R&D TAX INCENTIVES AND INNOVATION: EVIDENCE FROM MANUFACTURING FIRMS IN INDIA

Ph.D. Thesis

By

MANU JOSE

DEPARTMENT OF ECONOMICS

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **R&D TAX INCENTIVES AND INNOVATION: EVIDENCE FROM MANUFACTURING FIRMS IN INDIA** in the partial fulfillment of the requirements for the award of the degree of **DOCTOR OF PHILOSOPHY** and submitted in the **DEPARTMENT OF ECONOMICS, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from July, 2015 to December, 2020 under the supervision of Dr. Ruchi Sharma, Associate Professor, Discipline of Economics, Indian Institute of Technology.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Dec 16, 2020

Signature of the student with date

(MANU JOSE)

This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge

Ruchi Sharma Dec 16,2020

Signature of Thesis Supervisor with date

(Dr. RUCHI SHARMA)

MANU JOSE has successfully given his Ph.D. Oral Examination held on **04 May 2021.**

Rakesh Basant

Ruchi Sharma

Signature of Chairperson (OEB)
Date: May 4, 2021

Signature of External Examiner
Date: May 4, 2021

Signature(s) of Thesis Supervisor(s)
Date: May 4, 2021

Nirmala

Signature of PSPC Member #1
Date: May 4, 2021

Signature of PSPC Member #2
Date: May 4, 2021

Signature of Convener, DPGC
Date: May 4, 2021

Nirmala

Signature of Head of Discipline
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Manu Jose

SYNOPSIS

Introduction

This thesis contributes to the long-standing and ongoing debate on the effectiveness of R&D tax incentive schemes on firm innovation activity. It focuses on the impact of R&D tax credit scheme in an emerging country context such as India. The existing literature on R&D tax credit has largely focused on developed countries. In emerging country context, there are few overviews from China (Guo et al. 2016; Wang et al. 2017) and Taiwan (Yang et al. 2012), but the market environment and regulatory framework in these economies are much different from that in India. For instance, India spends 0.7-0.8% of R&D expenditure as a percentage of GDP compared to 1.8 % in China. In 2016-17, the private sector accounted for only 42 % of total R&D spending in India, as compared to 60-70 % in China (World Development Indicators; R&D statistics 2017-19, DST India). Mani (2010) has estimated the elasticity of R&D expenditure with respect to tax foregone due to the R&D incentives in India for a shorter period (2002-2006) and has not addressed the concern of self-selection into the program. Moreover, empirical evidence on the effect of the R&D tax credit scheme in India is also much required as India's private-sector R&D spending has increased in recent years, while the forces driving this change have remained widely unexplored.

R&D tax credit scheme was introduced in India to promote private in-house R&D investment and firm innovation during 1999-2000. In the period spanning 2001–2010, the policy offered weighted tax deductions of 150% for any capital and revenue expenditure incurred on in-house R&D by firms in select sectors. The country's R&D tax deduction was increased to 200% in the fiscal year 2010-11, and the eligibility was extended to firms in all sectors in 2009-10, placing India among the select few countries providing “super deduction” for investment in R&D, along-side an already generous tax regime for such investments.

Based on the above discussion, the thesis has the following objectives:

1. To investigate the impact of R&D tax credit scheme and its reform (2010-11), that increased the weighted tax deduction from 150 % to 200%, on the innovation activity of the firms.
2. To investigate the impact of R&D tax credit reform (2009-10), that extended the provision of the tax credit scheme to all manufacturing industries, on innovation activity of the firms.

This study considers the impact of R&D tax credit scheme on firm innovation input in the form of R&D expenditure and R&D intensity, and on firm innovation output in terms of the number of patent applications at IPO and USPTO. The inclusion of innovation outcomes accounts for the issues of unproductive and re-labelling of R&D activities for an effective evaluation of the R&D tax credit scheme.

The traditional R&D policy evaluation approaches have largely ignored the endogeneity problems along with the issue of selection bias in the estimation process (David et al. 2000), this study employs appropriate econometric techniques with consideration of the selection bias and endogeneity issues.

Literature review

The economic theory and empirical evidence support the view that innovation policy plays a vital role in firm-level innovation. Risky innovation efforts increase the marginal cost of the R&D, leading to under-investment in R&D activities and eventual market failure. The capital market imperfections make financing R&D more difficult because of the asymmetric information and agency problems between managers and investors, especially in the case of financially constrained firms.

The fiscal incentives encourage firms to start R&D or increase their R&D resources by reducing marginal costs and increases the profitability of R&D investments. On the other hand, public support for R&D could increase the new product development, as the firms would try to gain a competitive advantage in the market by inventing new products and processes. The rationale for the R&D support is based on the linear model of innovation, founded on the assumption that R&D activity of the firm will enhance innovation, which further leads to the development of new products, processes, or services (Arrow, 1972).

Over the last three decades, as a market-oriented scheme, R&D tax incentive has received more attention than direct subsidies to firms. Compared to subsidies, R&D tax incentives reduces the administrative burden and mitigates the risk of unfair use of subsidies. Stoneman (1991) argues that R&D tax incentives have a better effect than the grant system on improving the innovation ability of the firm. As compared to grant, tax incentive provides firms with a choice to conduct and pursue R&D program as per the firms' goals.

There is an expanse of literature examining the effectiveness of tax incentives on promoting R&D and firm innovation, with much of it focused on developed countries (David et al. 2000; Hall & Van Reenen, 2000). More recently, the attention has shifted to studying the effectiveness of tax incentives for R&D on innovation in emerging countries. Wang et al. (2017) argue that this shift is important as the popularity of government R&D programs in emerging economies is growing. The innovation ecosystem in such economies' is quite different from developed economies. Such differences are mainly attributed to the financial constraints and instabilities of emerging economies' financial markets in financing innovation and due to the ineffective systems in intellectual property rights etc. For instance, the success of government initiatives to encourage firm innovation depends on the resource and capability constraints to innovation that extends beyond those of finance (e.g., limited market opportunities and legislative or regulatory pressures).

Even between developed countries, the effectiveness of tax credit schemes has yielded a wide range of results. Hall and Van Reenen (2000) explain that this variance in results comes from the different treatment of R&D by the tax system across countries and over time, in addition to heterogeneity in the effects between firms. Moreover, the micro-level empirical studies differ in the extent of its attempt to address the potential endogeneity and selection bias that arises from firm selection into the R&D programs.

Most of the earlier literature on R&D tax incentives find a positive effect of the incentive program on R&D investment of the firm (i.e., input additionality). In recent years, the focus has shifted more towards a comprehensive evaluation by examining the effect of such incentive on firm's innovation outcome generated from R&D (i.e., output additionality), while evidence on innovation output has remained mixed.

Data and Methodology

Data

To evaluate the impact of R&D tax credit scheme and its reforms on innovation activity of the firms, this study uses firm-level data of Indian manufacturing firms during the period 2001 to 2016. The firm-level data for the study has been collected from the Centre for Monitoring Indian Economy (CMIE) prowess database. The CMIE database provides annual report data of firms that are listed on the Bombay Stock Exchange (BSE) and private limited companies. We acknowledge that most beneficiaries of the R&D tax credit scheme in India are small firms with low-scale R&D (Mani, 2010). Considering that our sample includes only the listed and large private limited companies in India, it is skewed towards larger firms. We address the issue of nominal and unreported R&D by including R&D reported by the recognized firms in the DSIR annual reports.

We identify the DSIR recognized firms from the annual reports of the Department of Scientific and Industrial Research (DSIR). We, then, classify firms into industries based on the National Industrial Classification (NIC) 2008 via NIC 2004. We define industry by the 4-digit NIC-2008 classification.

We have collected data on patent applications to the Indian Patent Office (IPO) over 2001-2016 from the website of the Controller General of Design, Trademark (CGPDTM) and verified using IPO annual reports. We have also collected data on USPTO patent applications for Indian assignees for the period of 2001-2016 from the USPTO Patent Assignment database.

Methodology

The empirical challenge is to reliably measure a causal effect of the R&D tax credit scheme and its reforms on firm innovation activity while accounting for potential endogeneity and the self-selection into the tax credit scheme. In India, firms registered with the Department of Scientific and Industrial Research (DSIR) were eligible for the R&D tax credit. We exploit the fact that not all firms have registered with the DSIR by 2016 and those that did, vary by year of registration. We use DSIR registration as a proxy to capture participation in the R&D tax credit scheme.

For the empirical purpose, we use Propensity Score Matching (PSM) and Difference-in-Difference (DID) approach to account for the issues of endogeneity and selection bias. In PSM framework, we use a non-parametric matching approach to control the possible selection bias and compare the innovation activities of DSIR recognized firms to a matched control group of non-DSIR firms. We, then, examine the counterfactual situation, i.e., how much the non-DSIR firms would have invested in R&D and filed patents if they would not have participated in the R&D tax credit scheme. In DID framework, we take advantage of the panel data and estimate the time or cohort dimension, which accounts for the bias from the unobservable cross-firm heterogeneity and firm-specific time trends. The DID framework assumes that the outcomes of DSIR recognized firms and non-DSIR firms would follow the same time trends in the absence of the treatment.

Empirical Results

We present the results of R&D tax credit reform and its 2010-11 reform that has increased the weighted tax deduction to 200 % on innovation activity of firms in Tables 1, 2 and 3.

Tables 1 and 2 present the estimation results of Propensity Score Matching (PSM). In PSM, we estimate the average treatment effect on the treated (ATT), which is given by the difference between expected outcome values with and without DSIR registration for firms that actually received DSIR recognition. The results show that the R&D tax credit is significantly enhancing the R&D and patenting activities at the firm level. The DSIR registered firms realise higher R&D expenditure and patents during the study period compared to the non-affiliated firms. We find that the R&D expenditure of the DSIR recognized firms on average increased during the study period. The R&D intensity of the firms recognized by DSIR increased compared to the non-DSIR firms during 2001-10. However, during 2011-16, compared to non-DSIR firms, R&D recognized firms increased the R&D intensity by a marginal level only. In the case of innovation outcome in the form of patents, the number of IPO and USPTO patent applications of DSIR recognized firms on an average increased compared to non-DSIR firms during the study period. The industry-wise estimates show that the R&D expenditure has increased for DSIR registered firms compared to the non-participants in all four industries, namely *chemicals, pharmaceuticals, transport and computer* sectors. The R&D intensity also shows a positive increase in the case of all industries except the *pharmaceutical* sector during 2011-16. The positive effect of the tax credit scheme on innovation outcome measured by the number of patent applications is mainly driven by the *chemical* and *pharmaceutical* sectors. The heterogeneities with respect to the firm characteristics reveal that the large firms benefit more from the tax incentive as compared to relatively small firms in terms of both R&D and patents. The effect of the scheme is more for the exporting firms compared to non-exporters. Other interesting findings with respect to the ownership of the firm reveal that the effect of the tax credit scheme is more for foreign-owned firms.

The Difference-in-difference results presented in Table 3 show that the firms R&D expenditure has increased by 78% after the reform, while the impact on their number of IPO and USPTO patent applications has increased by 11% and 6%, respectively. These impacts are both statistically and economically significant. Secondly, the reform has incentivized new firms to register with the DSIR, in order to become eligible for the 200% R&D tax credit. Following DSIR registration, these firms' R&D expenditure, R&D intensity, and the number of IPO patent applications increased by 113%, 1.06%, and 20% respectively. At the same time, we do not find strong evidence that the number of USPTO patent applications increased following DSIR registration in the pre-reform years; the relevant coefficient lacks precision. Furthermore statistically, there is no difference in the impact between firms initially recognized by the DSIR before 2011 and those initially recognized by the DSIR in or after 2011. It is important to keep in mind, here, that some impacts (e.g., on firm innovative output) may take more time to be fully realized. Following David et al. (2000), tax credit induces firms to start short-term projects which reflect only in terms of R&D, but not necessarily with the other innovation measures such as patents. R&D budgets of firms are typically small around the time of initial DSIR registration and gradually increase following registration. Also, firms initially recognized by the DSIR in 2011 or after, were not able to take advantage of the 200% R&D tax credit for a sufficiently long period as we have only a few years of data after initial DSIR recognition for such firms.

Tables 4, 5 and 6 show the results of R&D tax credit 2009-10 reform that extended the provision of the tax credit scheme to all manufacturing industries, on innovation activity of the newly affiliated DSIR firms in India.

The results of PSM presented in Tables 4, and 5 show that R&D tax credit reform has significantly enhanced the R&D and patenting activities at the firm level. The newly affiliated DSIR firms realize higher R&D expenditure and patenting during the study period compared to the non-affiliated firms. We find that the R&D expenditure of the DSIR registered firms on average increased compared to non-DSIR firms during the study period. Similarly, the R&D intensity of the DSIR registered firms increased compared to non-DSIR firms. In the case of innovation outcome in the form of patents, the number of IPO and USPTO patent applications of DSIR recognized firms on an average increased during the period compared to non-DSIR registered firms. The effect of the scheme is more for the exporting firms compared to non-exporters. Another interesting finding with respect to the ownership of the firm reveals that the effect of innovation input in the form of R&D expenditure and R&D intensity is higher for domestic firms, while innovation output in the form of patents is higher for foreign-owned firms. The industry-wise estimates show that the R&D expenditure has increased for DSIR registered firms compared to the non-DSIR firms in most of the sectors. The R&D intensity also indicates a positive increase in most of the industries during the period, except for *Electrical equipment* sector. The positive effect of the tax credit scheme on innovation outcome in the form of patent applications is mainly driven by the *Electrical equipment, Machinery and equipment, Metals, Retail and wholesale trade,* and *Other manufacturing* sectors. The heterogeneities with respect to the firm characteristics reveal that the large firms benefit more from the tax incentive as compared to relatively small firms in terms of both R&D and patents.

The estimation results of DID, presented in Table 6 show that the 2009-10 reform has spurred the firm innovation activity of the firms. First, the new firms, registered with the DSIR following the extended provision of the tax credit, increased the R&D expenditure and R&D intensity by 174.28 % and 0.009 % respectively. The industry-specific estimation results also show that most of the industries increased their R&D expenditure and R&D intensity following the DSIR affiliation. However, the reform did not spur innovation activity in the form of innovation outcomes, such as the number of IPO and USPTO patent applications. The lack of qualified R&D to carry out innovation activities may not be immediately reflected on innovation outcome in the form of patents. Also, firms recognized by the DSIR after the reform were not able to take immediate advantage of the R&D tax credit. It is important to keep in mind that the impacts on patenting may take more time to be fully realized.

Table 1: Summary of Average Treatment Effect (ATT)

	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications
	(1)	(2)	(3)	(4)
2001-2010	139.126***	0.013**	2.712***	0.797***
2011-2016	356.069***	0.003	2.455***	0.689***

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 2: Summary of Average Treatment Effect (ATT), by size, ownership and export status

	R&D expenditure (in million)		R&D intensity		IPO patent applications		USPTO patent applications	
	2001-2010	2011-2016	2001-2010	2011-2016	2001-2010	2011-2016	2001-2010	2011-2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Small firms	9.122	33.424	0.099	0.155***	-0.582***	-0.684	15.863	0.113**
Medium firms	18.463***	34.912***	0.0195***	0.030***	1.010***	0.394***	0.328***	0.169***
Large firms	480.261***	947.036***	0.015***	0.022***	6.852***	6.361***	2.326***	1.797***
Domestic firms	100.444***	283.577***	0.015***	0.030***	1.959***	1.664***	0.754***	0.716***
Foreign firms	223.689***	490.796***	0.021***	0.016***	7.555***	4.953***	1.554***	0.918***
Non-exporters	-8.553	84.429***	0.010*	0.059***	0.212*	1.096***	0.407	0.771***
Exporters	138.180***	349.118***	0.016***	0.030***	2.832***	2.291***	0.851***	0.281***

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 3: Summary of Difference-in-difference (DID)

	R&D expenditure	R&D intensity	IPO patent applications	USPTO patent applications
	(1)	(2)	(3)	(4)
Firms registered with DSIR throughout the period				
DSIR registration in the Pre-reform period	96.20***	1.19	-15***	-10.06***
DSIR registration in the Post-reform period	77.71***	1.60***	10.52***	6.08***
Firms with variations in DSIR registration status				
DSIR registration in the Pre-reform period	113***	1.06***	20***	2.43
DSIR registration in the Post-reform period	16.65	-0.024	-7.87	-0.99

Notes: This table presents the effect of DSIR registration measured in percentage. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 4: Summary of Average Treatment Effect (ATT)

	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications
	(1)	(2)	(3)	(4)
Full Sample	166.234***	0.027***	0.422***	0.041***

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5: Summary of Average Treatment Effect (ATT), by size, ownership, and export status

	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications
	(1)	(2)	(3)	(4)
Small firms	4.282***	0.051	0.001#	-
Medium firms	89.711***	0.024***	0.368***	0.011#
Large firms	1214.480***	0.001	1.225***	0.261#
Domestic firms	117.33***	0.023***	0.323***	0.017#
Foreign firms	100.463*	0.019***	0.594***	0.088**
Non-exporters	50.894***	0.055***	0.292***	0.029*
Exporters	133.827***	0.15***	0.375***	0.025#

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively

Table 6: Summary of Difference-in-difference (DID)

	R&D expenditure	R&D intensity	IPO patent applications	USPTO patent applications
	(1)	(2)	(3)	(4)
DSIR registration in the Post-reform period	174.28***	0.009***	4.71	0.90

Note: This table presents the effect of DSIR registration measured in percentage. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Conclusion

This thesis contributes to the literature on the effectiveness of R&D tax incentives and firm innovation. Mani and Nabar (2016) note that while the "cliché evidence-based policymaking has been doing the rounds in government circles recently", no empirical evidence on the effects of the R&D tax credit reforms in India has been provided yet. Such evidence is urgently needed, given the imminent policy changes to the R&D tax credit scheme. In this regard, while previous literatures have focused on developed countries, this thesis has examined the questions in an emerging country context and has provided an evidence-based policy evaluation with a specific focus on India.

We find that the R&D tax credit scheme and its reforms spurred firm innovation activity. The overall results support increasing tax credit incentives in India. Encouraging R&D with "super deductions" has real and economically significant effects on firms' input into innovation as well as their innovative output. Our findings do not support the government's decision to reduce the tax incentives in corporate firms to just 100% of R&D from 2020-21. On the contrary, the evidence supports increasing R&D tax credit incentives in India. The tax incentives and its reforms were successful in promoting firm innovation, but the level and growth rate of private R&D spending in India is still not internationally comparable. If India aims to make business R&D a major driver of the national innovation system, policymakers must continue encouraging additional R&D with "super deductions."

India's pharmaceutical industry, which has established abilities in process patenting, appears to be adjusting to the new developments in patent policy. For pharmaceutical firms that were registered with the DSIR, we do find evidence that the reforms increased the number of USPTO patent applications, but the estimates are not precise. Considering that few DSIR-registered firms have patents registered with the USPTO, India's policymakers may consider designing an award mechanism for businesses seeking international patent protection. Additional benefits could be conferred when patent applications are from R&D undertaken as a result of R&D tax incentives. The “Patent box” scheme introduced in 2016-17, encourages innovative output, but applies only for firms that receive income in the form of royalties and technology licensing. In the pharmaceutical sector, the road from product discovery to marketing is typically long (due to clinical trials, drug approvals, etc.) and incentives that also focus on patent applications are worthwhile to consider.

It is important to underscore that the effectiveness of government programs aimed at stimulating R&D activity in the private sector depends on the sensitivity of economic agents to build conditions. This sensitivity varies greatly across firms, depending on their size, export orientation and market characteristics, etc. We find that larger firms benefit more from the R&D tax credit scheme compared to the relatively small and medium firms. Policy initiatives aimed at promoting R&D activity of small firms are thus needed to ensure that firms continually innovate for the market. In this respect, a more flexible approach to R&D incentives might be more effective, and policymakers might consider abandoning the current ‘one size fits all’ approach to firm R&D investment and re-designing the R&D tax credit scheme to better suit individual firm needs.

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CONFERENCE PRESENTATIONS

1. Presented paper titled “R&D tax credits and innovation activity: Firm-level evidence from India” in Herrenhausen Conference- The New Role of the State for Diffusion and Emergence of Innovation at Herrenhausen Palace, Hannover, Germany organized by The Volkswagen Foundation during February 20 – 23, 2019.
2. Presented paper titled “Analysis of R&D tax incentives and innovation by Indian firms using matching approach” in Asia-Pacific Innovation Conference, 2018 (APIC-2018) organized by Department of Economics, Delhi School of Economics, India during December 13-14, 2018.
3. Presented paper titled “R&D Tax Incentives and Innovation in Indian High and Medium Technology Industries”, The 5th Biennial Indian Academy of Management Conference, 2017 (INDAM 2017) organized by Indian Academy of Management Conference at IIM Indore, India on December 18, 2017.

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Acronyms

ATT	Average Treatment effect on the Treated
BSE	Bombay Stock Exchange
BRICS	Brazil, Russia, India, China, and South Africa
CMIE	Centre for Monitoring Indian Economy
CGPDTM	Controller General of Design, Trademark
DID	Difference-in-Difference
DSIR	Department of Scientific and Industrial Research
DST	Department of Science and Technology
GDP	Gross Domestic Product
GMM	Generalized Method of Moment
GOI	Government of India
GERD	Gross expenditure on R&D
IPO	Indian Patent Office
IV	Instrument Variable
IPR	Intellectual Property Rights
IMF	International Monetary Fund
MRA	Meta-Regression Analysis
MSME	Micro, Small and Medium Enterprises
NNM	Nearest Neighbor Matching
NIC	National Industrial Classification
NIS	National Innovation System
NSTMIS	National Science & Technology Management Information System
PSM	Propensity Score Matching
STP	Science and Technology Policy
STIP	Science, Technology, and Innovation Policy
STPS	Second Technology Policy Statement
SBIR	Small Business Innovation Research

SME	Small and Medium Enterprise
SE	Standard Error
TSTAT	T-statics
UK	United Kingdom
USA	United States of America
WIPO	World Intellectual Property Organization
OECD	Organization for Economic Co-operation and Development
USPTO	United States Patent and Trademark Office

CHAPTER 1

INTRODUCTION

1.1 The Context

Innovation policy measures to stimulate innovation and economic growth have always been an important part of the science, technology, and innovation policies. Governments and policymakers around the world have devised various fiscal incentives and innovation programs such as research grants, loans, venture capital, tax incentives and the like, to foster an economic climate conducive to innovation and address market failure. The International Monetary Fund (IMF) emphasized that the advanced economies "governments should do more to boost private R&D," and calling the use of fiscal R&D incentives "imperative."[1]

The rationale for R&D incentive schemes is grounded in the theory of market failure (Arrow, 1972; Bozeman & Dietz, 2001), which occurs in R&D investments due to the gap between social and private returns. The private R&D fall short of the socially optimal level due to the limited appropriability of invention, uncertainty and risk allied with the R&D projects (Szücs, 2020). The classical argument to support private R&D originates from the characteristics of the public good that facilitates knowledge creation. The incentive system stimulates private R&D by reducing the risk and uncertainty involved in financing R&D projects that allow higher expected returns to the firms.

