patents, machinery and equipment, buildings, etc.)	13.5% as a one-off deduction or 20.5% spread over the depreciation period of the fixed asset.	No	Yes, indefinite	No
	Deduction for innovation income (replaced Patent Income Deduction)	Volume-based		85% deduction (PID: 80%)	N.A.	N.A.	No
	Wage withholding tax exemption	Volume-based	Labor	80%	Redeemable against payroll/ related taxes	N/A	Ceiling: Wage withholding tax liability
Canada	Scientific research and experimental development tax credit	Volume-based	Current/Capital	35% of the first $3M and 15% on any excess amount for Canadian-controlled private corporation. 15% of all qualified expenses for other Canadian entities.	Yes	20	Threshold: $3M
France	Tax credit	Volume-based	Current and depreciation	30% of the first €100M 5% for qualified RD expense exceeding €100M	SME: Immediate Large companies: 3	3	Ceiling: Subcontracted R&D fees limited to €10M; qualifying contract research limited to €2M where the taxpayer and the

							subcontractor are related entities.
Germany	No R&D tax incentives. Only R&D loans and R&D grants. SMEs receive additional support than large companies. For example, the Central Innovation Program for SMEs primarily target at SMEs.						
United Kingdom	Corporate tax credit for R&D (Tax allowance)	Volume-based	Current, intangibles	SME: 230% on R&D expenses incurred from 4/1/2015 Large companies: 30% of its eligible R&D costs	Yes (SME only)	Yes, indefinite	SME: €7.5M per project. Large companies: No ceiling
	R&D Expenditure Credit of 2013 (Tax credit)	Volume-based		11% (large companies only)			No ceiling
United States (Federal R&D tax credit)	Regular research credit			20%	Yes	Yes	Base amount.
				20%	Yes		Base amount.
	Start-up credit calculation						
	Alternative simplified credit	Incremental	Current	14%, 6% if no R&D in past 3 years	Yes		Base amount.
China	Tax allowance	Volume-based	Current and depreciation (the reduction of enterprise tax only available to companies granted High and New Technology Enterprise status)	150% reduction for qualified RD expense, in addition to the reduced 15% enterprise tax rate	No	5	Ceiling: subcontracted RD limited to 80% of eligible costs
Japan	Volume-based R&D tax credit	Volume-based	Current	SME: 12% for total R&D expenditure Large companies: 8-10% for total R&D expenditure	No	No	Ceiling: Limited to 25% of the company's national corporation tax liability before the credit is applied, for both SMEs and large companies.
	Tax credit for special R&D cost		Current	30% for joint R&D with a university or public research institution; 20% for R&D with other non-public entities	No	No	Ceiling: Limited to 5% of the company's national corporation tax liability before the credit is applied.
	Incremental tax credit	Incremental	Current	5-30% when the current period R&D expense exceeds (i) the annual average of the R&D expense for the three preceding fiscal years and (ii) the highest annual R&D expenditure for the previous two fiscal years. Alternatively,when the current period R&D expense exceeds 10% of the average annual sales for the four preceding fiscal years, the company is eligible for a credit calculation using a formula. [14]	No	No	Ceiling: Limited to 10% of the company's national corporation tax liability before the credit is applied.

[14] The formula: R&D expenditure less (average annual sales for the four prior years *10%) multiplied by R&D ratio reduced by 10%, multiplied by 20%. The R&D ratio is the amount of current year R&D expenses divided by average annual sales for the four preceding fiscal years.

4. Empirical Analysis

In this section, we first plot a few descriptive graphs which enhance our understanding on the distribution of firms eligible and qualified for R&D tax credit by industry and by state. Then, we conduct the panel analysis to examine the relationship between import competition, inequality in R&D tax credit, and U.S. innovation. U.S. innovation will be measured by two approaches, U.S. R&D capital and U.S. patents.