Financing of R&D is still a major challenge in the developing countries due to the capital market imperfection and the high uncertainty and risk associated with R&D projects. Thus, fiscal incentive schemes to promote innovation are likely to play an important role in financing R&D,

[1]https://www.imf.org/en/Publications/FM/Issues/2016/12/31/Acting-Now-Acting-Together-43655, p.44.

especially in the case of emerging economies. For example, in OECD countries, nearly 70% of the R&D cost is covered by various government support schemes during 2000 to 2013 (Appelt et al. 2016). The success of such schemes in the developed countries has motivated developing countries to follow suit (Hall and Van Reenen, 2000). For instance, India has adopted a mix of industrial and innovation policies since the 1990s aimed at building its National Innovation System (NIS).

India, an emerging economy, only spends 0.7-0.8% of GDP on R&D expenditure, while developed economies like the United States and another emerging economy, China, spend 2.8% and 1.8% of GDP respectively (World Development Indicators, 2017). Furthermore, in the US and China, a large share of R&D spening comes from business enterprises - upwards of 60-70% of total R&D expenditure in each. However, in India in 2016-17, as per the Department of Science and Technology (DST), India, only 42% of total R&D spend is by the private sector[2]. The number though not comparable with international values, has increased considerably from 19% in 2001-02.

Since the economic reforms in the 1990s, the Government of India has been focusing on developing global competitiveness and technological self-reliance through innovation practices. A large number of multinational companies have set-up their R&D units in India. The dynamism in the private sector with a focus on R&D can possibly be attributed to increased competition following the liberalized regime and policy initiatives to stimulate innovation. The Science and Technology Policy (STP) 2003 combines the science and technology policy for the development of the innovation eco-system in India. Later, the Science, Technology, and Innovation Policy (STIP) 2013 calls for “science,

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[2] Research and Development Statistics 2017-18, Department of Science and Technology (DST), December 2017, http://www.dst.gov.in/research-and-development-statistics-2017-18-december-2017

technology and innovation for the people" and emphasize the need for creating a national innovation system. The *National Innovation Act, 2008 and Decade of innovation 2010-20*, also set goals for a competitive knowledge-based economy and technological self-reliance through innovation in India. Such policy initiatives include not only tax credit schemes but also the changes in the intellectual property rights (IPRs) policies.

In recent times, India has emerged as a global hub for low-cost R&D and high-value innovative products and services (Bowonder et al. 2006). Empirical evidence shows that the positive impact of liberalization on R&D activity, albeit unequal influence conditioned by productivity differences and business conditions (Bas and Paunov, 2018). Dhanora et al. (2020) also explain that competition among Indian firms is not so intense to drive firm-level innovation activity due to higher technological gap among these firms. With respect to IPRs, studies show a positive impact of change in R&D and patenting activity of the industries, though industry and policy specific variations remain (Dhanora et al. 2018; Sharma et al. 2018). The lack of studies focusing on the impact of fiscal incentives on innovation in the context of an emerging economy like India is the primary motivation for the present study. The focus of the current doctoral dissertation is to evaluate the impact of India's R&D tax credit scheme and its reforms on innovation activity of the country's private firms.

The introduction chapter is organized as follows: Section 1.2 discusses the scope of the study. Section 1.3 provides an overview of R&D tax incentive scheme in India. Section 1.4 highlights the research gaps and objectives of the thesis. Section 1.5 outlines the measures of innovation. Section 1.6 explains the data sources and methodologies. Section 1.7 presents the organization of the thesis.

1.2. Scope of the study

There is expanse literature examining the effectiveness of R&D tax incentives on innovation activity, with much of it focused on developed countries and reviewed by David et al. (2000) and Hall and Van Reenen (2000). More recently, attention has shifted to studying the effectiveness of fiscal incentives for R&D on innovation in emerging economies. Wang et al. (2017) point out that this shift is important because of the growing popularity of government R&D programs in emerging economies, considering that the innovation ecosystem of such countries is different. The effectiveness of R&D incentives in emerging economies is expected to differ from that in the developed countries due to the relatively ample financial constraints and imperfect financial markets, substantial challenges to effective administration, ineffective systems of intellectual property rights, etc. Hewitt-Dundas (2006) notes that the success of government initiatives to encourage firm innovation depends on the resource and capability constraints to innovation that extends beyond financing R&D. The imperfections of the capital market lead to under-investment in R&D due to the financial constraints to fund R&D. The information asymmetry and the high risk associated with R&D investment also creates difficulties in accessing external finance to fund R&D (Hall & Bagchi-Sen, 2002; Czarnitzki & Licht, 2006). For example, Sasidharan et al. (2015) examine the effect of financing constraints on R&D expenditure of manufacturing firms in India during 1991-2011 and find that the cash flow sensitivity is higher in the case of small and young firms.

Godin and Gingras (2000) and Hewitt-Dundas (2006) highlight that government schemes have a significant role in stimulating the innovation processes of firms. However, the success of R&D incentive schemes relies on its ability to address market failure associated with the investment in innovation activities by the private sector. The aggregate empirical estimates on the effect of R&D incentives suggest a positive increase in private R&D of the firm (Bloom et al. 2002); however, the recent micro-level studies are rather mixed. For example, Dechezleprêtre et al. (2016) investigate the R&D tax scheme in the UK and find a positive effect on the firm's R&D and patenting activities. Cappelen et al. (2012) analyse the effects of Norwegian tax incentive scheme on the likelihood of innovating and patenting and find that projects receiving tax credits result in the development of new production processes and to some extent the development of new products for the firms. However, the scheme does not contribute to innovations in the form of new products for the market or patenting. Hall and Van Reenen (2000) explains that this variance in results comes from the different treatment of R&D by the tax system across countries and over time, in addition to huge heterogeneity in the effects between different firms. Moreover, the results of macro-econometric studies differ in the extent to which they attempt to address the potential endogeneity that arises from firm-selection bias into the R&D programs (Klette et al. 2000). The traditional R&D policy evaluation approaches have largely ignored the endogeneity problems as well as the issue of selection bias in the estimation process. David et al. (2000) found that studies before 2000 hardly consider the issue of selection bias while evaluating the impact of incentive policies.

Even between developed countries, such schemes have yielded a wide range of results. Hall and Van Reenen (2000) explain that this variance in results comes from the different treatment of R&D by the tax system across countries and over time, in addition to huge heterogeneity in the effects between firms. Moreover, the micro-level empirical studies differ in the extent to which they attempt to address the potential endogeneity that arises from the self-selection into the programs (Klette et al. 2000). Studies published before 2000, for example, have largely ignored this issue (David et al. 2000). The empirical evidence on the effects of the R&D tax credit scheme is also much needed because India's private R&D sector R&D spending has increased in recent years (from 19% since 2001-

02). However, the forces driving this change are still largely unexplored. Moreover, the popularity of R&D tax incentives in India raises important policy questions on the effectiveness of firm-level innovation, the heterogeneity of effects across different types of firms and the interaction of different policy reforms.

1.3. R&D tax credit scheme in India - An overview

India offers a volume-based incentive system, where the tax credit is availed based on R&D investment. The Department of Scientific & Industrial Research (DSIR), which is under the Ministry of Science & Technology, provides recognition and registration to in-house R&D set up of companies engaged in R&D activities in India. The affiliation is provided to the firms which have 100% in-house R&D centres in India. As per the scheme, the R&D departments of manufacturing companies of the affiliated firms provided the status of recognized in-house R&D centres, which in turn provides firms with indirect and direct tax benefits for their R&D activities. The benefits include income tax benefit for capital expenses, which includes computers and equipment for prototyping, testing, etc., and operating expenses, which includes salaries of technical and scientific staff including their official travel, raw materials consumed, maintenance of equipment, utility bills and other relevant expenses incurred on running the R&D under section 35 2(AB) of the Income Tax Act of India, 1961. The recognition is a necessary condition for the firms to receive the tax credit, which is given for three years and can be further extended on a continuous basis once every three years. As per the scheme, every recognised firm needs to submit the progress report of R&D activities every year. The criterion to get affiliation with DSIR is open with all the firms; however, only some firms self-select to apply and register. During 2001-10, the government offered a weighted tax deduction of 150% to only eight industries: namely drugs and pharmaceuticals, electronic equipment, computers, telecommunications equipment, chemicals, manufacture of aircraft and helicopters, automobiles, and auto parts. This was later extended to all manufacturing industries in the fiscal year 2009-10. In the fiscal year 2010-11, the country's R&D tax deduction was increased to 200% and eligibility was extended to firms in all sectors, except for a negative list[3], placing India among the select few countries providing a "super deduction"[4] for investment in R&D, alongside an already generous tax regime for such investments.

Along with this, a "Patent box" scheme was introduced, wherein income received in the form of royalties and technology license is taxed at a lower rate (10%) from the fiscal year 2016-17. From the fiscal year 2020-21, the R&D tax deductions will be further reduced to 100%. Given this imminent policy change, a study on the impact to date of India's super deduction scheme is warranted and going forward will serve as a useful report for policymakers. This thesis examines the effectiveness of R&D tax incentives in India and its 2010-11 reform, that increased the weighted tax deduction from 150% to 200%, and 2009-10 reform, that extended the provision of the tax credit scheme to all manufacturing industries, on innovation activity of the firms.

1.4. Research gap and objectives

The previous studies and findings on this subject have investigated mainly of the policy implementation in the developed countries. In the context of an emerging nation like India, there is a lack of empirical evidence on the effectiveness of R&D tax incentives and innovation. Earlier Mani (2010) estimates the elasticity of R&D expenditure with respect to the tax

[3] Firms involved solely in manufacturing or production of items under Schedule 11 of the Income tax act 1961 are not eligible for claiming the weighted tax credit. https://www.incometaxindia.gov.in/Acts/Income-tax%20Act,%201961/2008/102120000000022829.htm

[4] A weighted tax credit rate more than 100 per cent is known as "super deductions".

foregone due to the R&D tax incentive in India. The result shows that the R&D tax incentive has a significant effect only for the chemical industry during the period 2000-2006. However, it used data for a short period (2000-2006) and did not address the selection into the R&D program.

There is scant empirical evidence on the influence of R&D tax credit scheme initiated by the Government of India (GoI) in 1999. This thesis evaluates the impact of India's R&D tax credit scheme and its two major reforms on the innovation activity of the country's private firms. We examine the tax credit scheme and its 2010-11 reform that increased the weighted tax deduction to 150% and the 2009-10 reform that extended the provision of the tax credit scheme to all manufacturing industries, on innovation activity of the firms. Secondly, we also ask if the increase in R&D by the private sector in recent times is contributing to the new to world innovation proxied by patent data. Most of the previous empirical studies have considered R&D investment as an outcome measure while evaluating the effect of the R&D tax incentive policy (Kasahara et al. 2014; Liu et al. 2016). However, only a few studies that examine the interaction between government innovation support schemes and the firm's innovation output in terms of patenting and new product development (Cappelen et al. 2012; Lee & Wong, 2009). The major empirical challenge is to reliably measure a causal effect of the R&D tax credit scheme and firm innovation activity considering the potential endogeneity and the self-selection into the tax credit scheme. The policy reforms provide us a unique opportunity to study the changes in firm innovation activity at two different sets of tax incentive policy reforms (i.e., increase in the existing provision of weighted tax deduction and the extension of tax credit provision to all industries). Considering the policy change is on the horizon, a timely study on the impact assessment of such a scheme is warranted to contribute the evidence-based policymaking.

Based on the above discussion, the objectives of the study are as follows:

1. To investigate the impact of R&D tax credit scheme and its reform (2010-11), that increased the weighted tax deduction from 150 % to 200%, on the innovation activity of the firms.

2. To investigate the impact of R&D tax credit reform (2009-10), that extended the provision of the tax credit scheme to all manufacturing industries, on innovation activity of the firms.

1.5. Measures of innovation

Most of the previous empirical studies on R&D incentives have considered R&D investment as an outcome and estimated the input additionality of crowding-in or crowding-out effect. Crowding-in effect estimates how much private R&D has been increased due to the fiscal incentives and crowding-out indicates the substitution of private R&D investment with public R&D funding (Kasahara et al. 2014; Liu et al. 2016). There are few studies that examine the interaction between government innovation support schemes and the firm's innovation output in terms of patenting and new product development (Lee & Wong, 2009; Cappelen et al. 2012).

We measure the firm innovation activity using four different outcome variables; the level of R&D expenditure; the R&D intensity, measured as the ratio of R&D expenditure to sales; the number of patent applications filed at the Indian Patent Office (IPO); and the number of patent applications filed at the United States Patent and Trademark Office (USPTO).

The level of R&D expenditures is a proxy for firm innovation input. The R&D intensity is a proxy for the intensity of firm innovation input activities. The number of patent applications filed at the IPO and USPTO is proxies for firm innovation output. The territorial nature of the patent regime necessitates the use of patent data from the domestic patent office, while the USPTO patent applications account for the most valuable inventions.

1.6. Data and empirical strategy

1.6.1. Data

First, we conduct a meta-regression analysis (MRA) that uses a dataset of micro econometric empirical evidence on the effects of government R&D policies on innovation and investigates the factors that may explain the differences in the estimated effects. The meta-regression analysis includes a total of 497 estimates from 42 articles published between 1998 and 2019. We have used articles published in scientific journals, and working papers from well-renowned universities, and institutions such as The World Bank, The International Monetary Fund (IMF) and the OECD.

To evaluate the impact of R&D tax credit scheme and its reforms on innovation activity of the firms, we use firm-level data of Indian manufacturing firms during the period 2001 to 2016. The firm-level data for the study is collected from the Centre for Monitoring Indian Economy (CMIE) prowess database. The CMIE database provides annual report data of firms that are listed in the Bombay Stock Exchange (BSE) and private limited companies. We acknowledge that most beneficiaries of the R&D tax credit scheme in India are small firms with low-scale R&D (Mani, 2010). Considering the fact that our sample includes only the listed and large private limited companies in India, our sample skewed towards larger firms. We address the issue of nominal and unreported R&D by including R&D reported by the recognized firms in the DSIR annual reports.

We identify the DSIR recognized firms from the annual reports of the Department of Scientific and Industrial Research (DSIR). We then, classify firms into industries based on the National Industrial Classification (NIC) 2008 via NIC 2004. We define industry by the 4-digit NIC-2008 classification. We have also collected data on patent applications to Indian Patent Office (IPO) over 2001-2016, which we collected from the website of the Controller General of Design, Trademark (CGPDTM) and verified using IPO annual reports. We have also collected data on USPTO patent applications for Indian assignees over 2001-2016 from the USPTO Patent Assignment database.

1.6.2. Methodology

The objective of this dissertation is to evaluate the impact of India's R&D tax credit scheme and its reforms on innovation activity of private firms. Literature suggests that endogeneity and selection-bias are paramount in analyzing the policy impact of tax credit schemes and appropriate methodology needs to be employed. The empirical challenge is to reliably measure a causal effect of the R&D tax credit scheme and its reforms on firm innovation activity while accounting for potential endogeneity due to self-selection into the tax incentive scheme. The company's decision to seek recognition from the DSIR might have been endogenous to its innovation performance or driven by the tax incentive scheme itself. A more financially constrained company, for example, might have had a smaller R&D budget and been more likely to seek the R&D tax credit.

For the empirical purpose, we propose to use two methodological approaches to account endogeneity and self-selection; Propensity Score Matching (PSM) and Difference-in-difference (DID) approach. In propensity score matching, we create a matched control sample and examines the counterfactual situation and estimates the average treatment effect to measure the impact of the R&D tax credit scheme on firm innovation activity. The average treatment effect overcomes the selection bias by estimating counterfactual, i.e., how much the tax credit recipient firms would have invested in R&D and filed patents if they would not have participated in the R&D tax credit scheme. In DID framework, we take advantage of the panel data for evaluating the effect of R&D tax credit reform on innovation activity. The DID framework estimates the time or cohort dimension, which accounts for the unobservable firm characteristics. The DID framework assumes that the outcome tax credit recipient firms and non-recipient firms would follow the same time trends in the absence of the treatment.

1.7. Organization of the thesis

This thesis is presented in seven chapters. Chapter 2 provides an overview of fiscal incentives for innovation and the innovation ecosystem in India. It also discusses the R&D tax credit mechanism in India and the policy changes over the years.

Chapter 3 presents an extensive review of the existing theoretical and empirical literature on fiscal incentives for innovation. It also discusses the measurement issues and methodologies used to evaluate fiscal incentives. The review is further included a meta-regression analysis, which examines the existing empirical evidence on the effects of government R&D policies on innovation and investigates the factors that may explain the differences in the estimated effects.

Chapter 4 discuss the methodology, identification strategy and data used to examine the impact of R&D tax credit on innovation in India. It discusses the evaluation issues in detail and explains how our identification strategy accounts for the issue of potential section bias and endogeneity is addressed through our empirical approach. This section also discusses the data sources and outlines the variables used in the study.

Chapter 5 evaluates the impact of R&D tax credit scheme and its 2010-11 reform, that increased the weighted tax deduction to 200%, on innovation activity of the firms during 2001-2016. We use Propensity score matching and Difference-in-Difference framework and evaluates the change in innovation activity after the reform in DSIR-registered firms relative to non-DSIR-registered firms. In PSM framework, we examine the counterfactual situation, where how the innovation activity of the DSIR-registered firms changed if they would not be registered with DSIR. In DID framework, we study the timing of DSIR registration and examine how the changes in firm innovation activity following registration were impacted by the 2010-11 reform.

Chapter 6 examines the impact of R&D tax credit scheme and its 2009-10 reform, that extended the provision of the tax credit scheme to all manufacturing industries, on innovation activity of the firms in India. We use Propensity score matching and Difference-in-Difference framework and evaluates the change in innovation activity following the 2009-2010 reform among firms in the newly registered with DSIR. In the PSM framework, we examine the counterfactual situation, where how the innovation activity of the DSIR-registered firms changed if they would not be registered with DSIR. In DID framework, we study the timing of DSIR registration and examine how the changes in firm innovation activity following DSIR registration were impacted by the 2009-10 reform.

Chapter 7 summarizes the key findings of the thesis, followed by a discussion on the policy implications and contributions of the study. Then, the chapter enlists the limitations and future directions for research. Finally, the chapter gives a concluding remark.

CHAPTER 2

FISCAL INCENTIVES FOR R&D AND INNOVATION ECOSYSTEM IN INDIA

2.1. Introduction

Research and development play a vital role in promoting innovation, enabling competitiveness, and productivity. The R&D activity of a country is influenced by many factors such as the economic and industrial ecosystem, science and technology policy infrastructure, the extent of internationalization, channels between public and private R&D partnership, and the reach of intellectual property rights. The government contributes towards the national innovation system through funding public laboratories and universities. Governments also use a wide range of mechanism in the form of public private partnership, industry-institution linkages, and other fiscal incentives to promote business R&D in the country.

This chapter presents a detailed overview of the fiscal incentives and policy instrument initiated by various government to stimulate innovation in their respective countries. We further explore the R&D tax credit policies and various other reforms started by Indian government to promote innovative activities in the country. The rest of the sections in this chapter are presented as follows. Sections 2.2 and 2.3 discusses the fiscal incentives for innovation, its design and policy mix. Section 2.4 outlines India’s innovation polices over the past decades. Sections 2.5 and 2.6 discusses the R&D tax incentive mechanism in India and its reforms. Section 2.7 presents the innovation ecosystem in India. And section 2.8 concludes the chapter.

2.2. Fiscal incentives for innovation

Fiscal incentive promotes both R&D and patenting activities in the country which eventually leads to knowledge diffusion in the society. Governments around the world use various policy instruments to incentivize private R&D. The major objective of these incentives is to encourage demand-based business R&D and to reduce the financial snags of R&D. The rationale for the R&D support is based on the linear model of innovation, which increases innovation that leads to the development of new products, processes, or services.

A variety of fiscal incentives are in practice to encourage the private firms to undertake R&D projects and conducts innovation activities (David et al. 2000). The governments choose various tools and instruments to leverage private R&D investment. Such incentives are provided through direct supports like grants, subsidies, and indirect supports, such as tax incentives. Direct R&D grants or subsidies are provided based on the specific type of firm or project with high potential social returns, while tax incentives aim to encourage the investment in R&D by reducing its marginal cost. However, the popular approach is to let the firms choose their R&D activities by designing certain tax-based incentives for the eligible firms. Such a policy also reduces the costs and administrative burden associated with the incentive scheme but may be accounted for the externalities associated with the private returns of R&D that can lead to less social returns (Dechezleprêtre et al. 2016).

Over the past two decades, there has been a shift from the direct support of R&D projects to generic innovation-friendly instruments such as tax credits and patent-based incentives. Recently, several countries have introduced outcome-based incentives such as ‘patent boxes’, that allow tax rebates on the income generated by the firm’s intellectual property such as patents. Such incentives are often justified as the incentive or reward for innovation outcome. Hall and Van Reenen (2001) and Lev (2018) pointed out that the shift is important as the share of company assets that is intangible has grown in recent years, especially in the case of developed countries.

2.3. R&D tax incentives

Tax incentives are considered as the most generous incentive tool as part of the country's general tax policies, with a broader aim of promoting R&D and innovation. These tax provisions are directly linked with the R&D inputs (R&D expenditure) or output (income from patents, licensing etc.). The tax measures to support R&D is provided through three major forms; (i) tax deferrals, where the relief allowed on delay in payment of taxes, (ii) tax allowances, where the additional amount over business expenses is deducted from gross taxable income, (iii) tax credits, where the incentive is given from the tax liability, and (iv) reduced taxes on intellectual property (IP) income, such as 'patent box'. Tax allowances, tax deferrals and tax credit aim at cost reduction for innovative input and do not cover the non-R&D innovation, while patent boxes target the innovation output generated from R&D, and do not cover non-patentable innovation.