4.1 Distribution of Firms Eligible and Qualified to R&D Tax Credit by Industry

Figure 1 plots the histogram for the mean ratio of percentage of SMEs eligible and qualified to R&D tax credit to the percentage of large firms eligible and qualified to R&D tax credit all years by industry. If the ratio is above or below 1, it suggests that there exists inequality in R&D tax credits between SMEs and large firms. If the ratio is higher than 1, the increase in ratio indicates that the inequality favors SMEs. If the ratio is less than 1, the increase in ratio indicates the inequality favors large firms. From Figure 1, we have several interesting observations: First, the retail trade and the broadcasting industries have the highest ratio, 2, and the inequality favors SMEs. This is very interesting in that in the rising digital economy, a lot of small businesses with asset light and heavy digitized business model have entered the sectors in past decade. Second, R&D intensive industries in general have ratios below 1, and the inequality favors large firms. The degree of difference varies by industry: Professional, Scientific, and Technical Industry (coded as NAICS 541) has the lowest ratio than other R&D intensive industries during our sample period. This sector contains a lot of firms in the biotech industries. In addition, other R&D intensive industries have ratios less than 1, and the ratios are in the range of .5 to .7, an index that indicates the inequality favors large firms. Note that the R&D investment scale has been growing in the past few decades based on U.S. official statistics data (Li and Hall, 2018). These industries include

NAICS 325 (Chemicals and Pharmaceutical Industry), NAICS 334 (Computer and Electronic Industry), R&D intensive industries in NAICS 335 (Electrical Equipment Industry), NAICS 336 (Transportation and Motor Industry), NAICS 517 (Telecommunication and Video Entertainment Services Industry), and NAICS 518 (Data Processing, Hosting, and Related Services). Third, Figure 1 indicates that the inequality in R&D tax credit may either favor SMEs or large firms depending on the industry that we study. This indicates that unlike the U.K., U.S. R&D tax credits may not have bias toward either SMEs or large firms overall.

Figure 1: Distribution of Firms Eligible and Qualified to R&D Tax Credit by Industry