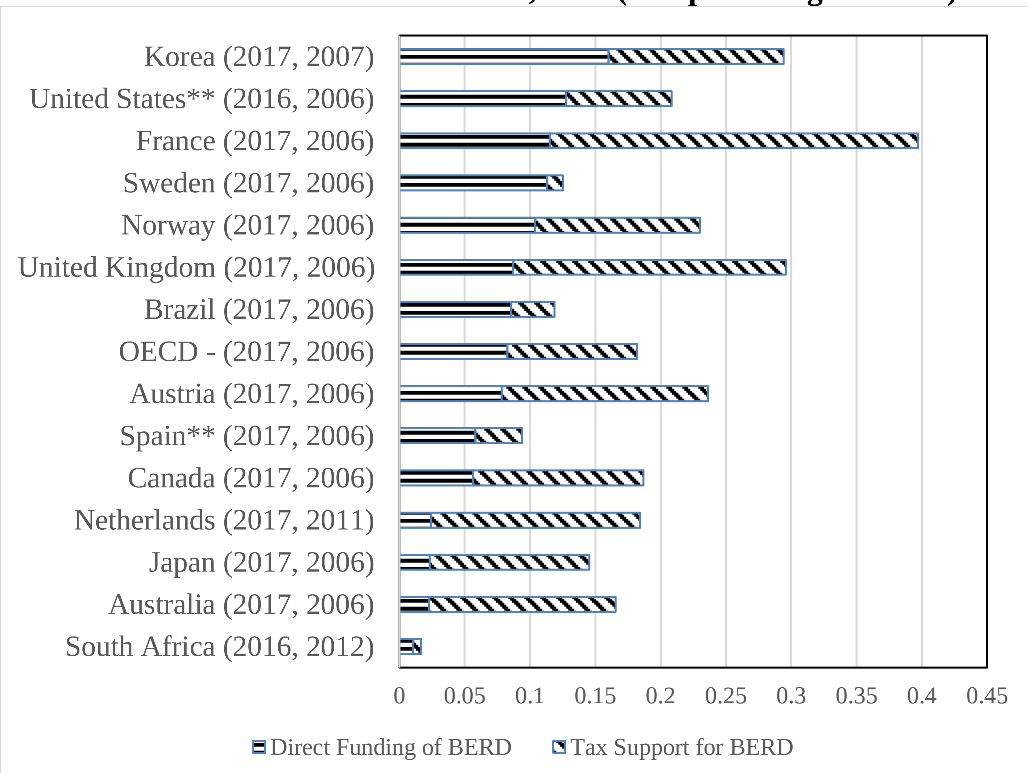
The R&D tax credit is a commonly used tax incentive mechanism to promote innovation around the world. Developed countries such as the US and Canada started using the tax credit in the early 1980s. In 2017, many developed and developing countries, including 30 out of 35 OECD countries use tax incentives to support firm-level innovation.

2.3.1. The policy mix and design of R&D incentives

Countries differ in terms of the extent to which they rely on the direct support and tax-based support for R&D. The policy mix and design of fiscal incentives vary across the country's innovation capabilities and focus on innovation. Such diversities in the policy mix and design makes the cross-country comparison even difficult (OECD, 2014). Figure 2.1

shows the policy mix of direct government funding and government tax support for business R&D in selected countries during 2017. Most countries use the combination of direct support and tax-based support as an ideal design for supporting innovation. However, tax-based incentives are less effective for countries with a low rate of corporate income tax (Hall & Van Reenen, 2000).

Figure 2.1: Direct government funding and government tax support for business R&D in selected countries, 2017 (as a percentage of GDP)



Source: OECD R&D Tax Incentive Database, http://oe.cd/rdtax, June 2020. ** Data on subnational tax support not available

The design of the tax incentives varies with respect to the definition of eligible R&D. Most countries have their own definition of qualified R&D for tax incentive eligibility. The qualified R&D expenditure can be the expenditure on salaries related to R&D, current R&D expenditure, or the combination of current and capital R&D expenditure. Other than that, some countries also offer the provision to carry-forward and cash refund for the unused portion of the credit in the preceding year.

Tax incentives are provided to all qualified R&D expenditure (volume-based credits) or only to the additions made in the R&D expenditure above the certain base amount (incremental credits). However, volume-based tax incentives are the most common tax incentive scheme in practice. Some countries offer the tax incentives to certain target groups such as start-ups, SMEs, young firms etc. Tax incentives are also provided to certain technology solutions (green technology in Belgium) and patents, licenses, know-how (e.g., Spain and Poland). The concept of patent-box is another type of incentive given by the government on successful patent filing. The 'patent boxes' are the most popular income-based tax incentive, where the income generated in the form of royalties and technology license is taxed at a lower rate (e.g., Belgium, Ireland). Table 2.1 presents the design of the R&D tax incentive scheme around the world.

Table 2.1: Main features of the R&D tax incentives in selected OECD and other countries

Design of the R&D tax incentive scheme	Countries
Expenditure-based R&D tax incentives	
• Volume-based R&D tax credit	Australia, Austria, Belgium, Canada, Chile, Denmark, France, Hungary, Iceland, Ireland, New Zealand, Norway, United Kingdom
• Incremental R&D tax credit	United States (credit on fixed, indexed base and incremental for simplified credit)
• Hybrid system of volume and incremental credits	Italy, Japan, Korea, Portugal, Spain
• R&D tax deduction beyond 100% recovery	Belgium, Brazil, People's Republic of China, Czech Republic, Greece, Hungary, Netherlands, Poland, Russian Federation, Slovenia, Slovak Republic, South Africa, Turkey, United Kingdom
Tax relief on wage taxes or related contributions	Belgium, France, Netherlands, Hungary, Russian Federation, Spain, Sweden, Turkey
More generous R&D tax incentives for SMEs, young firms or start-ups	Australia, Belgium, Canada, France, Italy, Japan, Korea, Netherlands, Norway, Portugal, Spain, United Kingdom
Ceilings on amounts that can be claimed for specific incentives	Australia, Canada, Chile, Denmark, France, Hungary, Iceland, Italy, Japan, Korea, New Zealand, Norway, Portugal, Slovak Republic, Spain, Sweden, Turkey, United Kingdom, United States
Income-based R&D tax incentives	Belgium, People's Republic of China, Colombia, France, Hungary, Ireland, Israel, Italy, Luxembourg, Netherlands, Portugal, Spain, Switzerland (Canton of Nidwalden), Turkey, United Kingdom
No R&D tax incentives	Estonia, Finland, Germany, Mexico

Source: OECD Directorate for Science, Technology, and Innovation, 2019

2.4. India's innovation policies

Innovation policies in India have evolved with the periodical Science, Technology, and Innovation Policy statements. Such policies, further, became the milestone of a transforming national innovation system. The first STI policy, 1958 aimed at the welfare of the state through investments in Science and technology, thus, initiating the foundational core of the *scientific enterprise and scientific temper* in India. The Second Technology Policy Statement (STPS), 1983 emphasized the need for technological self-reliance through the development of indigenous technology. The economic liberalization policies opened the market for foreign companies leading to the availability of newer products, technologies, and competition in domestic market. The Science and Technology Policy (STP) 2003 focused on the need to consider Science and technology together for a sound innovation infrastructure and set a target of 2% GDP investments in R&D. It also called for an incentive mechanism to promote R&D and innovation. The recent policy statement of Science, Technology, and Innovation Policy (STIP), 2013 has paved the way for a strong national innovation system. It envisions a robust private R&D investment for enabling India as a science and technology-led country. In addition to the STI policies, there have been several other policy initiatives enunciated over the past decades, especially in the business sector such as R&D tax incentives, promoting innovation in individuals, start-ups and MSMEs etc.

The business sector plays a major role in research and development and contributes nearly 41.7 % of R&D expenditure in 2017-18 compared to 23.2 % in 2000-01. Business sector participation in GERD has been just over 40% during the last five years. The Gross expenditure on R&D (GERD) in India has been consistently increasing over the years and has nearly tripled from Rs. 39,437.77 crore in 2007- 08 to Rs. 1,13,825.03 crore in 2017-18. This growth is in line with the government's science, technology, and innovation policies, where the private sector become an integral part of India’s national innovation system accounting for a significant portion of the gross domestic expenditure on R&D.

In India, incentives for financing the innovation activities are provided through three major instruments that are research grants, tax incentives and venture capital. Research grants and tax incentives are provided through various government agencies, while the venture capital functions entirely in the private sector. These innovations police are liked with the linear view of innovation where, research grants and venture capital are provided at the early stages of the firm evolution, while tax incentives are provided at the growth stage.

India offers a very generous tax incentive scheme to incentivize R&D investment, especially at the firm level, however, limited to the corporates engaged in the manufacturing and production industries. Mani (2014) noted that the R&D still concentrated in a few industrial sectors in India, where the tax incentive regime has failed to spread innovation across firms and industries.

2.5. R&D tax incentive mechanism in India

The Technology Policy Statement of Government of India on January 1983 emphasized the need for promoting in-house R&D units of Industries in India and had stated quote page number from the report that “Appropriate incentives will be given to the setting up of R&D units in the industry and for industry including those on a co-operative basis. Enterprises will be encouraged to set up R&D units of appropriate size to permit the accomplishment of major technological tasks". As part of the focus on promoting in-house R&D expenditure, several policy measures have introduced over the past few decades. In addition, various fiscal incentive schemes have been introduced to encourage the commitment of resources on in-house R&D and to establish in-house R&D units.

The Department of Scientific & Industrial Research (DSIR), under the Ministry of Science & Technology, aims at promotion of industrial research for indigenous technology promotion, development, utilization, and transfer. It contributes to the National Innovation System of the country by promoting private R&D, development of state-of-the-art globally competitive technological innovation, and facilitate scientific and industrial research in the country. Government of India has introduced a number of fiscal incentives for R&D from time to time, and many of these incentives are implemented through DSIR. The fiscal incentives provided through DSIR aims at promoting the in-house R&D expenditure and to encourage the utilization of locally available R&D options for industrial development.

In addition to the weighted tax deduction on in-house R&D expenditure under Section 35(2AB), manufacturing firms registered with the DSIR are eligible for the three other fiscal incentives: (i) ten-year tax holiday for commercial R&D companies (discontinued in 2007); (ii) excise duty waiver for three years on goods produced based on indigenously developed technologies and duly patented in any two countries amongst India, USA, Japan and any one country of the EU; and (iii) accelerated depreciation allowance on plant and machinery set-up based on indigenous technology.

The tax holiday for commercial R&D provides a ten-year tax holiday from income tax exemption to approved companies whose main objective is to undertake scientific and industrial research. The scheme introduced in 2000, however, was discontinued in 2007. The provision of excise duty waiver is provided for a period of three years on goods produced based on indigenously developed technologies and duly patented in any two countries amongst India, USA, Japan and any one country of the European Union. The accelerated depreciation allowance is provided for the plant and machinery using indigenous know-how as per provisions.

The Finance Bill, 1997 introduced Section 35(2AB) of the Income-tax Act, 1961, which provided for weighted tax deductions to the in-house R&D units registered with the Department of Scientific and Industrial Research. The 1999-2000 Union Budget set out weighted tax deductions of 125% of the expenditure made on in-house R&D available to corporate houses up to 31 March 2000. The Finance Act, 2000 raised the weighted tax deductions to 150%.

The weighted tax deductions offer a volume-based R&D tax incentive scheme, where volume-based credits apply to all qualified R&D expenditures (both capital and revenue) incurred by the in-house R&D units. The scheme implemented through the DSIR that provides recognition and registration to in-house R&D set up of companies engaged in R&D activities in India. The affiliation is provided to the firms which have 100% in-house R&D centers in India. As per the scheme, the R&D departments of manufacturing companies of the affiliated firms provided the status of recognized in-house R&D centers, which in turn provides firms with indirect and direct tax benefits for their R&D activities. The benefits include income tax benefit for capital expenses, which includes computers and equipment for prototyping, testing, etc., and operating expenses, which includes salaries of technical and scientific staff including their official travel, raw materials consumed, maintenance of equipment, utility bills and other relevant expenses incurred on running the R&D unit under section 35 2(AB) of the Income Tax Act of India, 1961.

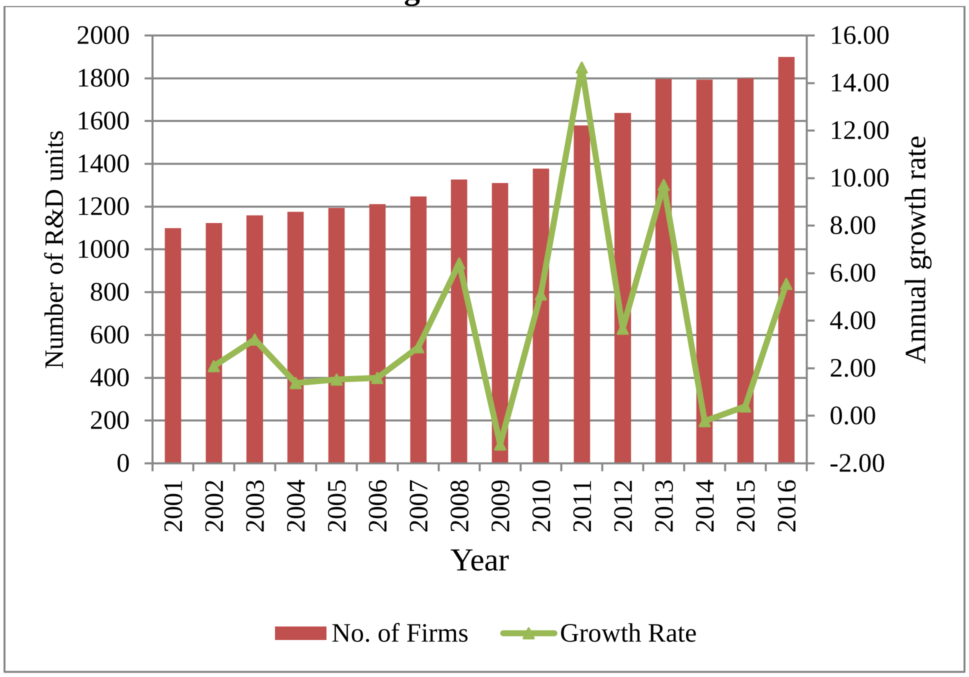
The recognition is a necessary condition for the firms to receive the tax credit, which is given for three years and can be further extended on a continuous basis once every three years. The in-house R&D units seeking recognition with DSIR are expected to engage in R&D activities such as the development of new technologies, design & engineering, process/product/design improvements, developing new methods of analysis & testing; research for increased efficiency in the use of resources, such as capital equipment, materials & energy; pollution control, effluent treatment & recycling of waste products or any other areas of research. The weighted tax deduction is available to the recognized firms, with 100% in-house R&D centers in India.

There are additional requirements for the R&D tax credit approval. For instance, firms must be in manufacturing or production industries; firms in technical services are eligible for the DSIR recognition, but not for the tax credit. Further, firms must not be involved solely in the manufacturing or production of items under Schedule 11 of the Income-tax Act. Last, firms must meet additional accounting disclosure requirements with respect to R&D expenditure, common to all registered and listed firms in India.

As per the scheme, every recognised firm needs to submit the progress report of R&D activities every year. The DSIR further requires that R&D activities are conducted in India but places no restrictions with respect to intellectual property rights arising from tax treated R&D to be used in India. The tax credit is available to both domestic and foreign corporates that satisfy the necessary conditions if the R&D is conducted within India. It also provides the provision to carry forward the unused benefits of tax credit if a firm is in a loss situation. The criterion to get affiliation with DSIR is open with all the firms; however, only some firms self-select to apply and register.

As discussed earlier, the recognition of in-house R&D units with DSIR is a prerequisite for claiming tax credit. An initial recognition of 3 years is given to firms that fulfil the criteria to affiliate with DSIR, and the recognition needs to be renewed after every three years. Figure 2.2 shows the number of in-house R&D units registered with the DSIR and its annual growth rate over the 2001–2016 period. It is apparent that the number of DSIR-registered units has almost doubled over this period, with as many as 1900 units registered in 2016. At the same time, the amount of tax forgone because of the R&D tax credit scheme has grown by 17% per annum. The utilization of the R&D tax credit scheme is rising over the years, at a noticeably faster rate around the 2010-11 reform.

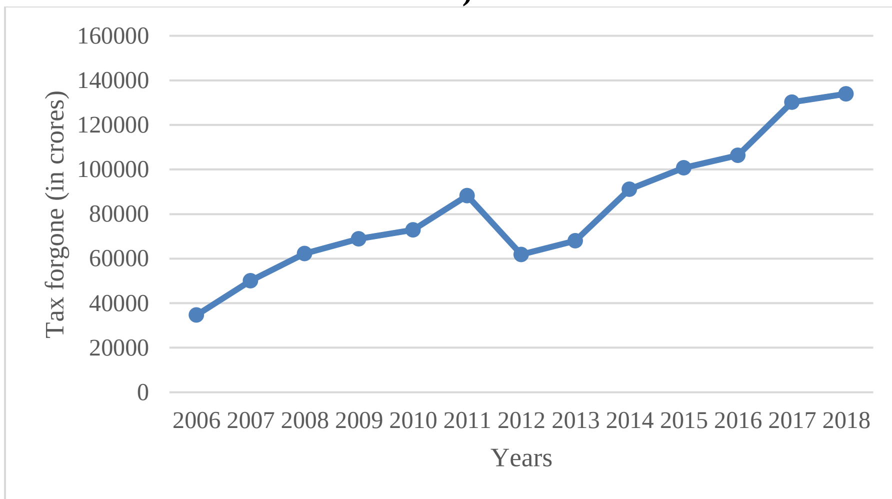
Figure 2.2: Number of DSIR recognized R&D units with annual growth rate



Source: DSIR annual reports

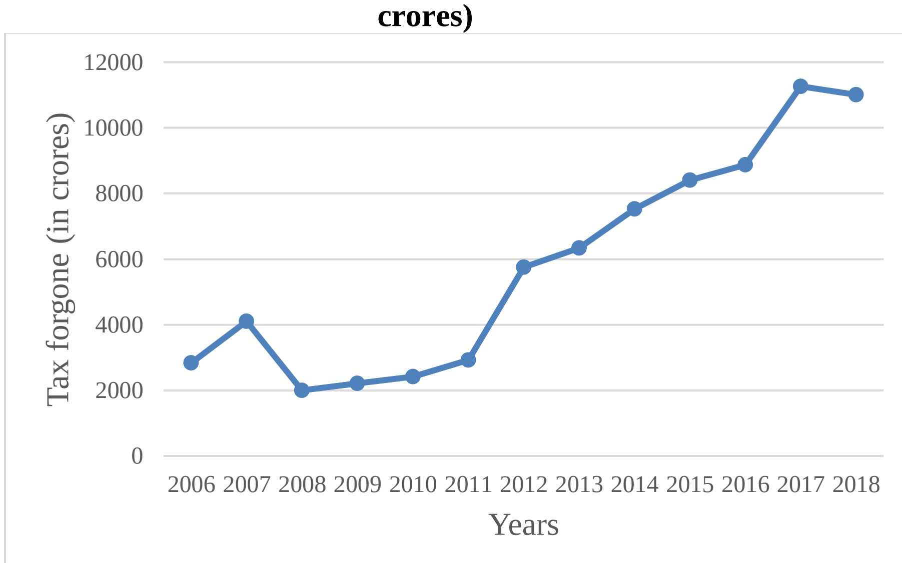
The total tax foregone because of the various incentives the government offers for R&D in India has been presented in Figures 2.3 and 2.4. During 2006 to 2018, the amount of tax forgone due to R&D tax incentives consists of only 6.9 % of total tax forgone due to all tax incentives during 2006-2018. The tax forgone as a result of the R&D tax incentives has an increasing trend except for the year 2007.

Figure 2.3: Revenue foregone due to all tax incentives in India (in crores)



Source: Government of India, Ministry of Finance (2019)

Figure 2.4: Revenue foregone due to R&D tax incentives in India (in crores)



Source: Government of India, Ministry of Finance (2019)

2.6. R&D tax credit reforms in India

The R&D tax incentive is a benchmarking scheme for promoting industrial R&D in India introduced in 1999 and had undergone several revisions over the last few years. The primary objective of the R&D tax credit scheme in India is to provide financial support to affiliated firms and prevent these firms from market failure resulting from under-investment in innovation activities. Over the years, the tax regime evolved with respect to the treatment of the R&D. The early tax treatment of R&D mainly targets eight high and medium technology industries.

During the period of 2001–2010, the government offered a weighted tax deduction of 150% for any capital and revenue expenditure incurred on in-house R&D by firms in the following eight industries: drugs and pharmaceuticals, electronic equipment, computers, telecommunications equipment, chemicals, manufacture of aircraft and helicopters, automobiles, and auto parts. In the fiscal year 2009-10, the scope of the existing provision of tax credit of 150% has been extended to all manufacturing industries except for a negative list. Policy changes announced in the Union Budget in February 2016 reverted the R&D tax deduction to 150% from the fiscal year 2017-18 onward. Along with this, a 'Patent box' scheme was introduced, wherein income received in the form of royalties and technology license is taxed at a lower rate (10%) from the fiscal year 2016-17. The introduction of the Patent box is expected to encourage innovation output through the increase of patenting, while the reduction in R&D tax incentive reduces the incentive for innovation input. From the fiscal year 2020-21, the R&D tax deduction will be further reduced to 100%.

The R&D tax credit scheme evolved its tax treatment of R&D over the period. Table 2.2 outlines the major R&D tax policy developments in India.