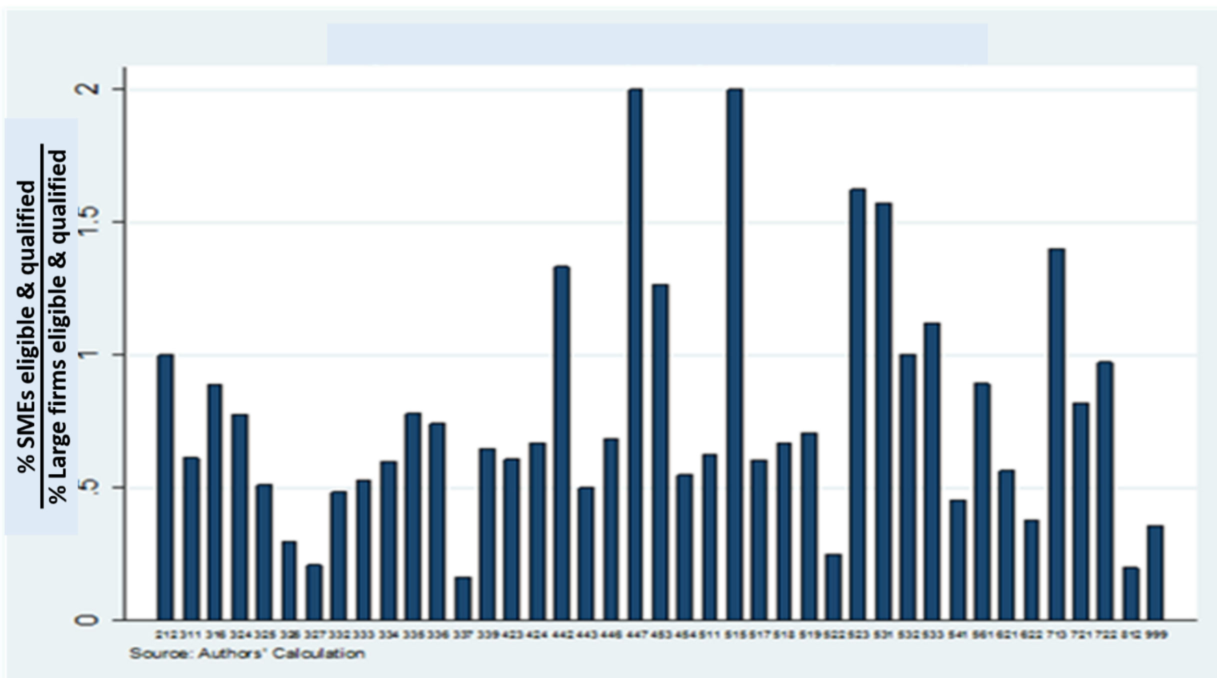
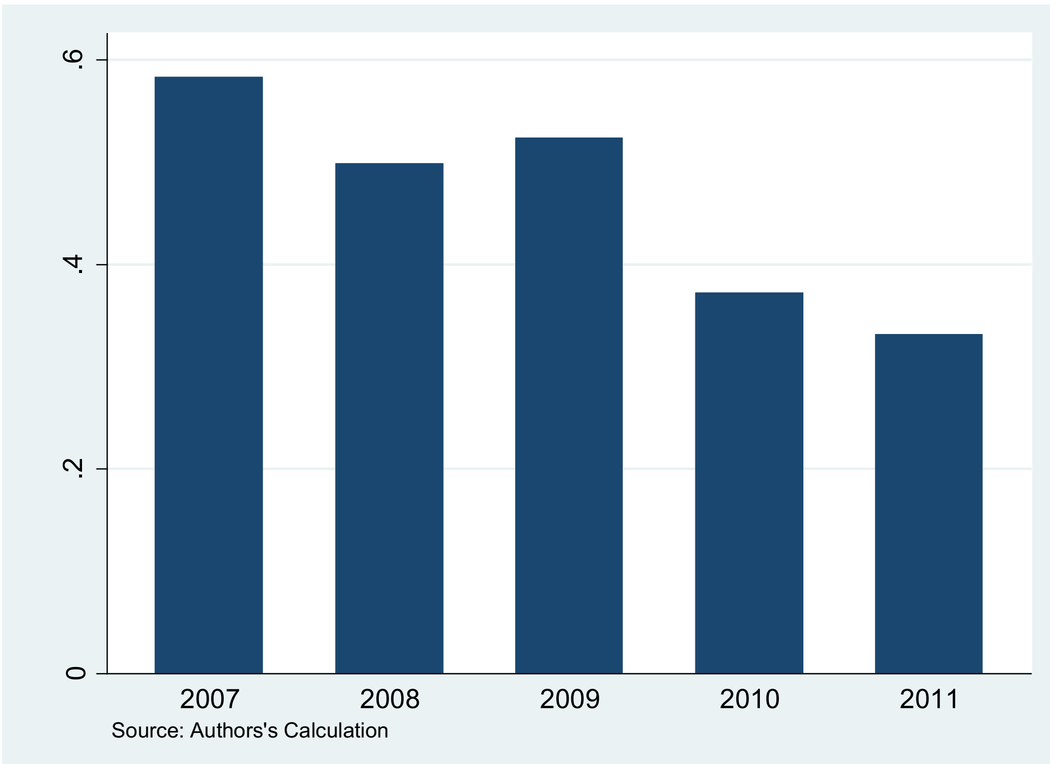


Figure 2 shows the historic histogram of average R&D inequality index for the economy as a whole from 2007 to 2011. As shown in the graph, after 2009, there is a dramatic drop in terms of the value of R&D inequality index. This is consistent with what we see in the data: After the U.S. Congress enacted Alternative Simplified Credit (ASC) in 2009, firms that originally cannot substantiate its claim for the regular R&D credit (RRC) can elect for an alternative calculation method. As shown in the data, more SMEs are now eligible and qualified for under ASC.