Table 2.2: R&D tax policy developments in India

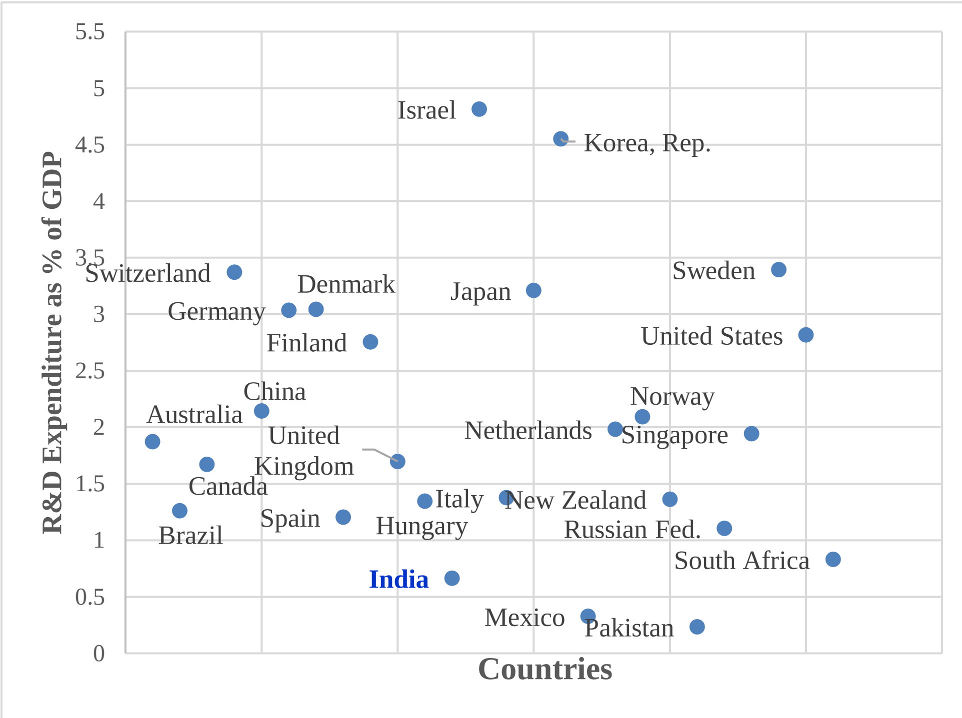
Union budget	Policy Implication
1999-00	R&D tax incentive of 150 % on in-house R&D available to corporates engaged in the production of drugs and pharmaceuticals, electronic equipment, computers, telecommunication equipment, chemicals, manufacture of aircraft and helicopters, automobile, and auto parts. Finance Act, 2000
2009-10	Tax incentive extended to all industries in India
2010-11	R&D tax incentive increased from 150% to 200%. Weighted deduction on payment to research associations, colleges, universities, and other scientific research institutions increased from 125% to 175%
2016-17	R&D tax incentive reduced to 150%
2020-21	R&D incentive expected to reduce to 100%

Source: Author's compilations

2.7. Innovation ecosystem in India

As an emerging economy, India spends on average 0.7-0.8 % of GDP on R&D expenditure in 2017-18, while developed economies like the United States spends and another emerging economy, China, spends 2.8 % and 1.8 % GDP, respectively. Other developing BRICS countries were Brazil 1.3 %, Russian Federation 1.1 %, and South Africa 0.8 %. Further, it is observed that most of the developed countries spent more than 2 % of their GDP on R&D. Figure 2.5 shows the R&D expenditure as % of GDP for selected countries as in 2017.

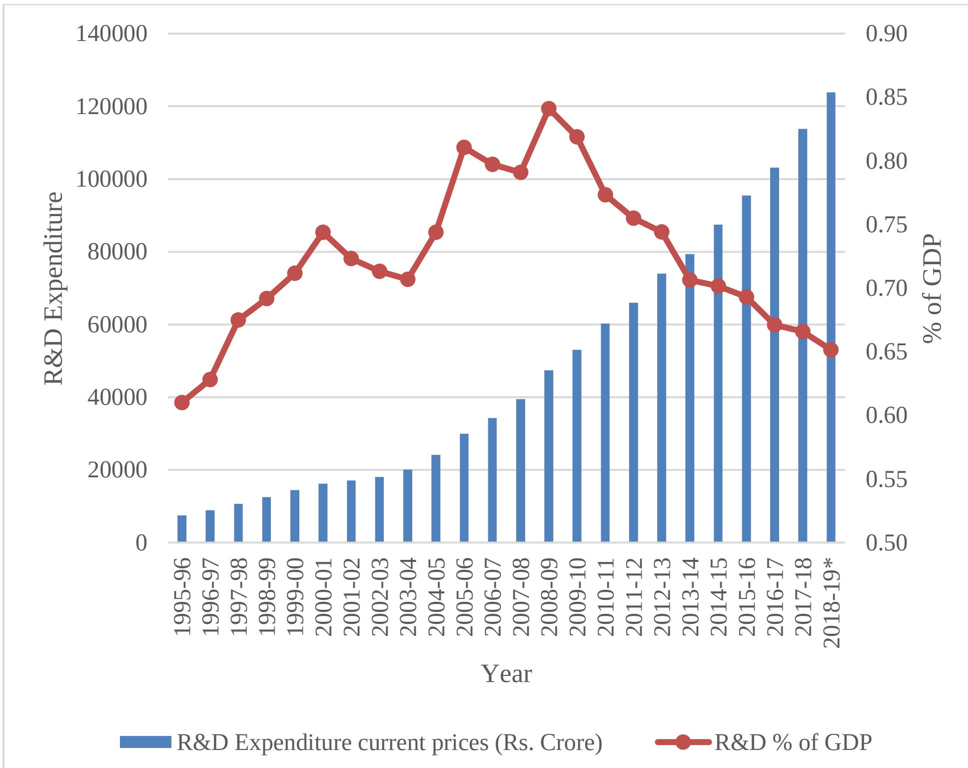
Figure 2.5: R&D Expenditure as % of GDP For Selected Countries, 2017



Sources: OECD Data; NSTMIS, Department of Science & Technology, Government of India.

In terms of gross expenditure on R&D in India, there has been a consistent increase over the past years and has nearly tripled from Rs 39437.77 crore in 2007-08 to 113825.03 crores in 2017-18. The growth is mainly driven by the government sector. The central sector and state sector jointly contribute to the aggregate government sector R&D. However, the central sector contributes the major portion of the R&D. During 2001-2002, central and state sector contributes 76.47 % of National Expenditure on Research and Development, while the private sector contributed 19.32 % and during 2017-18, the government and private sector contributed 53.38% and 36.77% respectively. Over the years, the government remained as the largest contributor of R&D. During 2001-02 to 2017-18 the private sector contributed on average of 32.55% and government sector contributed 62.50%. The changes in National Expenditure on Research and Development and its percentage with GDP during 1995-96 to 2018-19 is presented in figures 2.6.

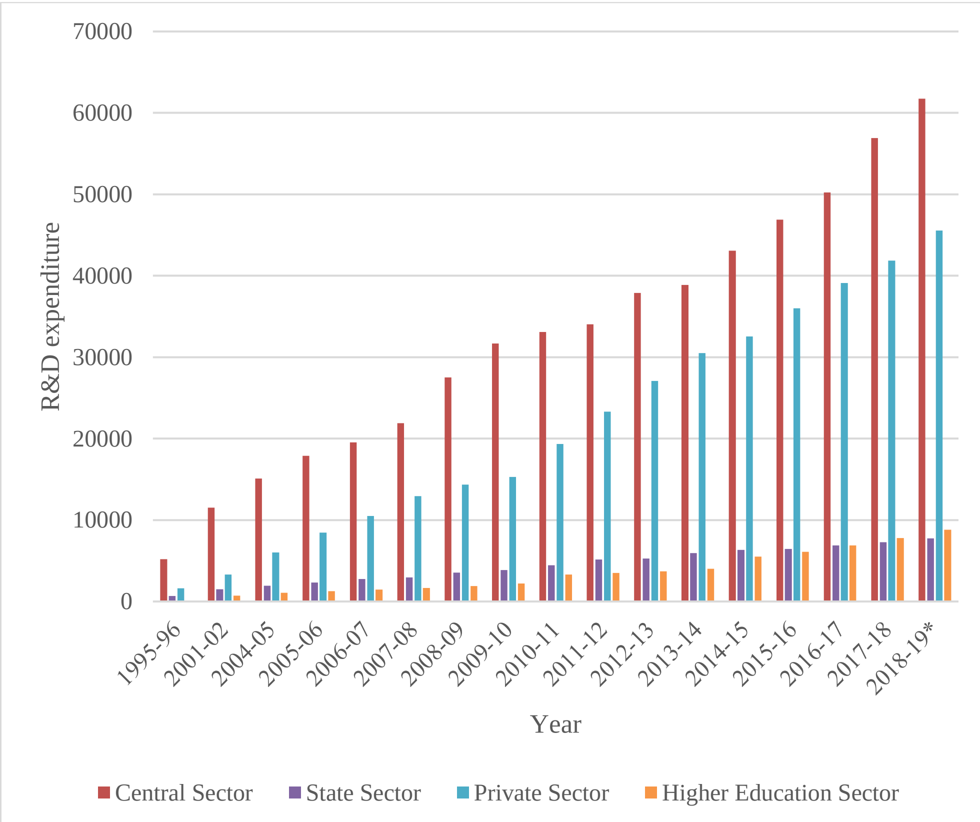
Figure 2.6: National R&D Expenditure and its Percentage with GDP in India



*Estimated. Source: NSTMIS, Department of Science & Technology, Government of India.

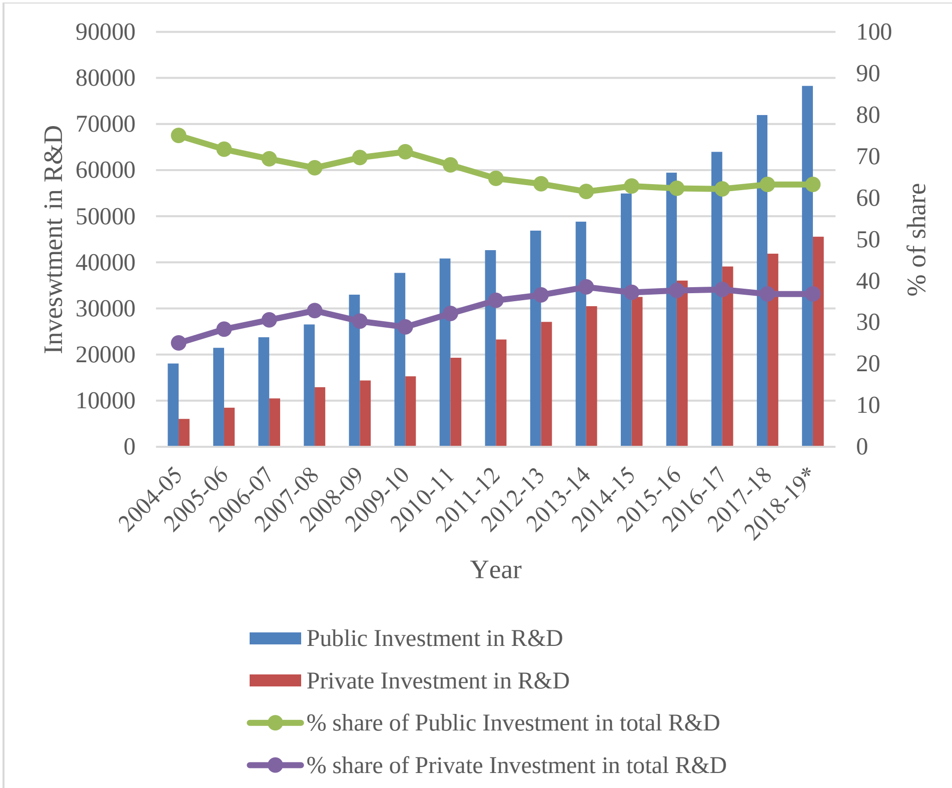
As shown in figures 2.7 and 2.8, the Gross Expenditure on R&D (GERD) is mainly driven by the Government sector comprising of Central Government 45.4%, State Governments 6.4%, Higher Education 6.8%, and Public Sector Industry 4.6% with Private Sector Industry contributing 36.8% during 2017-18. The numbers though not comparable with international values, has increased considerably from 19 % in 2001-02. In the case of the US and China, a large share of R&D spending comes from business enterprises-upwards of 60-70% of total R&D expenditure in each.

Figure 2.7 National Expenditure on Research and Development by Sector



*Estimated. Source: NSTMIS, Department of Science & Technology, Government of India

Figure 2.8: Contribution and Share of public and private investment in R&D Sector

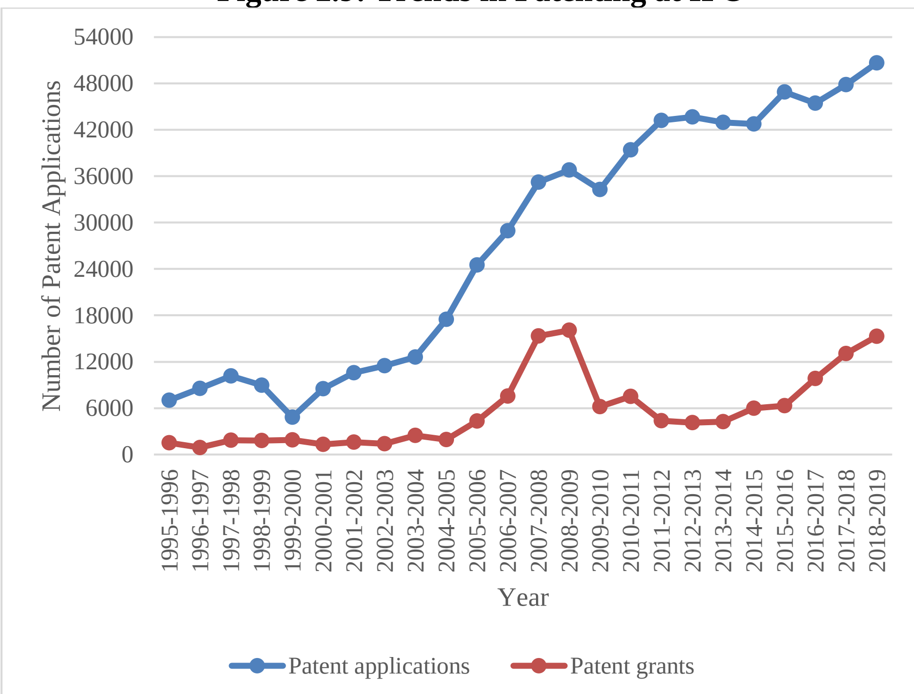


*Estimated. Source: NSTMIS, Department of Science & Technology, Government of India.

As per the WIPO report, India's Patent Office is at the 7th position among the top 10 Patent filing Offices in the world. In terms of resident patent filing activity, India is ranked at 9th position. During 2017-18, out of 47,854 patents filed in India, 15,550 (32%) patents were filed by Indian residents. In the case of foreign patent filings in India, around 62 % of the foreign patents filed in India during 2017-18 were from USA (31.5%), Japan (13.9%), Germany (8.6%) and China (8.0%).

As shown in figure 2.9, there is an increasing trend for patent applications at Indian Patent Office (IPO) during 1995-96 to 2018-19, while the patent grant has a sudden growth during 2006-2008. This growth is mainly attributed to the changes in India's domestic patent policy with the TRIPs Agreement. The Patent (Amendment) Act 1999 allowed the filing of product patents in the fields of pharmaceutical, drugs and agrochemical; however, such applications were examined and granted only after December 31, 2004.

Figure 2.9: Trends in Patenting at IPO



Source: Annual reports of CGPDT, various issues.

Table 2.3 shows the patent statistics for the major fields of technology in India during 1998-99 to 2018-19. Among the patents filed at IPO, technological fields such as chemical, drug, electrical, mechanical, and food have the major patent concentration.

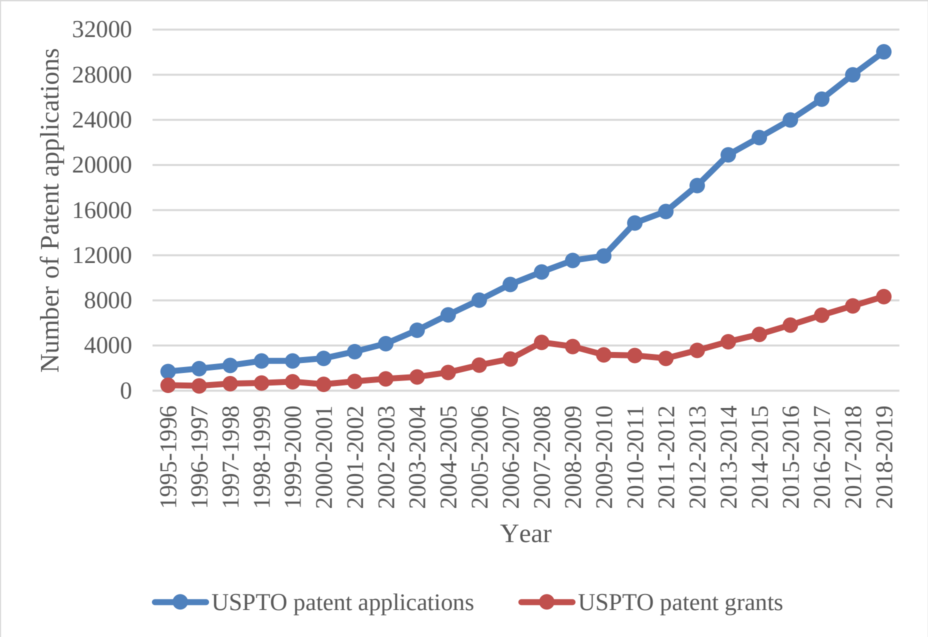
Table 2.3: Number of patent applications at IPO and share (% of total patent application) under major fields of technology

Year	Chemical		Drug		Electrical		Mechanical		Biotechnology		Food	
	Patent applications	Share (% of total patent application)	Patent applications	Share (% of total patent application)	Patent applications	Share (% of total patent application)	Patent applications	Share (% of total patent application)	Patent applications	Share (% of total patent application)	Patent applications	Share (% of total patent application)
1998-1999	2023	22.59	1555	17.37	1778	19.86	2125	23.73	3	0.03	140	1.56
1999-2000	840	17.41	1000	20.73	877	18.18	1187	24.61	9	0.19	107	2.22
2000-2001	787	9.26	883	10.38	921	10.83	1106	13.01	4	0.05	96	1.13
2001-2002	778	7.35	879	8.30	731	6.90	1174	11.08	2	0.02	110	1.04
2002-2003	776	6.77	966	8.42	690	6.02	1257	10.96	46	0.40	119	1.04
2003-2004	2952	23.40	2525	20.02	2125	16.85	2717	21.54	23	0.18	123	0.98
2004-2005	3916	22.42	2316	13.26	1079	6.18	3304	18.92	1214	6.95	190	1.09
2005-2006	5810	23.71	2211	9.02	1274	5.20	4734	19.32	1525	6.22	101	0.41
2006-2007	6354	21.96	3239	11.19	2371	8.19	5536	19.13	2774	9.59	1223	4.23
2007-2008	6375	18.10	4267	12.12	2210	6.28	6424	18.24	1950	5.54	233	0.66
2008-2009	5884	15.98	3672	9.98	2319	6.30	6360	17.28	1844	5.01	340	0.92
2009-2010	6014	17.54	3070	8.95	2376	6.93	6775	19.76	1303	3.80	276	0.80
2010-2011	6911	17.54	3526	8.95	2719	6.90	7782	19.75	1497	3.80	315	0.80
2011-2012	6698	15.51	2762	6.39	4160	9.63	9716	22.49	788	1.82	294	0.68
2012-2013	6812	15.60	2954	6.76	3568	8.17	10198	23.35	832	1.91	452	1.03
2013-2014	6769	15.76	2507	5.84	4371	10.18	11318	26.35	647	1.51	387	0.90
2014-2015	6454	15.09	2640	6.17	4380	10.24	10031	23.46	1035	2.42	395	0.92
2015-2016	6463	13.78	2966	6.32	5770	12.30	10164	21.67	887	1.89	387	0.83
2016-2017	5911	13.01	2122	4.67	5315	11.70	10715	23.58	876	1.93	283	0.62
2017-2018	6343	13.25	2741	5.73	5486	11.46	11573	24.18	992	2.07	344	0.72
2018-2019	6560	12.95	2683	5.30	6308	12.45	12414	24.51	882	1.74	430	0.85

Source: Annual reports of CGPDT, various issues.

Figure 2.10 shows that India's patent filings and grants at the USPTO have shown an increasing trend from 1995-96 to 2018-19. However, the growth rate of such patents has shown a faster pace 2005 onwards.

Figure 2.10: Trends in India's Patenting at USPTO



Source: USPTO, WIPO

2.8. Conclusion

Based on the above discussions, it is evident that the major policy reforms to promote R&D and firm level innovation took place in India over the past few decades. The private sector R&D spending in India has greatly increased in recent years, but the forces driving this change are still largely unexplored. In this context, we propose to evaluate the impact of recent changes in R&D tax incentive scheme in India, that is likely to highlight on the overall effectiveness of the policy.

CHAPTER 3

LITERATURE REVIEW[5]

3.1. Introduction

The economic theory and empirical evidence support the view that innovation policy plays a vital role in driving firm-level innovation (Griliches, 1992). The fiscal incentive for R&D encourages firms to start R&D or increase their R&D resources by reducing marginal costs and increases the profitability of R&D investments. On the other hand, public support for R&D could increase the new product development, as the firms could try to gain a competitive advantage in the market by inventing new products and processes. The rationale for the R&D support is based on the linear model of innovation, which is founded on the assumption that R&D activity of the firm will enhance innovation, that leads to the development of new products, processes, or services (Arrow, 1972; Bozeman & Dietz, 2001).

Godin and Gingras (2000) and Hewitt-Dundas (2006) find that government initiatives have a significant role in stimulating the innovation process of firms. Since the 1990s, many developed and developing countries have started implementing fiscal policies such as R&D subsidies and tax incentives. However, the design of the fiscal incentive varies among countries based on the innovation system and policies. R&D subsidies, grants and loans are provided based on the R&D proposal or project, whereas the tax credit is given on the increased R&D expenses or the volume of R&D. Few countries offer incentives only to specific or targeted industries.

[5] An earlier version of Meta-regression analysis in this chapter has been published as: Jose, M., & Sharma, R. (2020). Effectiveness of fiscal incentives for Innovation: Evidence from Meta-Regression Analysis. *Journal of Public Affairs*. https://doi.org/10.1002/pa.2146

An extensive empirical literature has investigated the role of fiscal incentives on promoting R&D and firm innovation (David et al. 2000; Hall & Van Reenen, 2000; Lokshin & Mohnen, 2012). However, empirical evidence is rather mixed. The earlier literature on public support for innovation estimated the effect of the incentive scheme or program on R&D investment of the firm (i.e., input additionality). In recent times, the focus has been shifted to a more comprehensive evaluation by examining the effect of such incentive on firm's innovation outcome generated from R&D (i.e., output additionality). In this chapter, we predominately discuss the theoretical background of fiscal incentives and innovation, followed by a discussion on the input and output additionality effect. It also discusses the methodological and measurement issues in detail and presents a meta-regression analysis (MRA) of the existing empirical evidence.

This chapter is structured as follows. Section 3.2 discusses the theoretical underpinning of financing innovation and the rationale for its support. Section 3.3 provides an overview of empirical evidence on the effectiveness of fiscal incentives for innovation with special emphasis on the input and output additionality. Section 3.4 elaborates literature on the evaluation of R&D tax incentives. Section 3.5 outlines the measurement issues of R&D tax incentive. Section 3.6 provides an overview of methodologies used to evaluate fiscal incentives for innovation. Section 3.7 examines the heterogeneity of the empirical results using a meta-regression analysis (MRA). And section 3.8 concludes the chapter.

3.2. Financing innovation and the rationale for its support: Theoretical background

The endogenous growth theory originated from Schumpeter's theory of creative destruction considers innovation activity as the major element of long-run economic growth. The theoretical argument to justify the public R&D policy is based on the traditional theory of market failure due to the under investments in R&D. The private sector underinvestment in R&D is due to the higher risk and uncertainty associated with the financing of innovation activities. The inefficiencies of the market create a gap between private and social return, as a result, less than optimal levels of spillover generates from the R&D. The rationale for supporting innovation is to prevent firms from under-investing in R&D in a free market due to the knowledge externalities associated with the private returns of R&D, that can lower that social returns (Nelson, 1959; Arrow, 1972). Due to public good characteristics of R&D, policymakers dynamically support the private R&D.

The investment in R&D involves higher risk and uncertainty than the other form of investments. The economic theory establishes the reason behind the gap between the external and internal costs of capital associated with financing R&D. The investment in R&D is riddled with the information asymmetry and the moral hazard from the separation of ownership and management between entrepreneur and investor (Greenwald et al. 1984; Hall & Lerner, 2010). The asymmetric information problem arises when the entrepreneur has better access to the information about the likelihood of success of R&D. The moral hazard problem arises due to the separation of ownership through external financing, where the principal-agent problem leads to the conflict in investment strategies that do not maximize the share value (Jensen & Meckling, 1976).

Brown et al. (2012) pointed out that the financing constraints is a major barrier for innovative firms. The capital market imperfections make financing R&D more difficult because of the asymmetric information and agency problems between managers and investors, especially in the case of financially constrained firms. As a result, most countries consider R&D investment more generously than capital investment. Fiscal incentives for R&D have become common in industrialized countries. Also, the majority of developed and developing countries provide fiscal incentives in the form of subsidies and tax incentives.

An important question from the policy assessment is to ensure whether the innovation policy enables the firm to undertake R&D activities or encourages to invest additional R&D in existing R&D projects (Jaffe, 2002). In other words, the success of an innovation policy depends on its ability to generate the complementary or substitution effect for private R&D spending. The complementary effect or crowding-in of the innovation policy indicates a positive effect of the innovation policy, whereas the substitution effect or crowd-out effect shows whether the firm substitutes the public fund on R&D activities that would have done even without the public support. In other words, the crowding-in effect shows how much private R&D has increased due to the fiscal incentives. However, the crowding-out effect indicates the substitution of private R&D investment with public R&D funding.

3.3. Overview of empirical evidence on the impact and effectiveness of fiscal incentives for innovation

Empirical studies examine the impact of R&D incentives on firms' innovation through various measures such as R&D expenditure, patenting, productivity growth and new product development. These measures are broadly classified as input additionality and output additionality. R&D is the most used measure of input additionality, while output additionality includes the innovation outcomes of the R&D such as productivity, patenting, and new product development. Most literature evaluates the impact of public support on input with few studies on firms' innovation output (Czarnitzki et al. 2011; Cappelen et al. 2012).

This next section reviews the existing empirical evidence on the effectiveness of input additionality and output additionality and discusses the heterogeneity in the empirical findings.

3.3.1. Empirical findings on input additionality

Studies on input additionality estimate the crowding-in or crowding-out effect of government funding on R&D expenditure (David et al. 2000), where the degree to which firm R&D expenditure has increased or decreased due to the public support is estimated. Crowding-in effect estimates how much private R&D has been increased due to the fiscal incentives, whereas crowding-out effect estimates the substitution of private R&D investment with public R&D funding. Most of the studies on input additionality estimate the crowding-in effect of R&D investment and find an increase in private R&D of the firms (Bloom et al. 2002). The empirical studies of Hewitt-Dundas and Roper (2010); Carboni (2011); Czarnitzki and Delanote (2017) largely confirm the existence of input additionality in the prevailing literature.

There are few overviews of the literature on R&D incentives, and in particular, Hall and Van Reenen (2000) review the econometric evidence on the effectiveness of fiscal incentives for R&D and discuss the methodological tools in specific. Similarly, David et al. (2000) review the economic effect of publicly funded R&D and found that 11 studies out of 33 reported substitution effect[6] for private R&D. The study also reveals that US-based studies report higher substitution effect compared to non-US based studies. García-Quevedo (2004) examine 74 studies and find that 38 studies with complementary effect (i.e., a positive impact of fiscal incentives on R&D), 17 with substitution effect, and 19 studies with an insignificant effect. The study also confirms that there are no specific study characteristics such as type of data and sub-sample that lead to a particular complementarity or substitution effect. Becker (2015) surveyed the empirical evidence of public R&D policies on R&D investment and observed that empirical evidence on crowding-in and crowding-out is

[6] Publicly supported R&D will serve as substitutes for privately invested R&D expenditures (David et al. 2000)

inconclusive before 2000; however, the recent research rejects the substitution effect and tends to find additionality effect.

The earlier literature on public support for innovation mostly based on the US firms finds a positive effect of fiscal incentives on R&D among these firms (Swenson, 1992; Hines Jr et al. 1993). Clausen (2009) estimated the effect of public subsidies on Norwegian firms during 1999-2002 and found a significant input additionality effect of subsidies on R&D expenditure. Similarly, Hud and Hussinger (2015) investigate the effect of public subsidies on R&D in Germany during 2006-2010 and find a positive impact of subsidies during the crisis.

Many studies find the circumstances where fiscal incentives crowd-out business R&D expenditures (Bentzen & Smith, 1999; Clausen, 2009). Wallsten (2000) find crowding-out effect of Small Business Innovation Research (SBIR) program on R&D expenditure in the United States. The crowding-out effect is mainly because the grants that did not allow firms to increase R&D activity, instead allowed firms to continue their R&D at a constant level. Marino et al. (2016) find that the crowding-out effect appears to be stronger under the R&D tax credit regime in France based on a firm-level study during the period 1993–2009. García-Quevedo (2004) also find that the crowding-out effect of R&D subsidies is more common in firm-level studies compared to industry and country-level studies. The author also notes that the studies with the aggregate level data have difficulties in the estimation process. It mainly arises because of government funding on input R&D prices may contribute to the existence of complementarity between public and private R&D. Dimos and Pugh (2016) find no evidence of substantial additionality of R&D subsidy using a meta-regression analysis while controlling for publication bias. Zhu et al. (2019) find that government grant for innovation facilitates firm performance, but the grant has a crowding-out effect on R&D. Similarly, Hud and Hussinger (2015) estimated the impact of public R&D subsidies on R&D investment of SME's in Germany during 2006-2010 and find a positive effect of R&D subsidies on SMEs' R&D investment; however, there is evidence for crowding out effect during the crisis year 2009.

Few studies find the mixed results of fiscal incentives on R&D expenditure. Lööf and Heshmati (2005) find a limited positive effect of fiscal incentives on R&D expenditure, except for small firms in Sweden. Zhu et al. (2006) find an inverted U-shaped relationship between public funding and R&D expenditure of manufacturing firms in China. Lach (2002) observes a positive additionality effect among smaller firms but finds no significant effect among larger firms in Israel. Clausen (2009) examines the effect of public subsidy in Norway during 1992-2002 and find input additionality on firm's R&D investment budget, but substitution effect on firm's development activities.

The existing literature shows a heterogenous effect of the fiscal incentives on innovation with respect to the types of firm and industry. For example, Callejón, and García-Quevedo (2005) found that public R&D support increases private R&D expenditure, especially in high and medium technology industries. About the size distribution of the firms, studies mostly estimated the effect among the SMEs and high-technology firms. A literature survey undertaken by Petrin (2018) suggests that the additionality effects of fiscal incentives are more common among smaller firms. Radicic and Pugh (2016) find that innovation support programs increase the probability of innovation and its commercial success among SMEs in Europe using a treatment effect.

3.3.2. Empirical findings on output additionality

Although the primary focus of fiscal incentive is to promote private R&D, from the point of view of evidence-based policy research, it is necessary to investigate whether such incentives promote innovation outcome generated from the R&D investment.

Most of the micro-level studies have considered R&D as an outcome measure; however, very few examined the interaction between government innovation policy and firm output additionality (Cappelen et al. 2012; Lee & Wong, 2009). The output additionality is measured by product and process innovation, patent filings, new product sales and productivity (Czarnitzki et al. 2011; Cappelen et al. 2012). The new products to the market or patents are considered as a direct outcome of successful R&D expenditure (Hall and Van Reenen, 2000). From the policy evaluation perspective, it is interesting to see whether innovation output has increased due to public support for R&D. It enables to capture how much the R&D incentive reflects on the innovation output in the form of patents, new product sale and productivity. Most studies on the additionality output use patent count as an important measure while evaluating the effect of R&D incentives (Cappelen et al. 2012) that is considered as an ideal measure of innovation activity. The positive effect of the incentives on R&D leads to innovation output in the form of patents and denote fewer chances of re-labelling the R&D activities. The empirical evidence on output additionality also suggests that fiscal incentives have mixed evidence on innovation outcomes. The results of Czarnitzki and Lopes Bento (2014) show that the subsidy has a positive impact on patenting in Germany. Similarly, Czarnitzki and Delanote (2017) find a positive effect of R&D subsidies on innovation output in Belgium, using the CDM model. Bronzini and Piselli (2016) support that innovation incentive has a significant impact on the number of patent applications, especially in the case of smaller firms. Guo et al. (2016) find that innovation scheme for SMEs has a positive impact on patenting, exports, and new products sales in China. However, Zemplinerova and Hromadkova (2012) observe that larger firms that availed subsidies are less efficient in transforming the innovation input into output, and the access to subsidies has a significant negative influence on innovation output in the Czech Republic. Hong (2017) also shows that R&D subsidies have a significant effect on private R&D, but not on innovation outcomes.

3.4. Evaluation of R&D tax incentives

Fiscal incentives are provided to the firms through direct government supports such as loans, grants, and subsidies, whereas indirect support includes tax incentives and patent-based incentives. Over the past two decades, there has been a shift from the direct support of R&D projects to more generic innovation-friendly instruments such as tax credits and patent-based incentives. The R&D tax credit is one of the most generous R&D incentives across the world. The successful implementation of the R&D tax credit in developed economies made developing economies such as Brazil, India, China, and South Africa to follow suit (OECD, 2010). At present, 20 OECD countries are using tax incentives to promote innovation (OECD, 2015). As a market-oriented scheme, tax incentive has recently received more attention than direct subsidies to firms. The most significant advantage of tax incentive compared to subsidies is that it reduces the administrative burden and mitigates the risk of unfair use. Stoneman (1991) points out that tax incentives have a better effect than the grant system on improving the innovation ability of the firm. As compared to grant, tax incentive provides firms with a choice to conduct and pursue R&D program as per the firms' goals. Tassey (1996; 2007) highlight that tax incentive likely to have more impact on the composition of R&D than direct funding.

The primary purpose of the R&D tax credit is to reduce the marginal cost of R&D investments by allowing firms to claim specific percentage tax from the revenue generated proportionate to the R&D invested (Hall and Van Reenen, 2000). Unlike subsidies, tax incentives require less administrative burden and do not require the approval of R&D proposals from government, however, the firm should have the capacity to generate the returns from its R&D investment to benefit from the incentive irrespective of the quality of the R&D project (Busom et al. 2012). Moreover, R&D tax incentive is more beneficial to stable R&D performers (Arque-Castells & Mohnen, 2012). In such a case, the firm's R&D capabilities and ability to generate profit are major determinants of the R&D tax credit claims. On the other hand, R&D subsidies are based on specific projects with high social returns and a higher marginal rate of return of R&D (David et al. 2000). Hall and Van Reenen (2000) pointed out that R&D tax incentives help the firms to manage their R&D programs that avoid the uninformed steering of R&D and avoid the inefficiencies of R&D investment. However, the relabeling expenses as R&D activities is a major weakness of R&D tax incentive, which can be addressed only through proper policy governance.

Studies on the effects of R&D tax incentives on firms' R&D investments mainly estimated the additionality ratio or the price elasticity ratio (Hall & Van Reenen, 2000; Parsons & Philips, 2007; Arvanitis, 2013). The additionality ratio estimates the degree to which firm R&D expenditures have increased because of the government support, whereas the user cost elasticity is the percentage change in R&D with respect to its price, measured by how much R&D will increase when its marginal cost decreases (Hall & Van Reenen, 2000).

Very few empirical studies so far estimated the effectiveness of R&D tax incentive on innovation output (Czarnitzki et al. 2011; Cappelen et al. 2012). Among the empirical studies on output additionality, Dechezleprêtre et al. (2016) find a positive effect on the firm's R&D and patenting activities in the UK. Czarnitzki et al. (2011) investigate the effect of R&D tax credit on new product performance of Canadian firms and confirms that tax credits lead to additional innovation output. Cappelen et al. (2012) analyse the effects of Norwegian tax incentive scheme (SkatteFUNN) on the likelihood of innovating and patenting and find that projects receiving tax credits result in the development of new production processes and to some extent the development of new products for the firms. However, the scheme does not contribute to innovations in the form of new products for the market or patenting.

Few studies specifically address the heterogeneous effect of R&D tax credit with special emphasize on the industrial sectors and size of the firms. The heterogeneous response helps to identify the effect of tax credit based on the characteristics of technological and market opportunities and innovation strategies (Dosi, 1988). For example, Freitas et al. (2017) examined the sectoral dimension of R&D tax credit using firm-level data of Norway, Italy and France and find that firms in industries with high R&D orientation have stronger input and output additionality effects.

Firms in different industries substantially differ in terms of utilising incentives to promote innovation. Agrawal et al. (2020) estimated the effect of R&D tax credit on small firms' R&D spending in Canada and found that an increase of 17 per cent in total R&D among tax credit participants. Similarly, Castellacci and Lie (2015) examined of R&D tax incentives using meta-regression technique and find R&D tax incentives have a stronger effect on SMEs.

The widespread popularity and adoption of tax incentives have attracted scholars to evaluate the impact of such a policy on innovation. The earlier studies were mostly focused on firms in the US; the empirical studies have recently made available in other countries as well. Recently, researchers focus on studying the effectiveness of R&D tax incentives on innovation in emerging economies. Few overviews from emerging economies show a positive impact of tax incentives. For example, Liu et al. (2016) find that R&D subsidy significantly stimulates firm-level business R&D and result in a significant raise of R&D intensity of the high-technology firms in China. Similarly, Wang and Tsai (1998) and Yang et al. (2012) also confirm evidence on the positive R&D effect of tax credits in Taiwan using firm-level data. In the Indian context, Mani (2010) estimates the elasticity of R&D expenditure with respect to the tax foregone due to the R&D tax incentive in India. The result shows that the R&D tax incentive has a significant effect only for the chemical industry in India during the period 1996-2006.

3.5. Measurement issues of R&D tax incentive

Measuring the effectiveness of R&D tax incentive is difficult due to the variation of macroeconomic factors. First, it is hard to measure the exact effect of the R&D tax credit from other macroeconomic events. The second issue is that measuring R&D incentive is also difficult because the effectiveness of R&D support schemes is not homogenous across firms. The effect of the tax credit may vary among the firms due to their different tax positions and size because the tax credit incentive is availed from the taxable portion of the profit of the firm. For example, Bronzini and Piselli (2016) find a positive effect of R&D incentives only for small firms in terms of R&D investment and patenting activities.

Bérubé and Mohnén (2009) find that firms using both R&D tax credit and subsidy have a higher innovation performance than firms only using tax credits. Oh et al. (2009) evaluate the effect of credit guarantee policy by comparing a large sample of guaranteed firms and matched non-guaranteed firms from 2000 to 2003 in South Korea. The findings suggest that credit guarantee significantly influenced the firms' ability to maintain their size, and increase their survival rate, but not to increase their R&D investment.

The choice of innovation measure and the empirical strategy has an important role in R&D policy evaluation (Zúñiga-Vicent et al. 2014). Even with the same sample, different innovation indicators may lead to different conclusions. For example, Freitas et al. (2017) evaluate the existing literature on R&D fiscal incentives and find a stronger input additionality effect; however, the output additionality varies. However, Chen and Yang (2019) find evidence that the R&D tax credit promotes both innovative input and output in China.

About the empirical strategies, Lach (2002) examines the effect of R&D subsidy using before-after estimator, DID estimator and different dynamic panel data models and find heterogeneous results from the different models used. The identification issues that arise from endogeneity and selection bias is a major challenge while estimating R&D tax credit (Guceri & Liu, 2019). We discuss the issues of endogeneity and selection bias detail in chapter 4.

The tax incentives could increase the existing R&D to take advantage of the tax incentive without much effect on innovation output, for example, firms re-label the existing R&D activities to take benefit from tax credit or only expand low-quality R&D projects. These issues can be addressed by considering the effect of tax incentives on innovation outcomes such as patents, productivity, sale of new products, process, or services etc.

3.6. Overview of methodologies used to evaluate fiscal incentives for innovation

The choice of evaluation methodology has a significant impact on the estimated coefficient and the empirical result. As discussed earlier, a major challenge with evaluating the innovation support schemes, pointed by Klette et al. (2000) and David et al. (2000), is the potential endogeneity and selection problems that arise from the identification issue. The traditional methodological approaches have been criticized for not considering the endogeneity problems as well as selection bias in the model construction and the estimation process. David et al. (2000) found that studies before 2000 hardly consider the issue of selection bias while evaluating the impact of incentive policies.

The traditional empirical approach mostly relies on the least square estimation of the linear regression models. Recently, researchers started using ‘non-structural’ models for policy evaluation. Busom (2000) used a two-stage econometric treatment model to account the selection bias, in which the first stage estimates the probit model on the participation probability of the public funding program. In the second stage, the R&D investment is regressed on the covariates, including a selection term that accounts for different propensities of firms to be publicly funded.

The recent econometric frameworks offer different ways of tackling the existence of an endogenous incentive variable in policy evaluation to overcome the selection bias. These techniques are: (i) regression with controls; (ii) fixed effects or difference-in-difference models (DID); (iii) sample selection models; (iv) instrument variable (IV) estimators; and (v) non-parametric matching of treated and untreated firms. DID is used to compare before and after-effects of a particular policy or treatment.

Propensity score matching is a popular method widely used to control the potential selection issues when the R&D tax incentive programme is not random. PSM approach to proxy for estimating the counterfactual situation, where the innovation activity of the recipients is compared with non-recipients. Recent studies have used propensity score matching method to evaluate the effect of R&D incentives (Oh et al. 2009; Carboni, 2011; Cappelen et al. 2012; Liu et al. 2016; Petelski et al. 2019)

Czarnitzki et al. (2011) have used a propensity score approach to estimate the impact of the R&D tax credit in Canada and find that approximately 17% of the firms using tax credits introduced innovations that were world-first. The study concludes that R&D tax credits have a positive influence on improved firm performance. Yang et al. (2012) used propensity score matching and find an average of 53.80% increase in R&D expenditure among the tax credit recipients compared to non-recipients in Taiwan. They also employ an instrumental panel variable (IV) and generalized method of moment (GMM) techniques to control the endogeneity of R&D tax credits and firm heterogeneity in determining R&D expenditure. Guo et al. (2016) examine the government R&D programs on firm innovation in China using a propensity score matching (PSM) to account for the potential selection bias and a two-stage estimation with instrumental variables (IV) for the endogeneity issue. The study finds a positive effect of R&D programs on technological and commercialized innovation output. Similarly, Liu et al. (2016) used a propensity score matching (PSM) to investigate the effect of R&D subsidies on business R&D investments of high-tech manufacturing firms in China and find a stronger effect among small and financially constrained firms.

The difference-in-difference approach is also widely used to evaluate the post-trends of the policy. The DID facilitates an overtime comparison of the change in R&D spending among the firms following the introduction of the R&D scheme. Haegeland and Moen (2017) evaluate the R&D tax credit scheme in Norway and find that the scheme increased private R&D spending of the firms. Recently, Guceri and Liu (2019) examined the tax incentive policy reform in the UK using DID framework and find that R&D expenditure has increased in medium-sized enterprises relative to large firms. A study by Agrawal et al. (2020) estimate the effect of R&D policy reform in Canada and find a 17 per cent increase in total R&D among the eligible firm.

3.7. Effectiveness of fiscal incentives for innovation-A meta-regression analysis

Despite many evaluations, the empirical evidence on the effect of public R&D policies shows a high heterogeneity of the estimated results. As discussed earlier, the effectiveness of R&D incentives may differ among the types of incentive and innovation indicators. Although the primary focus of R&D incentives is to promote private R&D, it is necessary to investigate whether such incentives promote innovation by examining the effect on other innovation indicators. Thus, from the point of view of policy research, it is important to assess which incentive promotes more innovation. The existing micro-econometric studies estimated the average effect of country-specific policy instrument based on a large sample of firms. So far, the existing literature has not questioned whether the effect of such incentive varies among the innovation indicators (i.e., input additionality and output additionality). Although, studies like Castellacci and Lie (2015) and Dimos and Pugh (2016) have investigated the evidence of meta-analysis of fiscal incentives for innovation. However, an evaluation of the effects of the fiscal incentives, which jointly considers the impact of subsidies and tax credit together, is a significant addition to the existing literature.

In this context, this thesis aims to fill the gap in the current literature by reviewing previous empirical findings on public support for R&D on innovation using a meta-regression analysis (MRA) to test whether the effect of public support varies among the innovation indicators. Secondly, we also investigate the reasons that may explain differences in the estimated effects reported in the literature. We aim to uncover the underlying factors behind the specific results of the empirical studies. Such an analysis is needed for evidence-based policymaking specifically for developing and under-developed economies that mirror the stimulation policy of the developed economies.