Figure 2: R&D Inequality Index – 2007 to 2011



4.2 Geographical Distribution of Firms Eligible and Qualified for R&D Tax Credit

Figures 3(A)-(B) show the geographical distribution of SMEs eligible and qualified to R&D tax credit and that of large firms eligible and qualified to R&D tax credit in the United States. The states with the higher density of SMEs eligible and qualified to R&D tax credit are similar to the states with higher density of large firms eligible and qualified to R&D tax credit with only few exceptions. We note that that the states with highest or the 2nd highest densities of firms eligible and qualified to R&D tax credit are normally higher technology intensive in terms of the number of technology jobs.[15]

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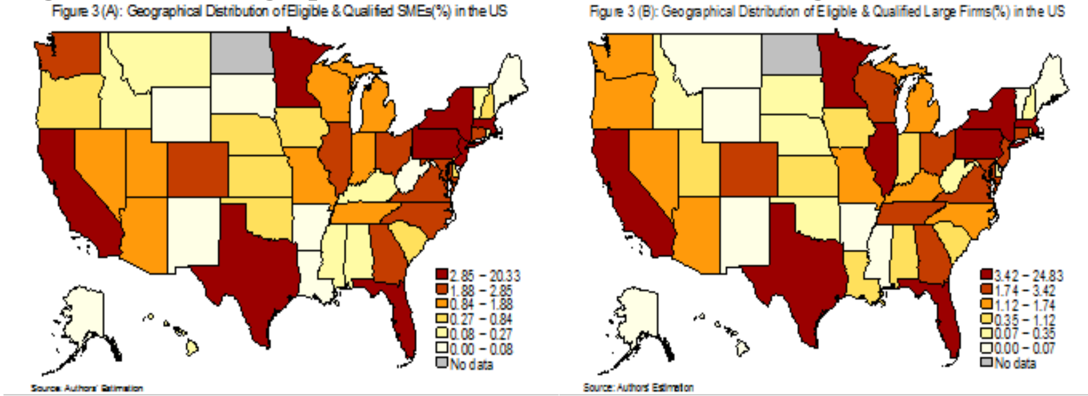
[15] https://www.bloomberg.com/news/photo-essays/2010-12-07/u-dot-s-dot-cities-with-the-most-tech-jobs

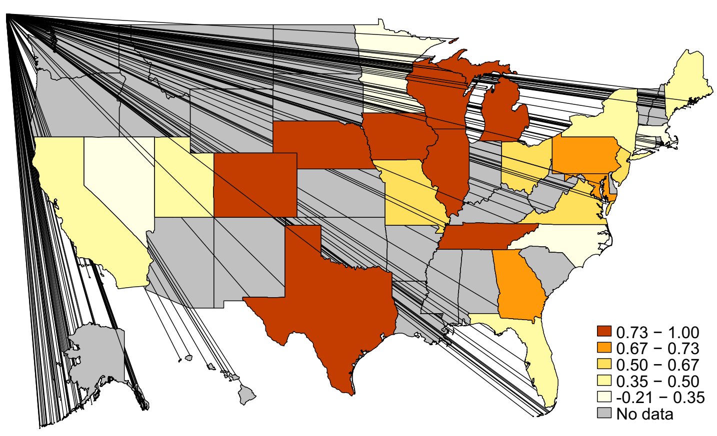
Figure 3: The Geographical Distribution of SMEs and Large Firms in the U.S.



4.3 Geographical Distribution of Inequality in R&D Tax Credit Ratio

Figure 4 shows the R&D inequality ratio (RDI) by state in 2010. Recall, when RDI ratio is greater than zero, the inequality favors large firms. Accordingly, the darker areas on the map, most in the mid-west and the south, imply relatively higher R&D inequality among firms within states. Note that technology intensive states show different degrees of inequality in R&D tax credit depending on the composition of the industries in each state.

Figure 4: R&D Inequality Ratio in the United States in 2010



4.4 Panel Analysis: Import Competition, Firm Size Distribution in R&D Tax Credit, and U.S. Innovation Measured by R&D Capital

After calculating firms eligible and qualified to R&D tax credit in the U.S., we find that the percentage of SMEs eligible and qualified for R&D tax credit is smaller than that of large firms. Therefore, we are interested in understanding how the distribution in R&D tax credit relates to U.S. innovation and how the relationship interacts with import competition. As mentioned in Section 3, we define the R&D inequality index to measure the relative degree of large firms to SMEs in terms of the eligibility and qualification to R&D tax credit. In addition, we measure innovation by R&D capital stock (Dechezlepretre et al., 2016). Following Hall (1999) and Hall et al. (2005), we use the perpetual-inventory method with depreciation rate of 15% to calculate R&D capital stock for U.S. firms in the Computstat dataset. As to the measurement of the degree of import competition, we use VAX ratio (See Section 2).