3.7.1. Methodology, variables, and data

To investigate the factors behind the difference in the estimated effects of fiscal incentives on innovation, we use a meta-regression technique. Meta-regression is a statistical method to examine the relationship between the estimated effect and the study characteristics to explain the differences in the estimated effect (see García-Quevedo, 2004; Castellacci & Lie, 2015; Dimos & Pugh, 2016)

Methodology

To compare the results of the existing studies, it is necessary to have a summary statistic, which is the dependent variable in the meta-regression. The baseline specification of the meta-regression model regresses the effects of the estimate and measure statistical precision, i.e., the standard error (SE) presented in the studies. The dependent variable is the t-statistic reported by the studies. As suggested by

Stanley (2008) and Doucouliagos and Stanley (2009), using the t-statistic as the dependent variable, the variables should be transformed using the corresponding standard error. In the analysis, the t-statistic is regressed on a set of study characteristics that are meta-independent and presumed to influence the outcome of the study. Each observation is weighted by the precision (standard deviation) of the estimated effect.

The model for estimating additionality effect suggested by Castellacci & Lie (2015) is as follows:

$$Y_{ij} = \eta + \beta TC_{ij} + \theta X_{ij} + \mu_{it} \qquad (1)$$

Where Y_{ij} is the innovation measure of firm i in industry j. TC_{ij} is an indicator for measuring the fiscal incentive received by the firm, and X_{ij} is the firm-specific characteristics affecting R&D. Here, β indicates the average increase that a fiscal incentive causes the firm's innovation measure (after controlling for other factors).

Our meta-regression model regresses the effect (i.e., the estimated additionality effect) on an intercept and measures the statistical precision, i.e., the standard error (SE).

Hence, the effect estimate is:

$$E_{s,i} = \alpha + \beta_0 * SE_{s,i} + \epsilon_{s,i} \qquad (2)$$

Where, s is the index of the study (1….,42), and i is the individual regression estimates reported (i.e., 1….497). α and β will be estimated and $\epsilon_{s,i}$ is the error term.

To avoid heteroscedasticity, we weighted Eq. (2) by the standard error (SE) associated with each estimation (Stanley, 2008; Castellacci & Lie, 2015).

The final estimation equation for the multivariate meta-regression model is as follows:

$$TSTAT_{s,i} \ = \alpha * (\frac{1}{SEs,i}) + \beta 0 + \varepsilon_{s,i} \ \ x(\frac{1}{SEs,i}) \qquad (3)$$

Now, the dependent variable is the t-static ($TSTAT_{s,i}$), and as suggested by Stanley (2008), we have included the inverse of the standard error ($1/SE_{s,i}$) to avoid heteroscedasticity. In addition to that, we have added some common variables, such as the number of observations or the year of the publication corresponding to the estimation characteristics. We have also added variables for the type of R&D incentive, econometric specification, and other controls used in the estimation. The rationale for including these variables and their definitions are explained in the next section.

Variables

We have used variables with respect to the study period, type of incentive, data and econometric methodology used in the studies. The key variable for our paper is the R&D incentive type. Our meta-analysis considers two major types of fiscal incentives: R&D subsidy and R&D tax credit. We have included a dummy variable, SUBSIDY, to indicate the type of incentive (i.e., subsidy and R&D tax credit). The variable INVSE indicates the inverse of the standard error of the studies. With respect to the econometric methods, a wide variety of methodological tools were used to analyses the effectiveness of R&D incentives. The use of methodological design makes a difference in the estimated coefficient. The earlier literature mostly used regression models to control for endogeneity. Recently, researchers have used four approaches to tackle the issue of endogeneity and selection bias. These include instrumental variable (IV), matching approach, difference-in-difference (DID) and using lagged R&D among the regressors. Among these techniques, matching and DID are commonly used while evaluating the effectiveness of public support to R&D in recent studies. Accordingly, we introduce a dummy variable (ENDO) to indicate whether the study considers any of these approaches to tackle the issue of endogeneity and selection bias. As discussed earlier, empirical evidence of public R&D policies on R&D investment finds crowding-in and crowding-out are inconclusive before 2000 (Becker, 2015). Moreover, studies before 2000 hardly consider the issue of selection bias while evaluating the impact of incentive policies (David et al. 2000). The variable YEAR of publication of the study (before or after 2000). Most of the empirical evidence on fiscal incentives is country specific. However, few studies have used the firm-level data of multiple countries. The variable COUNTRY indicates whether the study used firm-level data for more than one country. Over time researchers started to use more comprehensive data on micro-level (panel data and industry-level data) to control for the effects of cross-section and temporal variations in technological opportunities. We have included dummies for FIRM and PANEL for studies that estimated the additionality effect for sub-sample of firm-level and panel data. We have also included a dummy variable for SMEs, which captures if the effect is estimated on a sub-sample of small and medium firms (SME). In addition, we have included a dummy variable for high technology industries (HITECH), indicating if the estimated effect of incentive evidence on a sub-sample of high technology industries.

Data

The meta-regression analysis considers the microeconomic evidence on R&D incentives on firm's innovation. The keywords used to collect the empirical studies are "R&D policy; "R&D subsidy"; and "R&D tax incentives." The data in the meta-analysis is obtained after a search using electronic databases such as Google Scholar, JSTOR and websites of international institutions. The main selection criteria followed is to consider only the papers that presented the econometric analysis of R&D incentives on firm innovation. We have collected the latest empirical evidence which is published after the year 1998. The empirical evidence before this period mostly used the survey data. We have used articles published in scientific journals and working papers from well-renowned universities and institutions such as The World Bank, The International Monetary Fund (IMF) and The Organization for Economic Co-operation and Development (OECD).

The meta-analysis is structured to include both the direct and indirect government support for R&D and innovation. Each study on the effect of R&D incentive on firm innovation has several regression results based on different econometric specifications, methods, time periods, and sub-sample. We have included all the regressions reported in the same micro-econometric study to have a border variability and selection criteria. We have collected a total of 497 estimates from 42 articles published between 1998 and 2019. Tables 3.1 and 3.2 provide a summary of studies considered and their key characteristics. Table 3.1 presents all the papers on input additionality, i.e., R&D as the dependent variable. Table 3.2 provides the details of all the papers on output additionality, i.e., patents, productivity growth, and new product development. Table 3.3 presents the list of the indicators we constructed for the meta-regression database along with their definition.

Table 3.1: List of papers included in the meta-regression analysis: Impact of R&D incentive on R&D (input additionality)

Sl no	Label	Country	Incentive	Time period	No. of obs.	No. of firms	Innovation indicator	No. of estimates	Avg. effect measure	Avg. value of t-statistic
1	Yang et al. (2012)	Taiwan	Tax incentives	2001-2005	2588	576	R&D Expenditure	6	0.155333	2.219124
2	Callejón and García-Quevedo (2005)	Spain	Subsidy	NA	240	-	R&D Expenditure	22	0.12631	1.109313
3	Billings et al. (2001)	USA	Tax incentives	1992-1998	1848	231	R&D Expenditure	2	0.19065	1.035
4	Feldman and Kelley (2006)	US	Subsidy	1998	92	122	New R&D funding	2	3.2465	2.09940
5	Görg and Strobl (2007)	Ireland	Subsidy	1999-2002	4192	-	R&D Expenditure	33	-0.083878	-0.3353881
6	Kobayashi (2014)	Japan	Tax incentives	2009	1452	-	R&D Expenditure	28	1.361785	5.99497
7	Guceri and Liu (2019)	UK	Tax incentives	2002-2011	3165	463	R&D Expenditure	11	0.283818	2.3814
8	Lokshin and Mohnen (2012)	Netherlands	Tax incentives	1996-2004	1185	-	R&D Expenditure	6	-0.503333	-.3111375
9	Clarysse et al. (2009)	Belgium	Subsidy	2001–2004	192	84	R&D Expenditure	5	0.1624	1.178908
10	Harris, Li, and Trainor (2009)	Ireland	Tax incentives	1998-2003	2063	563	R&D Expenditure	2	-0.9465	-4.645
11	Kasahara et al. (2014)	Japan	Tax incentives	2001-2003	6165	-	R&D Expenditure	18	-2.2005388	1.49078
12	Wang and Tsai (1998)	Taiwan	Tax incentives	1997	2588	124	R&D Expenditure	2	-12.785	-3.23
13	Czarnitzki and Delanote (2015)	Germany	Subsidy	1994-2006	3272	2399	R&D, R&D Intensity, R&D Employees intensity	24	-5.9071666	-.3732261
14	Almus and Czarnitzki (2003)	Eastern Germany	Subsidy	1994-1998	925	-	R&D Intensity	1	3.94	8.24
15	Lee (2011)	Japan, Canada, Korea, Taiwan, China and India	Tax incentives	1997	815	-	R&D Intensity	19	0.18457	0.13098
16	Lee (2011)	Japan, Canada, Korea, Taiwan, China and India	Subsidy	1997	815	-	R&D Intensity	19	0.118421	0.13817
17	Mercer-Blackman (2008)	Colombia	Tax incentives	2000-2002	2278	-	R&D Expenditure	3	1.06666	0.488545
18	Özçelik and Taymaz (2008)	Turkey	Subsidy	1993-2001	96984	-	R&D Intensity	4	2.8025	8.92370
19	Aiello et al. (2019)	Italy	Tax incentives	2001-2003	-	1334	R&D Expenditure, R&D intensity	2	0.199	2.43414
20	Aiello et al. (2019)	Italy	Subsidy	2001-2003	-	1334	R&D Expenditure, R&D intensity	2	0.389	5.96818
21	Hussinger (2008)	Germany	Subsidy	2000	3744	-	R&D Intensity	11	0.11181	5.7518
22	Liu et al. (2016)	China	Subsidy	4729	729		R&D Expenditure, R&D intensity	14	0.06771	2.6486
23	Baghana and Mohnen (2009)	Canada	Tax incentives	1997-2003	1386	-	R&D Expenditure	8	-0.33875	0.24510

Table 3.2: List of papers included in the meta-regression analysis: Impact of R&D incentive on innovation outcome (output additionality)

Sl no	Label	Country	Incentive	Time period	No. of obs.	No. of firms	Innovation indicator	No. of estimates	Avg. effect measure	Avg. value of t-statistic
1	Czarnitzki and Delanote (2015)	Germany	Subsidy	1994-2006	3272	2399	Patent Applications	6	0.023	2.9033
2	Cappelen et al. (2012)	Norway	Tax incentives	1999-2004	2467	5000	Patenting	6	1.6066	4.78899
3	Gao et al. (2016)	US	Tax incentives	1987-2010	12537	-	Patent count and patent citation	8	-0.00263	0.004898
4	Aiello et al. (2019)	Italy	Tax incentives	2001-2003	-	1334	Probability of Patenting, Patent applications	2	-0.1915	-1.27959
5	Aiello et al., (2019)	Italy	Subsidy	2001-2003	-	1334	Probability of Patenting, Patent applications	2	-0.164	-0.67833
6	Hussinger (2008)	Germany	Subsidy	2000	3744	-	New Product sales	4	0.5575	5.06818
7	Bronzini and Piselli (2016)	Italy	Subsidy	2005-2011	-	612	Probability of Patenting, Patent applications	36	3.917306	7.2482
8	Ernst and Spengel (2011)	EU	Tax incentives	1998-2007	13512	-	Patent Applications	10	-1.4011	-0.84808
9	Westmore (2013)	OECD	Tax incentives	NA	428	-	Productivity	3	0.007	0.003051
10	Guo et al. (2016)	China	Tax incentives	1998-2007	-	2638	Patents, New product sale, and Export	14	1.057285	6.75681
11	Czarnitzki and Delanote (2017)	Belgium	Subsidy	NA	-	3272	Patenting	4	23.1112	1.0162
12	Radicic and Pugh (2016)	EU	Subsidy	2005-10	671	671	Innovative sales	42	0.133241	1.276079
13	Cerulli and Potì (2012)	Italy	Subsidy	2000-2004	11605	2321	Patents	4	0.4255	1.562322
14	Colombo et al. (2011)	Italy	Subsidy	1994-2003	1198	247	Productivity	3	0.1243	0.945888
15	Billings et al. (2004)	US	Subsidy	1996-1999	-	779	Productivity	5	-2.869	1.42215
16	Czarnitzki and Hussinger (2018)	Germany	Subsidy	1992-2000	-	-	Patent Applications and Patent Citations	4	0.0875	8.75
17	Czarnitzki and Licht (2006)	Germany	Subsidy	1994-2000	6462	988	Patent application dummy and Patent applications	4	0.3875	4.98888
18	Le and Jaffe (2017)	New Zealand	Subsidy	2005-2013	23979	-	Process Innovation, Product innovation, new product to the world, new product sales, patents and Trademark	84	0.42001	2.93766
19	Czarnitzki et al. (2011)	Canada	Tax incentives	1997-1999	3656	-	Number of new products, sales with new products, originality of innovation	8	1.251	0.0335
20	Petelski et al. (2019)	Argentina	Subsidy	2010-2012	NA	3691	Employment in R&D and Employment in innovation activities	4	0.01030	0.01425

Table 3.3: Definition of indicators and descriptive statistics

Variable	Definition
INVSE	The inverse of the standard error (SE) of the effect estimate
YEAR	Dummy: 1 if the study published before 2000
COUNTRY	DUMMY: 1 if the sub-sample is included data from multiple countries
FIRM	Dummy: 1 if sub-sample is firm-level data
PANEL	Dummy: 1 1 if sample uses panel data
SUBSIDY	Dummy: 1 if the study used data for a subsidy-based incentive, and 0 for a tax-based R&D incentives
HIGHTECH	Dummy: 1 if the sub-study is high technology industries
SME	Dummy: 1 if the sub-sample is small and medium-sized firms (SMEs)
ENDO	Dummy: 1 if the study used an instrumental variable, propensity score matching, difference-in-difference (DID) and lag of R&D to control endogeneity and selection bias

3.7.2. Results and Discussions

The main objective of meta-regression analysis is to investigate the main factors that explain differences in the estimates that have been reported by different micro econometric studies and to uncover the underlying factors behind the specific results of empirical studies. The meta-regression estimation presented in Table 3.4 reveals the heterogeneity of empirical studies with respect to the time, type of incentive, data and econometric methodology used.

Figures 3.1 and 3.2 present the estimated additionality effects for each estimate using funnel graphs. The graphs illustrate the evidence on the existence of publication bias. In the absence of bias, the additionality estimates should spread symmetrically around the vertical axis. However, both the additionality measures show an asymmetric pattern indicating the existence of positive additionality estimates among the sample studies.

The variable INVSE (measured as the inverse of the standard error of the effect estimates) shows a positive and significant effect on input additionality effect, denotes the significant evidence of true empirical effect.

In Table 3.4, the adjusted R-square of both input additionality and output additionality estimates indicates that the meta-regression has a relatively good explanatory power. In meta-analysis, we have included control variables related to data, industries, and methodological aspects. As described earlier, the main econometric issue while evaluating the R&D incentives is the endogeneity of the R&D incentive. This variable ENDO is positive and significant in case of both input and output additionality, indicating that the estimated additionality effect of studies that used econometric tools such as instrumental variable (IV), matching approach, difference-in-difference (DID) and lagged R&D has on average stronger additionality effect compared to the studies that did not consider the endogeneity and selection bias issues. The results also show that the studies that used firm-level data of more than one country have on average stronger input and output additionality effect. One possible reason for this difference may arise since only a few studies have used firm-level data on a cross-country level. Most of the studies have investigated the effect of fiscal incentives in a single country. The results in Table 3.4 also indicate that studies using firm-level data have on average negative additionality effect in case of input additionality and positive in case of output additionality. However, the studies that used panel data have on average smaller effect on input additionality and did not have any significant impact on output additionality.

The key variable in the paper is the incentive type. We have included dummy variable SUBSIDY to classify the type of fiscal incentive (i.e., subsidy and tax incentive). The estimation results show that subsidy has a negative and significant influence on the output additionality, indicating that R&D tax incentives have substantially stronger output additionality effect than R&D subsidies. It indicates that firms that availed subsidies are on average, less efficient in transforming innovation input into innovation output. However, the estimated coefficient of SUBSIDY does not have any significant effect on input additionality. In summary, the output additionality effect on an average is stronger for R&D tax credit than subsidies. One possible reason for this difference is that the tax credit is provided in proportion to the amount of R&D invested by the firm. The subsidies are provided based on a specific R&D project, where the social return of the project is also considered. Moreover, subsidies induce firms to carry out short-term small R&D projects which reflect only in terms of R&D, but not necessarily with the other innovation outcome measures such as patents and productivity.

The estimated coefficient of HIGHTECH is negative and significant in the case of input additionality, indicating that the estimated effect of high technology industries has a smaller additionality effect on R&D. However, it is positive and significant in case of output additionality indicating that the output additionality is on average stronger for high technology industries. Moreover, the high technology sector is considered as R&D intensive sector. It also points out that industry-targeted incentives will be more effective in promoting innovation. As discussed earlier, SMEs have a major role in utilising incentives due to the limited access to finance innovation. Studies that used the sub-sample of small and medium firms find stronger additionality input; however, the estimated additionality output is on average smaller for SMEs. It indicates that, on average, SMEs utilises the incentives more effectively to promote their R&D. The variable YEAR controls the publication period of the study. The estimated coefficients of YEAR are not significant in the case of additionality input, indicating that the estimated effects of studies published before and after

2000 do not have any significant difference. However, in the case of output additionality, all of the studies in our sample are published after 2000.

Figure 3.1 Input additionality measures

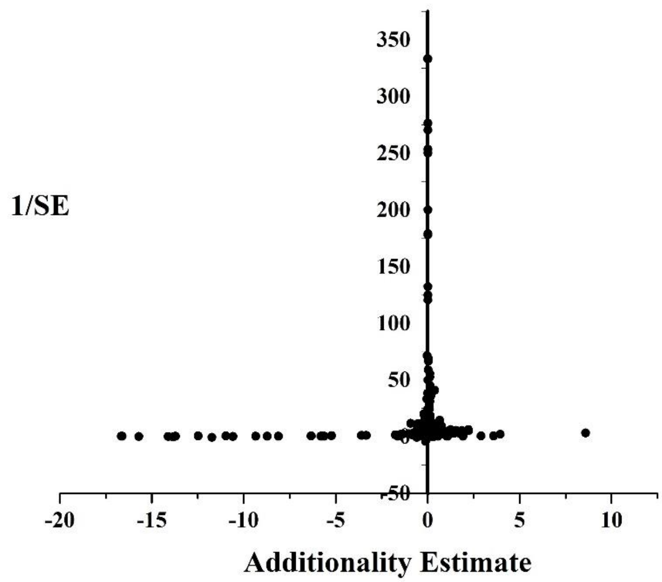


Figure 3.2: Output additionality measures

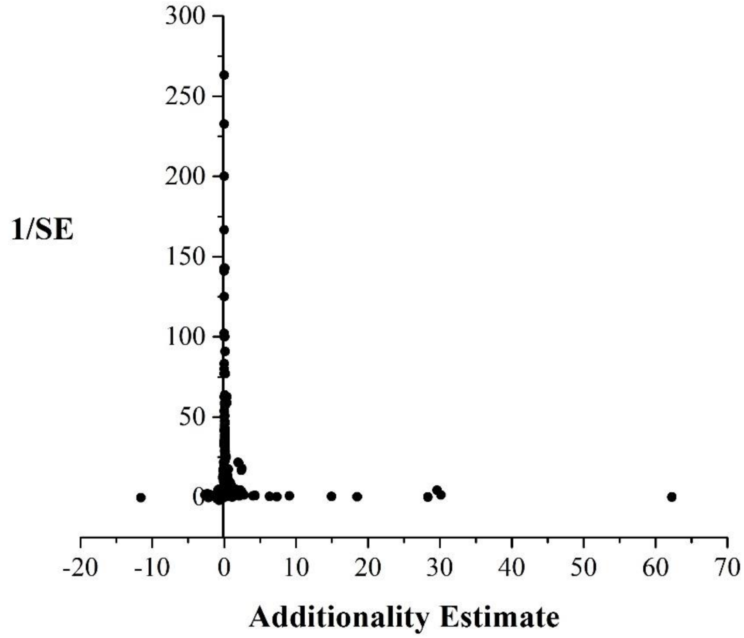


Table 3.4: Meta-Regression Analysis (MRA) Results

Variables	Input additionality measures	Output additionality measures
INVSE	0.011*** (.003)	-9.83e-09 (9.39e-09)
YEAR	1.518 (2.162)	
COUNTRY	2.584** (1.302)	13.71*** (3.617)
FIRM	-2.152*** (0.824)	4.053*** (0.654)
PANEL	-1.801** (0.743)	-0.779 (1.854)
SUBSIDY	-0.549 (0.685)	-4.813*** (1.849)
HIGHTECH	-3.125*** (0.719)	16.18*** (2.837)
SME	3.234*** (0.974)	-17.29*** (3.501)
ENDO	2.075* (1.122)	13.19*** (2.560)
CONSTANT	1.301 (2.076)	-4.160* (2.308)
Observations	244	253
Adjusted R-square	29.59	19.81

Note: Dependant variable is TSTAT (t-static of the estimated additionality ratio). Here *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

3.8. Conclusion

In this chapter, we review the empirical evidence on the impact and effectiveness of public support for R&D and innovation. The meta-analysis reveals the heterogeneity of empirical studies with respect to the type of incentives, data and econometric methodology used. Moreover, the effectiveness of R&D incentives varies with the measurement and definition of innovation indicators. The results reveal that the output additionality on average is stronger for R&D tax incentive than subsidy. The studies that have used sub-sample of small and medium enterprises (SMEs) have stronger input additionality, which confirms that input additionality effects of fiscal incentives are more common among smaller firms. This study also confirms that firms from high technology industries have a higher additionality effect. The evaluation methodology has a significant impact on the estimation of results. The meta-regression analysis reveals that studies that used various econometric tools to tackle the issue of endogeneity and selection bias have a stronger additionality effect than the studies which have not considered the endogeneity and selection bias. These results also motivate us to use appropriate econometric techniques in our study that we discuss in the next chapter.

CHAPTER 4[7]

METHODOLOGY, IDENTIFICATION STRATEGY AND DATA

4.1. Introduction

This chapter addresses the methodological framework, identification strategy, and data used to evaluate the effect of R&D tax credit policy in India. We employ propensity score matching (PSM) and Difference-in-difference (DID) framework to account for the specific issues related to policy evaluation and the potential problems of evaluating the R&D tax credit policy. We also highlight the basic assumptions and practical measurement issues related to each methodology. The specific issues of policy evaluation include the selection bias and the heterogeneity of estimating the long-term effect of the R&D tax credit. We have discussed the literature on endogeneity and selection bias in chapter 3. In this chapter, we discuss our empirical strategy to account for these issues based on the key identifying assumptions.

The rest of the chapter is structured as follows: Section 4.2 discusses empirical challenges and measurement issues of R&D tax credit with a detailed review of the various measurement tools and techniques. We discuss the issues of selection bias and the endogeneity associated with R&D tax credit policy evaluation. Section 4.3 provides the empirical frameworks used to evaluate the effect of the R&D tax credit in India. Section 4.4 discusses the identification strategy used in the empirical setting. Section 4.5 elaborates the innovation outcome measures used to

[7] The methodological framework of Difference-in-difference (DID) in this chapter has been published in: Ivus, O., Jose, M., & Sharma, R. (2021). R&D Tax Credit and Innovation: Evidence from Private Firms in India. *Research Policy*, 50 (1), 104128. https://doi.org/10.1016/j.respol.2020.104128

estimate the effect of the R&D tax credit on firm-level innovation. Sections 4.6 and 4.7 outline the data sources and the definitions of variables used in the study, respectively.

4.2. Empirical challenges and measurement issues of R&D tax credit

Over the last two decades, as a market-oriented scheme, R&D tax incentive has received more attention than other fiscal incentives for innovation. The effectiveness of R&D tax incentive on innovation outcomes is the fundamental interest in empirical economics and policymakers worldwide. Measuring the effectiveness of fiscal provisions is difficult due to the variations in the macroeconomic factors. Moreover, the effectiveness of R&D tax credit scheme may not be homogenous across firms due to the different tax positions and after-tax money of the firms. For example, Bronzini and Piselli (2016) find a positive effect of R&D incentives only for small firms in terms of R&D investment and patenting activities.

4.2.1 Issues of selection bias

The characteristics of firms that apply for R&D incentives are likely to differ from those that do not apply. These differences are mainly due to the high absorptive capacity and past innovation activities of the firms (Czarnitzki et al. 2001). Due to these inherent characteristics, the applicant firms have potentially more innovation capabilities than non-applicants, even without utilizing the R&D promotion programs. Hence, the evaluation of R&D policy should consider the selection bias that arises due to the allocation of R&D scheme. In the case of R&D credit, both application and claim for the tax credit can be viewed random. Hence, the selection into such program or scheme has to be considered while estimating such policy's effect. Hall and Maffioli (2008) also point out that a simple comparison of innovation outcomes of recipients and non-recipients leads to selection bias and misleading the estimation effect of the policy.

4.2.2 Endogeneity issues

The company's decision to seek recognition from the DSIR might be endogenous to its innovation activities. For example, a financially constrained company might have had a smaller R&D budget and is more likely to avail the R&D tax credit. In the case of tax credit, the amount of weighted tax deduction depends on the amount of R&D undertaken by the firm. Hence, using a dummy variable to indicate the tax credit claim leads to endogeneity issues, since some firms decide not to apply for the tax credit, producing biased estimates. Busom (2000) suggests that the simple regression models will not account for the problem of endogeneity of public funding. For instance, Lichtenberg (1988) estimated R&D expenditure on the value of competitive and non-competitive government contracts and other non-government revenue using a sample of 169 firms in the US. The estimated results show a positive and significant effect of government R&D with the OLS regression; however, the coefficient becomes negative and significant when accounted for the endogeneity by using an instrumental variable approach.

There is also the concern of endogeneity due to confounding policy changes in India during 2010–2011. The 2010-11 R&D tax credit reform could have coincided with other domestic policy changes that had a differential effect on DSIR-registered firms. The endogeneity and selection bias may arise at model construction as well as in the estimation phase (Cerulli, 2010).

The econometric evaluation offers different ways of tackling an endogenous variable's existence in the policy evaluation to overcome the selection bias. Researchers use micro-level data (panel data and industry-level data) to control for the cross-sectional effects and temporal variations in estimating the effect of fiscal incentives. Over the last two decades, researchers also employ more comprehensive ‘non-structural’ models to eliminate the endogeneity and selection bias, based on the availability and type of data. These techniques include: (i) regression with controls; (ii) fixed effects or difference-in-difference models (DID); (iii) sample selection models; (iv) instrument variable (IV) estimators; and (v) non-parametric matching of treated and untreated firms. The selection models and IV estimators are used if at least one valid exclusion restriction or instrumental variable is available. In our study, it is difficult to find an instrumental variable that affects the likelihood of the firms to get the tax credit but does not correlate with the outcome variable (R&D and Patenting). Non-parametric matching methods are used to control the potential selection issues when the R&D incentive programme is not random. It estimates the counterfactual situation, where how much the R&D incentive recipient firms would have innovated if they would not have participated in the R&D incentive program. The DID approach is used to compare the before and after effects of a particular policy or treatment. Among the different micro-econometric approaches, propensity score matching (PSM) and DID are considered as the efficient approaches that provide a reliable evaluation of the causal effect between fiscal incentives and firm innovation.

Considering the policy structure that not all firms have registered with DSIR by 2016, and those who did, vary by year, PSM and DID are the ideal frameworks to control the endogeneity and potential selection issues. Few studies use a combined matching and DID framework to estimate the effect of R&D program (Marino et al. 2016; Dai et. al. 2020). Given recent discussions on the use of pre-treatment outcomes in a matching DID framework (Chabe-Ferret, 2015; 2017), we do not combine DID with matching on pre-treatment outcome. Chabe-Ferret (2017) studies the bias of DID with conditioning on pre-treatment outcomes that are observed at different dates. The study finds that when selection is due to both permanent and transitory confounders, combining DID with conditioning on pre-treatment outcomes might increase the bias of DID and even generate bias for an otherwise consistent DID estimator. This is because conditioning on pre-treatment outcomes in this case generates time varying selection bias, while the validity of DID requires selection bias to be constant over time. When selection is only due to permanent confounders and transitory shocks are persistent, DID without conditioning on pre-treatment outcomes is consistent but DID conditioning on pre-treatment outcomes is not. Hence, we use PSM and DID separately that also address different research issues that have been discussed in detail below.

4.3. Empirical framework

For PSM, we create a matched control sample and estimate the counterfactual. The matched control sample comprises of the non-DSIR firms, matched with DSIR firms on a predicted probability of registering with DSIR. This approach selects a matched control group of firms that has the closest predicted probabilities of registering with DSIR for each DSIR firm in each year and industry from 2001 to 2016. However, the PSM requires strong robustness and sensitivity analysis to confirm the exact effect of the R&D scheme. Furthermore, it is impossible to identify the bias from the unobservable cross-firm heterogeneity and firm-specific time trends over the period. Hence, we also use a DID framework and take advantage of the panel data for evaluating the impact of R&D tax credit reform on innovation activity. The DID framework estimates the time or cohort dimension, which accounts for the unobservable firm characteristics. The ex-post analysis of the reform and its impact further contributes to an effective evaluation of the tax credit scheme.

Selection of treatment and control groups

We select the treatment and control groups based on the registration of the firms with the DSIR. The treatment group consists of firms registered with the DSIR (i.e. availed the tax credit) and the control group consists of the non-DSIR firms (i.e. not availed the tax credit). We measure treatment by a binary indicator that takes on the value 1 if a firm has been registered with the DSIR in the respective year. The indicator takes on the value 0 if a firm has not been registered with the DSIR in the respective year. Thus, our control group solely consists of non-DSIR firms, allowing us to compare how innovation activity changed following the registration with the DSIR. Our empirical framework assumes that the outcome in the treated of DSIR firms and control group of non-DSIR firms would follow the same time trends in the absence of the treatment.

The detailed framework of PSM and DID is discussed below:

4.3.1. Propensity Score Matching (PSM)

We examine the counterfactual situation, where how much the tax credit recipient firms would have invested in R&D and filed patents if they would not have participated in the R&D tax credit scheme.

The key argument is to find a ‘twin’ firm with the similar characteristics of a DSIR registered firm. This matched firm which is not registered with DSIR (hence did not receive tax credit) provides evidence on what would have happened if a firm did not use R&D tax credit scheme. The matched firms are compared based on pre-defined outcome variables to identify the effectiveness of the tax incentive scheme. As the difference in the outcome variable between the participants and non-participants should only be due to the treatment. The propensity score indicates the probability of participating in the programme, conditional on the characteristics of the covariables.

We use the PSM developed by Heckman et al. (1997) to estimate the average treatment effect on the treated firms (ATT). The non-parametric matching estimation based on PSM measures the average treatment effect on the treated by comparing the average outcomes of the DSIR affiliated firms and non-DSIR affiliated firms.

In PSM, the implementation is confronted with two major parts. First, the selection of covariates and the model. To estimate the propensity score, we use a probit estimation for the DSIR affiliation. The propensity score indicates the conditional probability to affiliate with DSIR when observable characteristics of the participants are given. Once the propensity score is estimated, each DSIR affiliated firm is matched with a firm in the non-affiliated list which belongs to the same industry and year based on the propensity score. We follow the matching protocol used by Hud and Hussinger (2015) to match the treated group with the control group. We determine the nearest neighbour based on the propensity score, i.e. the likelihood of being affiliated with DSIR.

Literature suggests various matching methods such as nearest neighbour matching, radius matching, kernel matching and stratified matching for identifying the matched control group. In nearest neighbour matching, the individual from the comparison group is chosen as a matching partner for a treated individual that is closest in terms of propensity score obtained from the covariates (Caliendo & Kopeinig, 2008). We use 1-1 nearest neighbour matching (NNM 1-1) as suggested by Liu et al. (2016) to estimate the ATT. We also include other matching methods as robustness checks, namely 1-3 nearest neighbour matching (NNM 1-3), 1-5 nearest neighbour matching (NNM 1-5) and kernel matching.

The matching procedure finds the participants and non-participants with equal or similar propensity score or probability of participating. However, there should not be any systematic differences between the participants and the non-participants in terms of unobserved characteristics that may influence the participation in the R&D programme. The matching is feasible only when the observations in both groups with similar propensity score and the propensity scores are based on similarly observed covariates. The matching provides to estimate the effect of R&D policy with more focus on the selection process and underlying assumptions. The use of common support ensures the comparability of the two groups.

First, we estimate the propensity score, defined as the conditional probability of receiving a treatment given pre-treatment firm's characteristics as follows:

$$p(X) \equiv Pr\,(D = 1|X) = E(D|X) \qquad (1)$$

where $D = \{0, 1\}$ is the indicator of treatment, and X is the multidimensional vector of pre-treatment characteristics.

To construct a valid control group, we use a propensity score with the probability of receiving treatment that is conditional upon the covariates suggested by Rosenbaum and Rubin (1983). The choices of the model and the variables have an important role while estimating the propensity score. Smith (1997) suggests that any discrete choice model can be used while estimating the propensity score. In the case of a binary treatment, the probability of participating can be estimated using logit or probit models. Moreover, the treatment effect depends on the quality of selection control variables used to estimate the propensity score.

In the next step, we estimate what would be the innovation activity of the participating firms if they would not have participated in the tax incentive scheme. (i.e. the counterfactual situation). It is measured through the Average Treatment Effect on the Treated (ATT). The ATT estimates the average of the difference between the outcomes of participants and the matched control group.

The average treatment effect (ATT) is measured as follows:

$$ATT = E\ (Y1 - Y0\ |S = 1) \qquad (2)$$

where, *Y1* is the outcome of the firms that have received tax incentive (DSIR affiliation firms) and *Y0* is the outcome of the firms that have not received the incentives (non-DSIR affiliation firms) and *S* denotes the treatment status of the firms (DSIR affiliation status). While evaluating the treatment effects of a public policy program, it is important to address the counterfactual question; what the change in the outcome variable is given treatment, *Y (1)*, compared to the potential outcome of non-treatment, *Y (0)*. We also assume that the treatment status and the potential outcome are affected by a set of observable covariates. The average effect of R&D tax credits of innovation is measured using a series of innovation indicators that are discussed in detail in section 4.7 in this chapter.

Score calculation and validity

The propensity score is defined as the probability to register with DSIR and represents a valid methodology to reduce all the dimensions of the firm and industry characteristics to a single index (Rosenbaum & Rubin, 1983; Dehjia & Wahba, 2002). Hence, to calculate the propensity score, we need to understand the factors that contribute significantly to determining affiliation of a firm with DSIR. We use probit estimations, where the dependent is the DSIR affiliation status of the firm, a binary indicator that takes on the value 1 if a firm is affiliated to claim the tax credit. It takes 0 if a firm is not affiliated. The covariates are selected based on the literature review, which identified the R&D characteristics of firms in India. A detailed discussion on these covariates is provided in section 4.7.

Assessing the Quality of Matching

The matching quality ensures an effective comparison of treated and control group of firms after matching. Hence, matching quality has to be assessed using various parameters before estimating the treatment effect. The covariates of treated and control group are expected to have a close propensity of registering with DSIR. The t-statistic and the corresponding p-value between the covariates of the treated group and the control group is a good indicator of matching quality. In addition, we also provide the mean standardised bias (MSB) of variables as suggested by Caliendo and Kopeinig (2008). The MSB indicates the distance in marginal distribution of the variable. Most of the empirical studies considers MSB values as a sufficient indication of the success of matching (Caliendo and Kopeinig, 2008). Moreover, the distribution of treated and control observations should have the same probability of participating in the R&D tax credit scheme.

Heterogeneous effect of the tax credit

Different characteristics of market structure and industrial dynamics can lead to differences in the way a support program affect its outcome variable (Scherer, 1982; Tirole, 1988). The literature on innovation activities by firms in India has revealed heterogenous results among firms. The innovation activities of the firm considerably vary with the firm size, ownership category and export status. The estimation of ATT also facilitates the assessment of heterogeneous effects using various sub-groups of the sample. Thus, we attempt to study if the impact of tax credits varies with such specific firm characteristics. As discussed earlier, the firm’s size is associated with its innovation activities, which may further influence the firm’s utilisation of R&D tax credit. Based on the discussion on the heterogeneous effect of the R&D tax incentive in chapter 3, we classify the firms into different sub-sample groups to tackle the heterogeneous effect of the policy reform. We test the heterogeneity of the estimated treatment effect with respect to the industry, firm size, ownership, and export status of the firm.

4.3.2. Difference-in-Difference Approach

As discussed earlier, a mere comparison of treated and control firms may not yield acceptable guidelines for appropriate policy recommendations. For a complete policy evaluation, it is important to consider how the timing of DSIR affiliation and its overtime variation reflects the innovation activities of the firm. Moreover, it is necessary to identify the bias from the unobservable cross-firm heterogeneity and firm-specific time trends over the period. The ex-post analysis of the reform and its impact further contribute to an effective evaluation of the tax credit scheme. In the next section, we take advantage of the panel data and use a DID framework to examine the timing of DSIR affiliation and its variations overtime to capture the effect of the policy reform.

The empirical challenge is to credibly measure a causal effect of the R&D tax credit scheme and its reform on firm innovation activity while accounting for potential endogeneity due to self-selection into the DSIR registration. The key concern we address is that the company's decision to seek recognition from the DSIR might have been endogenous to its innovation performance or driven by the reform itself.

The DID framework allows us to evaluate how the effects of DSIR recognition changed after the reform. This is possible because our panel is fairly long, and the timing of DSIR registration varies widely across firms in our sample. To address the endogeneity concern due to firm selection on individual permanent characteristics, we take advantage of the panel structure of our data and estimate different specifications that are discussed below.

4.3.2.1 Specification for R&D tax credit reform (2010-11), that increased the weighted tax deduction from 150 % to 200%

First, we examine the impact of the R&D tax credit scheme and its 2010-11 reform, that increased the weighted tax deduction to 200%, on innovation activities of the private firms in India. During the 2001-2010 period, the policy offered weighted tax deductions of 150% for any capital and revenue expenditure incurred on in-house R&D by firms in selected industries. Further, until 2009-10, the R&D tax credit was available to companies engaged in the production of drugs and pharmaceuticals, electronic equipment, computers, telecommunication equipment, chemicals, manufacture of aircraft and helicopters, automobiles, and auto parts. The existing provision of the tax credit scheme was extended to all industries in 2009-10.

The unit of analysis is firm i in industry j in year t. Let D_{ijt} denote the DSIR registration status dummy variable, which is equal to one if the firm i is registered with the DSIR in year t and equal to zero otherwise. A large number of firms in our data were either always registered with the DSIR or never registered with the DSIR during our sample period of 2001-2016. We refer to these firms as "DSIR registered" and "non-DSIR registered", respectively. Thus, ($D_{ijt} = D_{ij} = 1$) for a DSIR registered firm and ($D_{ijt} = D_{ij} = 0$) for a non-DSIR registered firm.

The basic statistical model for the observed outcomes is specified as follows:

$$Y_{ijt} = exp\,(\alpha + \alpha_t + \alpha_j + \alpha_j t + \varphi D_{ij} + \gamma D_{ij} R_t + X_{ijt}\delta\,) e_{ijt,} \quad (3)$$

where, the outcome variable Y_{ijt} is one of the four measures of firm innovation activity. The independent variable D_{ij} is the treatment group dummy variable, equal to one if firm i is in the treatment group of DSIR-registered firms and equal to zero if firm i is in the control group of non-DSIR- registered firms. The variable R_t is the post-reform dummy variable, which is equal to one for the year 2011 and all years thereafter and is equal to zero otherwise. The interaction term $D_{ij}R_t$ is the product of D_{ij} and R_t. The control for D_{ij} allows the outcome to differ across the two groups of firms in the absence of the reform, while the control for $D_{ij}R_t$ allows the impact of the reform to differ across the two groups of firms. The vector $Xijt$ contains time-varying firm controls, which we discuss in Section 4.7. The model also includes fixed effects for each year (α_t), industry (α_j) and the vector of industry-specific time trends (α_{jt}). Last, α is the constant term, and ε_{ijt} is the stochastic error term which is mean independent of firm group and time, controlling for α_j, α_{jt}, *and* X_{ijt}: $E\ [\varepsilon_{ijt}\ |1,\ \alpha_t,\ \alpha_j,\ \alpha_j\ t,\ X_{ijt},\ D_{ij}] = 1$.

We rewrite the exponential model (3) in the log-linear form as follows:

$$ln\, Y_{ijt} = \alpha\ + \alpha_{\mathrm{t}} + \alpha_{\mathrm{j}} + \alpha_{\mathrm{j}}t + \varphi D_{ij} + \gamma\, D_{ij}R_t + X_{ijt}\delta + e_{ijt} \tag{4}$$

where, $e_{ijt} \equiv \ln e_{ijt}$, and estimate the model (4) by ordinary least squares (OLS). The exponentiated coefficient on $D_{ij}R_t$ identifies the multiplicative treatment effect[8] on the average as a ratio of ratios:

$$\exp\ (\gamma) = \frac{Ratio\ for\ treated}{Ratio\ for\ control}\text{, where} \tag{5}$$

$$Post - reform\ ratio = \frac{E\left[Y_{ijt}\middle|\ \alpha_{t,}\alpha_{j,}\alpha_j t, X_{ijt}, D_{ij} = 1,\ R_t = 1\right]}{E\left[Y_{ijt}\middle|\ \alpha_{t,}\alpha_{j,}\alpha_j t, X_{ijt}, D_{ij} = 0,\ R_t = 1\right]}; \tag{6}$$

$$Pre - reform\ ratio = \frac{E\left[Y_{ijt}\middle|\ \alpha_{t,}\alpha_{j,}\alpha_j t, X_{ijt}, D_{ij} = 1,\ R_t = 0\right]}{E\left[Y_{ijt}\middle|\ \alpha_{t,}\alpha_{j,}\alpha_j t, X_{ijt}, D_{ij} = 0,\ R_t = 0\right]} \tag{7}$$

[8] The multiplicative effect of DSIR registration estimates the average outcome in the control group of non-DSIR-registered firms as compared to the average outcome in the treatment group of DSIR-registered firms.

The post-reform and pre-reform ratios measure the multiplicative effect of DSIR registration on the average outcome in the post-reform and pre-reform years, respectively. Compared to the average outcome in the control group of non-DSIR-registered firms, the average outcome in the treatment group of DSIR-registered firms is exp $(\varphi + \gamma)$ times greater in the post-reform years and exp(φ) times greater in the pre-reform years. The factor impact of DSIR registration is thus exp(γ) times greater in the post-reform years. The treatment effect can also be interpreted in terms of percentage, rather than factor, differences. The percentage difference in the outcome between the treatment and control groups equals [exp (φ) − 1]100 in the pre-reform years and [exp $(\varphi + \gamma)$ − 1]100 in the post-reform years. The percentage treatment effect of the reform thus equals [exp(γ) − 1]100.