To ensure the exogenous variation in our measure of innovation, we instrument R&D capital stock at the firm level using tax-induced changes to the user cost of R&D capital. We obtain the user cost of R&D capital for our sample using the methodology adopted in Belenkiy, Li and Xu (2016). Furthermore, to capture the degree of R&D exposure to import competition, we define the measurement of the degree of import competition for R&D following Autor et al. (2013) in Equation (1). At the industry level *j*:

$$\Delta ICR_{jt} = \sum_{u} \frac{RD_{jt}}{RD_{ut}} VAX_{jt} \tag{1}$$

We define the R&D inequality index as RDI_{jt}. With the industry-level measurement of *RDI* and the degree of import competition, we estimate the impact of R&D inequality on U.S. innovation in Equation (2).

$$\begin{aligned} &RDStock_{ijt} \\ &= \beta_0 + \beta_1 IPR_{jt-1} + \beta_2 RDI_{jt-1} + \beta_3 ICR_{jt-1} \times RDI_{jt-1} + FirmControls_{ijt-1} + \zeta_i + \xi_{jt} \\ &+ \varepsilon_{ijt} \end{aligned} \tag{2}$$

In the specification (2) $FirmControls$ are the firm controls, including firm age and asset value. The interaction term between the degree of *ICR* and *RDI* captures the isolation effect of R&D from import competition with the respect to the degree of R&D inequality. The firm fixed effects ζ_i absorb all time-invariant determinants of innovation at the firm level. The industry-year fixed effects ξ_{jt} ensure that the model is identified from comparing firms with different eligibility and qualification for R&D tax credits within the same industry-year.

Table 3 shows our preliminary findings. In the following panel regression analysis, we use data from 2007 to 2011 to examine the relationship between import competition, R&D inequality, and U.S. innovation.

Table 3: Import Competition, R&D Inequality, and U.S. Innovation

Variables	[1]	[2]	[3]
Import Competition (ICR)	-0.001	-0.025*	-0.202
	(0.112)	(0.014)	(0.136)
R&D Inequality (RDI)	0.001	0.034*	0.066
	(0.061)	(0.021)	(0.161)
ICR X RDI	0.057***	0.039*	0.217
	(0.021)	(0.023)	(0.175)
Assets		-0.007	0.422***
		(0.008)	(0.095)
Age		0.004**	0.013
		(0.001)	(0.017)
Fixed Effects			
Industry	Yes	No	No
Year	Yes	No	No
Firm	No	Yes	Yes
Industry X Year	No	Yes	Yes
Observations	48	774	1706
R-Squared	0.999	0.999	0.804

Notes: ***1%; **5%; *10%

Dependent variables for [1] and [2] R&D capital (in logs) [3] TFP

Robust standard errors clustered on (industry and year) pairs are in parenthesis

Table 3 shows the analysis of the industry R&D panel regression in the industry level on equation (1) and the analysis at the firm-level sample on equations (2) and (3). The dependent variables of equations (1) and (2) are the log of predicted industry-level R&D capital. The predicted R&D capital is estimated using perpetual-inventory method with the constant depreciation rate of 15%, a traditional assumption. We have estimated R&D expenditures using user cost of R&D capital as an instrument. The dependent variable of equation (3) is TFP level.

After controlling fixed effects on industry and time, in equation (1), we find that import competition have a negative relationship with U.S. innovation, but the relationship is not statistically significant. On the contrary, R&D inequality has a positive relationship with U.S.

innovation, but the relationship is also not statistically significant. However, the interaction term between import competition and R&D inequality has a statistically positive relationship with U.S. innovation. This suggests that the negative relationship between import competition and U.S. innovation can be mitigated when the industries have higher degree of R&D inequality.

After controlling fixed effects on firm and industry, equation (2) indicates that import competition has a statistically negative relationship with U.S. innovation. This finding is consistent with the fining in Autor et al. (2017) for the U.S., even though our measure of import competition differs from theirs. However, this finding is different from the finding in Bloom et al. (2015) where they find import competition has statistically positive impacts on the innovation of some OECD developed countries with different R&D tax mechanisms. In addition, R&D inequality has a statistically positive relationship with U.S. innovation. This suggests that as relatively more large firms eligible and qualified for R&D tax credit, it will have a positive relationship with U.S. innovation. This may be consistent with findings by Harberger (1998) that as shown in his famous sunrise –sunset diagrams that across industries, a small or modest fraction of firms accounting for 100 percent of the productivity growth of an industry. Furthermore, it is also consistent with findings in other OECD studies that R&D tax credits have a positive relationship with a country's innovation (Bloom, 2002; Dechezlepretre, 2016) Moreover, the interaction term between R&D inequality and import competition has a statistically positive relationship with U.S. innovation. This suggests that import competition can negatively affect U.S. innovation, but the negative effect can be mitigated as the degree of R&D inequality increases. This is consistent with studies that compared with SMEs, large firms can better compete with import competition (Feinberg, 2008).

Although firm age has a positive impact on innovation, the magnitude is much smaller. This indicates that it takes time for firms to accumulate knowledge stocks. In equation (3), the regression signs of each variable are the same, yet the only variable, total assets, has a statistically significant effect. Since our analysis covers the period of 2007-2011, a period that the economy has experienced a lot of technological advances, there may be a significant lag problem, and TFP cannot show those advances (Bryjolfsson et al., 2017; Elnasri and Fox, 2015).

4.5 Panel Analysis: Import Competition, Firm Size Distribution in R&D Tax Credits, and U.S. Innovation Measured by U.S. Patents

In this section, we consider U.S. patenting as an alternative way to measure innovation of U.S. firms. Although a lot of innovations such as process innovations may not be patented and firms have been increasingly kept some innovations as trade secrets, patents can still provide a useful and supplementary measure of innovation. We modify our empirical strategy to estimate the impacts of import competition and R&D inequality on U.S. innovation. Following Autor et al. (2017), we measure the growth rate in patenting activity (ΔP) for each firm i in industry j in year t in averaged first differences as shown in expression (3).

$$\Delta P_{ijt} = 100 \times \frac{\left(P_{ijt_1} - P_{ijt_0}\right)}{0.5 * \left(P_{ijt_1} + P_{ijt_0}\right)} \tag{3}$$

Using the expression in (3) as our dependent variable, our empirical specification is given in (4).

$$\Delta P_{ijt} = \alpha_t + \beta_1 IPR_{jt} + \beta_2 RDI_{jt} + \beta_3 IPR_{jt} \times RDI_{jt} + \gamma F_{ijt} + \theta S_{jt} + \epsilon_{ijt} \tag{4}$$

In the specification (4) measures of import competition (IPR) and R&D inequality (RDI) are as previously defined; F_{ijt} is a vector of firm-specific characteristics such as number of employees, sales, share of R&D expenditures in sales and assets; S_{jt} is a vector of industry-specific controls such as industry fixed effects, and share of firm's patents that fall into each of the six major patent technology classes.

We estimate the specification (4) using OLS and consider potential confounding issues that may prevent causal interpretation of our results. As noted by Autor et al. (2017), the causal estimation of (4) may be confounded for several reasons. First, observed changes in the import penetration ratio may in part reflect domestic shocks to U.S. industries, which in turn have impact on both U.S. import demand and innovative activity. Second, variation across industry characteristics, such as industry factor intensity and earnings, could all drive systematic differences across firms and industries in the potential for successful innovation. The first issue does not present a concern for us since we construct the measure of R&D import competition using VAX. To address the second concern, we add a rich set of firm-level controls such as employment, sales, and capital assets; and industry level controls such as 11 manufacturing sectors that are listed in Table 3 to control for industry and technology intensity. Finally, to absorb changes in patenting that are driven by diverging trends across technology classes, we control for the technology mix of firm patents using fraction firm's patents that fall in each of the six major technology classes.

As shown in Table 1, the distribution of patents by industries is highly non-uniform in our sample. For example, there were almost 42,000 patents filed by firms in Chemicals, and only 242 patents in Textiles. To account for this variation and to capture overall scale of innovative activities, we weight observations by patent count average (PAW). The patent count average is calculated as number of patents in a firm, averaged over patents at the start and end of a period. Patent counts may provide an imperfect indication of the significance of innovation (Trajtenberg, 1990), since only small fraction of patents lead to major innovations and very few really matter for a firm performance. Accordingly, we also use citation weight (CW) calculated as a sum of all subsequent citations to each firm's start-of-period and end-of-period patents.

Table 4 shows the estimation results. For every speciation we find that import competition has statistically negative effect on the growth rate in patents. Depending on the specification the elasticity of patent growth rate with the respect to import competition ranges between -0.9 to -1.4. These estimates imply that all else equal increase in R&D import competition reduces the growth of rate of patents by as much as 1.4%. Interestingly, this elasticity estimate is larger when we weigh the observations by citations. This suggests that import competition has a greater effect on higher impact innovations. These results are consistent with our earlier findings when the innovation is measured with R&D capital, and the related findings by Autor et. al (2017).

Next, we turn to R&D inequality. Contrary to the result when the innovation is measured by R&D capital, the increase in R&D inequality has statistically negative effect on patent growth rate. The elasticity estimate is fairly consistent across all specifications and implies that 1 percent increase in R&D inequality decreases patenting growth by 0.04%. The result implies that while larger firms eligible for R&D tax credit increased their R&D capital, the increased investments in R&D did not translate into increased patenting. Consistent to previous result when we use R&D capital to measure innovation, the negative effect of import competition is mitigated by increase in R&D inequality. This may due to the fact that larger firms are better insulated in patenting propensity but this effect is not statistically significant.

Lastly, in specifications [5] and [6] we added a control for post financial crisis of 2007-2008 beginning in 2009. We find that once the recovery began, there has been significant and positive effect on patenting growth. However, as U.S. became relatively more attractive for international investment, import competition exacerbated negative effect on patenting growth and R&D inequality. There is also a significant positive mitigating effect for larger firms patenting propensity post financial crisis recovery.

Table 4 - Import Competition, R&D Inequality, and Patenting

Variables	[1]	[2]	[3]	[4]	[5]	[6]
	PW	PW	CW	CW	PW	CW
Import Competition (ICR)	-0.871**	-1.082***	-0.985***	-1.204***	-1.203***	-1.374***
	(0.238)	(0.347)	(0.365)	(0.346)	(0.366)	(0.369)
R&D Inequality (RDI)	-0.043**	-0.043**	-0.038**	-0.039**	-0.039*	-0.035**
	(0.018)	(0.020)	(0.018)	(0.017)	(0.020)	(0.017)
ICR X RDI	0.182	0.207	0.257	0.332	0.083	0.225
	(0.340)	(0.353)	(0.410)	(0.402)	(0.360)	(0.411)
Post Financial Crisis (Post)					0.093**	0.111**
					(0.044)	(0.047)
POST X ICR					-1.540**	-1.427*
					(0.686)	(0.760)
POST X RDI					-0.104	-0.101
					(0.090)	(0.086)
POST X ICR X RDI					2.528**	2.425**
					(0.970)	(1.170)
Firm Controls						
Employees (in logs)	0.012	-0.008	0.026	-0.002	0.006	0.023
	(0.028)	(0.027)	(0.036)	(0.034)	(0.028)	(0.038)
Assets (in logs)	-0.024	-0.049**	-0.023	-0.041**	-0.052**	-0.044**
	(0.019)	(0.020)	(0.018)	(0.020)	(0.021)	(0.019)
Sales (in logs)	0.011	0.042*	-0.002	0.031	0.033	0.013
	(0.023)	(0.024)	(0.034)	(0.032)	(0.022)	(0.033)
Industry Controls						
11 Manufacturing Sectors	Yes	Yes	Yes	Yes	Yes	Yes
Patent Technology Classes	No	Yes	No	Yes	Yes	Yes
Observations	2,104	1,926	1,908	1,837	1,926	1,837

Notes: Dependent variable in each specification is the averaged between first and last period first difference in patent counts by firm; Each specification is weighted either by patent counts (PW) or citation total (CW); Standard errors are in parenthesis and clustered on 4-digit SIC industries.
p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01

Until now we have measured R&D inequality between large firms and SME's using quantile of sales to define them. However, it is likely that R&D activity is not directly proportional to firm sales. In fact, in our sample the correlation between firm sales and counts of filed patents is only 0.5. To consider the differences in R&D inequality using patents directly, we define patent inequality (PI):

$$\boldsymbol{PI = 1 -} \frac{(\boldsymbol{number\ of\ patents\ by\ \ SMEs\ eligible}\ \&\ \boldsymbol{qualified})/(\boldsymbol{total\ number\ of\ SMEs})}{(\boldsymbol{number\ of\ patemts\ by\ large\ firms\ eligible}\ \&\ \boldsymbol{qualified})/(\boldsymbol{total\ number\ of\ large\ firms})}$$

Similar to our original index (RDI) the value of patent inequality index greater than one indicates that R&D tax credit policy benefits patenting propensity of small firms. Conversely, the indicator less than one indicates that R&D tax credit policy benefits patenting propensity of large firms.

Table 5 shows the estimation results obtained by replacing RDI index with PI index in the specification (4).

Table 5- Import Competition and Patent Inequality

Variables	[1]	[2]	[3]	[4]	[5]	[6]
	PW	PW	CW	CW	PW	CW
Import Competition (ICR)	-0.939**	-1.080***	-1.070***	-1.180***	-1.074**	-1.274***
	(0.312)	(0.283)	(0.333)	(0.262)	(0.420)	(0.439)
Patent Inequality (PI)	-0.052*	-0.056**	-0.066*	-0.070**	-0.058*	-0.065*
	(0.034)	(0.033)	(0.034)	(0.035)	(0.038)	(0.040)
ICR X PI	0.323	0.207	0.521	0.413	0.131	0.349
	(0.594))	(0.353)	(0.601)	(0.568)	(0.664)	(0.677)
Post Financial Crisis (Post)					-0.063	-0.047
					(0.080)	(0.080)
POST X ICR					0.015	0.086
					(0.306)	(0.351)
POST X PI					-0.013	-0.090
					(0.066)	(0.078)
POST X ICR X PI					1.160	1.650
					(0.961)	(1.142)
Firm Controls						
Employees (in logs)	0.01	-0.008	0.021	-0.007	0.006	0.017
	(0.023)	(0.027)	(0.036)	(0.028)	(0.026)	(0.023)

Assets (in logs)	-0.021	-0.049**	-0.017	-0.034**	-0.052**	-0.038*
	(0.017)	(0.020)	(0.018)	(0.023)	(0.021)	(0.021)
Sales (in logs)	0.013	0.041*	-0.003	0.030	0.033*	0.012
	(0.60)	(0.023)	(0.027)	(0.026)	(0.022)	(0.025)
Industry Controls						
11 Manufacturing Sectors	Yes	Yes	Yes	Yes	Yes	Yes
Patent Technology Classes	No	Yes	No	Yes	Yes	Yes
Observations	2,079	1,903	1,885	1,815	1,903	1,815

Notes: Dependent variable in each specification is the averaged between first and last period first difference in patent counts by firm; Each specification is weighted either by patent counts (PW) or citation total (CW); Standard errors are in parenthesis and clustered on 4-digit SIC industries.
p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01

5. Conclusion

Studies in OECD countries have shown that R&D tax credits have positive impacts on firm innovation, and that SMEs are more responsive to the credits. However, countries are different in the mechanism design of R&D tax credits. Unlike OECD countries that use the total R&D investment as the assessment for the R&D tax credit, the U.S. assesses the qualified R&D investments in incremental amounts. In this paper, we find that the U.S. R&D tax mechanism is less favorable to SMEs, but the inequality in the R&D tax credit has been declining after the U.S. Congress enacted ASC policy. Moreover, in the rise of globalization, we find that import competition has a negative relationship with U.S. innovation, but the negative effect can be mitigated as the degree of R&D inequality increases. Fourth, the degree of R&D inequality has a statistically positive relationship with U.S. innovation measured by U.S. R&D capital. However, when measured by U.S patents, U.S. innovation has a statistically negative relationship with the degree of R&D inequality. That is, lowering R&D inequality can increase U.S. patenting.

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