The estimate of exp(γ) can be given a causal interpretation under the key assumption of common time trends in a multiplicative form. This assumption requires that in the absence of the reform, the outcome in the treatment group would have changed over time by the same factor as it did in the control group. In terms of the potential outcomes, the key identifying assumption is:

$$E[\, y_{0ijt} |\, \alpha_{t\,,} \alpha_{j,} \,, \alpha_j t \,, X_{ijt} \,, D_{ij}] = E[\, y_{0ijt} |\, \alpha_{t\,,} \alpha_{j,} \,, \alpha_j t \,, X_{ijt}], \qquad (8)$$

where $y_{0ijt} \equiv \ln Y_{0ijt}$ is the potential outcome when not treated (i.e., the outcome for firm *i* had this firm not been registered with the DSIR, irrespective of whether it actually was registered). The assumption says that counterfactual outcomes in the absence of treatment are independent of treatment, conditional on the year effects *(α_t)*, industry effects *(α_j)*, industry-specific time trends *($\alpha_{j,t}$)*, and covariates X_{ijt}. It would hold if the DSIR-registered and non-DSIR-registered firms were similar in all respects except that for some random reasons, the firms in the treatment group have registered with the DSIR and those in the control group did not. This is unlikely, because the treatment was not randomly assigned, but rather was determined by firms' self-selection into the DSIR registration. As such, the DSIR-registered firms are expected to be different from the non- DSIR-registered firms, and these differences could be related to firm innovation outcomes and be unobserved. For example, more financially constrained firms might have smaller R&D budgets and be more likely to seek R&D tax credit. The DID estimation alleviates the concern of endogeneity due to self-selection by eliminating the group-specific effects (i.e., the comparison of overtime changes in the means for the treatment and control groups is absent of the group-specific effects), but it does not eliminate any confounding differences across firms within each group that existed prior to the treatment. To address the endogeneity concern due to firm selection on individual permanent characteristics, we take advantage of the panel structure of our data and estimate the following specification:

$$In\, Y_{ijt} = \alpha + \alpha_i + \alpha_t + \alpha_j t + \gamma D_{ij} R_t + X_{ijt}\delta + e_{ijt} \qquad (9)$$

where α_i denotes fixed effects for each firm. The inclusion of α_i allows us to control for unobserved cross-firm heterogeneity and thus, weaken the assumption (6). The identifying assumption now allows the treatment to be determined by the firm-specific effects (α_i), in addition to the year effects (α_t), industry-specific time trends ($\alpha_j t$), and covariates X_{ijt}. It only requires that conditional on α_i, α_t, α_j t, *and* X_{ijt} , counterfactual outcomes in the absence of treatment are independent of treatment: $E[\, y_{0ijt} |\, \alpha_{t\,,} \alpha_{j,}\,, \alpha_j t\,, X_{ijt}\,, D_{ij}] = E[\, y_{0ijt} |\, \alpha_{t\,,} \alpha_{j,}\,, \alpha_j t\,, X_{ijt}]$

We then use the sample of firms with over time variation in the registration status ($D_{ijt} \neq D_{ij}$). Among these firms, some firms received initial recognition from the DSIR during the pre-reform years (i.e., they first registered before 2011) while others received initial recognition from the DSIR during the post-reform years (i.e., they first registered in or after 2011). Using within-firm variation in the data, we estimate the changes in firm innovation activity following DSIR registration. The analysis of the timing of registration allows us to address the concern of endogeneity due to confounding policy changes implemented in India in tandem with the 2010-11 R&D tax credit reform. It also allows us to evaluate how the changes in firm innovation activity following DSIR registration were impacted by the 2010-11 reform. We estimate the following specification:

$$ln\, Y_{ijt} = \alpha + \alpha_{\mathrm{i}} + \alpha_{\mathrm{t}} + \alpha_{\mathrm{j}} t + \phi\, D_{ij} + \psi\, D_{ij} R_t + X_{ijt}\delta + e_{ijt} \qquad (10)$$

This specification yields estimates of the effect of DSIR registration in the pre-reform years and the differential effect of DSIR registration in the post-reform years, which are respectively captured by the coefficients on the variable D_{ij} and the interaction term $D_{ij}R_t$. Identification comes purely from the within-firm over time variation in the variables of interest. The percentage change in the outcome following DSIR registration equals *[exp(φ) − 1]100* for firms that registered before the reform and *[exp (φ + ψ) − 1]100* for firms that registered after the reform. The percentage effect of the reform thus equals *[exp(ψ) − 1]100*.

Our analysis allows us to disentangle the three distinct effects of DSIR registration. From the specification (8), the average outcome changed following DSIR registration by a factor of exp(φ) for firms that registered during 2001-2010. This first effect is due to the eligibility for the 150% R&D tax credit. For firms that registered during 2011-2016, the average outcome changed following DSIR registration by a factor of $exp(\varphi + \psi)$. This second effect is due to the eligibility for the 200% R&D tax credit. Last, from the specification (7), the estimate of $\exp(\gamma)$ measures the impact of the reform due to the increase in R&D tax deduction from 150% to 200% for firms long registered with the DSIR.

4.3.2.2 Specification for R&D tax credit reform (2009-10), that extended the provision of the tax credit scheme to all manufacturing industries

In this section, we discuss the specification used to investigate the R&D tax credit policy reform in 2009-10, that extended the provision of R&D tax credit to all industries in India. The R&D tax credit was available only to the firms from drugs and pharmaceuticals, electronic equipment, computers, telecommunications equipment, chemicals, manufacture of aircraft and helicopters, automobiles, and auto parts industries. The 2009-10 reform permit firms from other industries to recognize with DSIR to claim the tax credit. We have classified the firms from new sectors into various sectors based on the NIC-2008 classification. These sectors include firms from Architecture and Civil engineering, Computer programming, consultancy and related activities, Financial service activities and pension funding, Manufacture of coke, beverages, refined petroleum and food products, Manufacture of electrical equipment, Manufacture of leather, textiles and wearing, Manufacture of machinery and equipment, Manufacture of metals, Manufacture of other non-metallic mineral products, Manufacture of rubber and plastics products, Manufacture of wood and products of wood and paper, Retail and wholesale trade and Other manufacturing firms. We evaluate the impact of including all industries under the tax credit scheme.

We study the changes in firm innovation activity following DSIR recognition due to the 2009-2010 reform. For this analysis, we use a sample of firms from the new industries. In case of new industries, the policy reform in 2009-2010 made new industries to register with DSIR, and these firms received initial recognition during post-reform years (i.e. they first affiliated with the DSIR in or after 2010). Accordingly, in our DID setting, we estimate the post-reform trends in the innovation outcome of the firms recognized with DSIR following the new eligibility reform.

We estimate the following specification:

The unit of analysis is firm *i* in industry *j* in year *t*. Let D_{ijt} denote the DSIR registration status dummy variable, which is equal to one if the firm *i* is registered with the DSIR in year *t* and equal to zero otherwise.

The basic statistical model for the observed outcomes is specified as follows:

$$Y_{ijt} = exp\ (\alpha\ + \alpha_t + \alpha_j + \alpha_{jt} + \psi\, D_{ijt} + X_{ijt}\delta\ )e_{ijt,} \qquad (11)$$

where the outcome variable Y_{ijt} is one of the four measures of firm innovation activity. The independent variable D_{ijt} is the treatment dummy variable, equals to one if the firm *i* is registered with the DSIR in year *t* and equal to zero otherwise. D_{ij} allows the outcome to differ across the two groups of firms in the absence of the reform. The vector *Xijt* contains time-varying firm controls, which we discuss in Section 4.7. The model also includes fixed effects for each year (α_t), industry (α_j) and the vector of industry-specific time trends (α_{jt}). Last, α is the constant term, and ε_{ijt} is the stochastic error term which is mean independent of firm group and time, controlling for α_j, α_{jt}, *and* X_{ijt}: $E\ [\varepsilon_{ijt}\,|1,\ \alpha_t,\ \alpha_j,\ \alpha_j\ t,\ X_{ijt},\ D_{ij}] = 1$.

We rewrite the exponential model (11) in the log-linear form as follows:

$$ln\ Y_{ijt} = \alpha\ + \alpha_{\mathrm{t}} + \alpha_{\mathrm{j}} + \alpha_{\mathrm{j}}t + \psi\, D_{ijt} + X_{ijt}\delta + e_{ijt} \qquad (12)$$

This specification estimates the effect of DSIR recognition in the post-reform years, which is captured by the coefficient D_{ijt}. The percentage change in the outcome following the DSIR recognition during the reform thus equals *[exp (ψ)-1]100*.

The DID estimation alleviates the concern of endogeneity due to self-selection by eliminating the group-specific effects (i.e., the comparison of overtime changes in the means for the treatment group is absent of the group-specific effects), but it does not eliminate any confounding differences across firms within each group that existed prior to the treatment. To address the endogeneity concern due to firm selection on individual permanent characteristics, we take advantage of the panel structure of our data and estimate the following specification:

$$ln\, Y_{ijt} = \alpha + \alpha_{\mathrm{i}} + \alpha_{\mathrm{t}} + \alpha_{\mathrm{j}} + \alpha_{\mathrm{j}}t + \psi\, D_{ijt} + X_{ijt}\delta + e_{ijt} \qquad (13)$$

where α_i denotes fixed effects for each firm. The inclusion of firm-fixed effects (α_{t}), in the specifications (11), allows us to control for unobserved cross-firm heterogeneity, as explained earlier. The identifying assumption now allows the treatment to be determined by the firm-specific effects (α_i), in addition to the year effects (α_t), industry fixed effects (α_t), industry-specific time trends ($\alpha_{\mathrm{j}}t$), and covariates X_{ijt}.

4.4. Identification strategy

We use DSIR registration as a treatment indicator for both PSM and DID frameworks. We understand that DSIR registration is a requirement for entering into the treatment group. Hence, there is always a possibility 1) that some DSIR-registered may not apply and hence never got the tax credit; 2) that there are other requirements that made some DSIR-registered companies need to fulfil to avail the tax credit.

We attempted to collect data of firms that availed tax credits. However, the publicly available DSIR Annual Reports list firms that have received tax credits from 2007-08 onwards, but the relevant data are plagued with omissions and inconsistencies. We also undertook substantial steps to clarify the data with the DSIR. This included contacting DSIR agents, via email and telephone, as well as writing the Joint Secretary of the DSIR personally, requesting either the revised data or more reliable data sourced from DSIR's database. Unfortunately, we were not granted access to the data, reportedly due to confidentiality requirements. Despite the unavailability of direct tax credit data, we still expect the DSIR registration variable to effectively capture the R&D tax credit treatment for the following three reasons:

1. The sample of firms: Our sample is skewed towards large companies, which are large R&D spenders. These companies benefit significantly from the R&D tax credit and are thus highly likely to apply for it.

2. The DSIR registration costs and benefits: Registration with the DSIR is costly for a firm, in terms of time and effort spent to meet the stringent requirements for both initial recognition and subsequent maintenance of the DSIR registration status. Given these costs, a firm that does not reap sufficient benefits from the registration would choose to "exit" the registration. Some firms in our sample do in fact exit. So we also conduct sensitivity analysis of results by dropping these firms from our data. The major benefit of DSIR registration is the R&D tax credit scheme. The manufacturing firms registered with the DSIR are eligible for three other fiscal benefits, but only 8 (out of 806) firms in our sample claimed these benefits (used in DID framework).
3. Dropping these firms from our data does not have a significant impact on our results. The major benefit of DSIR registration is the R&D tax credit scheme. The manufacturing firms registered with the DSIR are

eligible for three other fiscal benefits, but only 8 (out of 806) firms in our sample claimed these benefits (used in DID framework).

4. The empirical strategy: We are not confident that *all* DSIR-registered firms in our sample have utilized the R&D tax credit annually. Our treatment variable is likely noisy. So, in the DID framework, we designed our empirical strategy to minimize the impact of such noise on our estimates. Our controls for firm-specific effects, for example, absorb much of the noise, since they account for permanent differences in the outcomes not only across the two groups of firms (DSIR-registered and non-DSIR registered) but also across individual firms within each group. The controls for firm-specific trends further absorb some of the time-varying noise (that could lead to a violation of the common trends assumption). The analysis of the timing of DSIR registration reveals that the treatment effects do not emerge gradually but rather, firm innovation activity changes sharply around the DSIR recognition year.

We also undertake the sensitivity analysis further to affirm that our results are robust to the noise in the treatment variable. For this analysis, we excluded firms that initially recognized by the DSIR during 2001-2016 but did not maintain their DSIR status in all years and "exited" the registration in some years. Despite being eligible, these firms most likely failed to utilize the tax credit.

Last, we would like to note that working with the DSIR registration data has one important advantage: variation within firms over time in these data reflects long-term changes in R&D taxation, which matter for firm innovation strategy. In contrast, variation within firms over time in the R&D tax credit grants data would largely reflect transitory short-term changes, which are less likely to affect innovation strategy.

4.5. Outcomes of interest

The effectiveness of the R&D incentive differs substantially in terms of the innovation measure used. Yang, Huang, and Hou (2012) estimated the effect of the R&D tax credit on firm innovation in Norway and found that the scheme contributes to innovation in the form of new products for the firm. However, the study did not find positive impact on innovations in the form of new products for the market or patents. It implies that the effectiveness of R&D incentives on innovation may vary depending on the innovation measure.

Thus, in this dissertation, the empirical evidence on the effect of R&D incentives is based on different innovation measures such as R&D expenditure, and patenting. The first level refers to the input additionality, where the degree to which the R&D expenditure of the firm has increased due to the fiscal incentive. The second level refers to the output additionality, which estimates the degree of change in innovation activities of the firm increased by the number of patents.

Most of the micro econometric literature on R&D incentive policies provide estimates of input additionality effect. The additionality of input mainly estimates the crowding-in or crowding-out effect of incentive policy on R&D (David et al. 2000), where the degree to which firm R&D expenditures have increased or decreased due to the public support is estimated. On the other hand, the output additionality estimates the degree of changes in innovation behaviour of firms measured by productivity and increased number of patents (Czarnitzki et al. 2011; Cappelen et al. 2012). The distension of R&D and patents (input and output outcome of innovation) is considered to include the two components of innovation, which differ in many regards, including the purpose, knowledge base and strategic decision of the firm (Hall & Van Reenen, 2000).

While Comparing to empirical evidence on the input additionality, fewer studies looked at the effect of R&D support programs beyond the immediate impact on R&D expenditure, such as patents, which are considered as “new to the market innovations”. Moreover, the aim of the fiscal incentives is to encourage firms’ innovation outputs and to promote the productivity, growth and employment in the economy.

We estimate the effect of R&D tax credit on four different outcome variables: the level of R&D expenditure; the R&D intensity, measured as the ratio of R&D expenditure to sales; the number of patent applications filed at the IPO; and the number of patents filed at the USPTO. The level of R&D expenditures is a proxy for innovation input. The R&D intensity is a proxy for the intensity of the firm input activities. The number of patent application at the IPO and USPTO are proxies for firm innovation output.

First, we examine if the tax incentive program affects firms’ composition of R&D investment. The firm’s orientation towards the R&D composition is an important dimension of behavioural additionality (Dai et al. 2020). We use R&D intensity as a proxy for the intensity of firm’s innovation input activities. González and Pazó (2008) used R&D intensity as a proxy for innovation and find that R&D incentives significantly enhance the R&D intensity of the Spanish manufacturing firms. Czarnitzki and Licht (2006) examined the effect of R&D subsidies on R&D intensity of the firm and estimated the incremental R&D on innovation output.

We also examine the impact of the tax credit on innovation outcomes of the firm measured by patent applications. Patenting is considered as an important measure while evaluating the effect of R&D incentives (Cappelen et al. 2012). It is interesting to see whether innovation output in the form of patenting has increased due to the use of tax credit. The positive effects denote fewer chances of re-labelling the R&D units. Wang et al. (2018) considered USPTO patents as a proxy to study the relationship between the level of government intervention and innovation performance in Singapore and Hong Kong. In India, empirical studies like Ambrammal and Sharma (2014, 2016); Dhanora et al. (2018) employed patent data from the Indian Patent Office (IPO) as a measure of firm innovation. Thus, we consider the patents filed by the sample firms in IPO and USPTO as a measure of innovation outcome. The patent data from both the IPO and the USPTO strengthens our analysis. The territorial nature of the patent regime necessitates the use of patent data from the domestic patent office, while the USPTO data allows us to account for most valuable inventions. Moreover, obtaining an international patent is much costlier than obtaining a national patent, and firms; R&D budgets are typically small around the time of initial DSIR registration.

4.6. Data sources

We identify firms based on the National Industrial Classification (NIC) 2008 via NIC 2004. The firm-level data for the study is collected from the Centre for Monitoring Indian Economy (CMIE) prowess database. CMIE database provides annual report data of firms that are listed in the Bombay Stock Exchange (BSE). Considering we have data for listed and large private limited companies, the sample does not include the small firms. We acknowledge that most beneficiaries of the R&D tax credit in India are small firms with low-scale R&D centre (Mani, 2010). However, given the data constraints, we are not able to cover those firms.

The patent data is collected from the website of the Controller General of Design, Trademark and Patent during 2001-2016. The Indian Patent Office (IPO) maintains the patent record in India. To check the authenticity of the collected sample, we have verified it with IPO annual reports with their respective years.

To estimate the effect of R&D tax incentive scheme on innovation, we construct a panel dataset which contains firm-level observations of DSIR and non-DSIR firms during the period 2001-16. The firm-level data is suitable to compare continuity of participation in the tax credit scheme throughout the period. To account for the issue of potential selection bias, our study considers only the firms that invest in R&D. As mentioned earlier, firms should have in-house R&D facility to DSIR to avail the tax credit; thus we consider only innovating firms. To capture the R&D tax policy change, we have used two time periods- i.e., 2001-2010 and 2011-2016. The literature suggests that R&D behaviour of the firm is industry-specific and to capture such effects of the R&D tax credit, we have segregated the analysis into different industries.

Till 2009-10, the R&D tax credit was available only to the companies engaged in the production of drugs and pharmaceuticals, electronic equipment, computers, telecommunications equipment, chemicals, manufacture of aircraft and helicopters, automobiles, and auto parts. These industries are matched with three-digit National Industrial Classification (NIC) 2008 to categorize the firms on industry groups. The NIC classification of industries is presented in Table 5.1.

In India, firms are not obliged to report R&D expenditure if the R&D investment is below 1% of their total sales; hence the value for such firms in CMIE shows nil (Kumar & Aggarwal, 2005; Kathuria, 2008). The present study addresses this problem of nominal unreported R&D expenditure by including the R&D reported by the recognized firms in DSIR annual reports. For the control group firms, as we are using data of innovating firms only, the issue of nominal unreported data does not arise. Table 4.1 lists the industries considered for the study, after the data cleaning process.

Table 4.1: Industry coverage

Manufacture of	NIC 2008 code
Original Industries	
Chemicals & chemical products	2011, 2012, 2013, 2021, 2022, 2023, 2029, 2030
Pharmaceuticals & botanical products	2100
Computer, electronic & optical products	2610, 2620, 2630, 2640, 2651, 2652, 2660
Motor vehicles & transport equipment	2211, 2910, 2930, 3091, 3092, 3099
New Industries	
Architecture and Civil engineering	7100, 7110, 8106, 8108, 8109, 4210, 4220, 4220, 4290
Computer programming, consultancy and related activities	6201
Financial service activities, except insurance and pension funding	6419, 6430, 6499
Manufacture of coke, beverages, refined petroleum and food	1010, 1040, 1062, 1071, 1072, 1073, 1075, 1079, 1102, 1104, 1118, 1920
Manufacture of electrical equipment	2710, 2720, 2732, 2740, 2750, 2790
Manufacture of leather, textiles and wearing	1311, 1312, 1313, 1399, 1410, 1430, 1463, 1512
Manufacture of machinery and equipment	2811,2813, 2814, 2816, 2819, 2821, 2822, 2824, 2825, 2826, 2829
Manufacture of metals	2410, 2420, 2431, 2432, 2511, 2513, 2591, 2599
Manufacture of other non-metallic mineral products	2302, 2310, 2391, 2392, 2393, 2394, 2399
Manufacture of rubber and plastics products	2219, 2220
Manufacture of wood and products of wood and paper	1620, 1640, 1701, 1702
Retail and wholesale trade	4530, 4610, 4620, 4649, 4651, 4652, 4659, 4661, 4663, 4669, 4690, 4700, 4773
Other manufacturing	3200, 3211, 3230, 3250, 3290, 3400 3510, 6100, 7200, 7210, 7700, 8299, 8911

4.7. Definition of variables

As discussed earlier, to deal with the selectivity issues, we use propensity score matching estimators that have recently been used in firm-level studies (Arnold & Hussinger, 2005; Lööf & Heshmati, 2005; Yasar & Rejesus, 2005). To calculate the propensity score, we need to understand the factors that contribute significantly to determine the firm's participation in the R&D incentive scheme. The selection of covariates is made based on the existing empirical studies in India. The summary of variables is presented in Table 4.2.

We consider factors that influence simultaneously the participation decision and the outcome variable based on economic theory, previous research, and our understanding of the c (Sianesi, 2004; Smith & Todd, 2005; Caliendo & Kopeinig, 2008; Petelski et al. 2019). A detailed discussion of the covariates is given below:

Location:

An industrial cluster consists of a large number of firms located in a small geographical region. The industrial clusters enable knowledge spillover between the firms (Stewart & Ghani, 1991). It facilitates the information diffusion of markets and technologies, which benefits firms and may promote firm R&D investment. Thus, we assume that a firm located in an industrial cluster has a high possibility of participating in the program as others may be doing so.

Foreign Ownership:

Studies suggest that the R&D behaviour of firms may vary with foreign and domestic ownership status. Sasidharan and Kathuria (2011), for example, find that Foreign Direct Investment (FDI) inflows influence the innovation activity by providing access to more funds. There is also evidence that foreign affiliation can reduce the probability of receiving

R&D incentives (Busom, 2000; Hussinger, 2008; Hud and Hussinger, 2015). Ghosh (2009) also argues that the capital structure has an impact on the R&D decisions of the firms, and find evidence of R&D efforts across the firm ownership. We include this control since the R&D tax credit is available to both domestic and foreign firms operating in India with in-house R&D units. To test the relationship between participation in R&D tax incentive and firm ownership, we use foreign ownership status measured through the percentage of foreign equity promoters (Basant, 1997)

Age of the firm:

A company will accumulate experience and knowledge which is necessary to innovate (Sørensen & Stuart, 2000). The age of a firm is expected to have a positive influence on its motivation to participate as it will have resources to conduct R&D. Older firms in India are more R&D intensive (Sasidharan & Kathuria, 2011) and so, may be more likely to seek recognition for their R&D units from DSIR. The age of the firm is calculated as the difference between the present year and the year of incorporation of a firm.

Exporter:

Goldar and Renganathan (1998) and Aggarwal (2000) document a positive relationship between the R&D intensity and export orientation of Indian firms. The export orientation captures the international experience of the firm. Therefore, the exporting firms are more likely to seek recognition from the DSIR. Accordingly, we introduce a dummy variable for the export status of the firm.

Raw material imports:

In an emerging economy context, raw materials imports influence the decision of the firm to conduct R&D and hence participate in the schemes. The adoption and absorption of imported raw material to local conditions may warrant in-house R&D. Recent studies on manufacturing firms in India show a positive effect of raw material imports on R&D investment (Bhat & Narayanan, 2009; Sasidharan & Kathuria, 2011).

Technology Imports:

Import of technology is a major source of technology transfer, especially in the case of developing countries. The technology acquisition helps firms to adopt new technologies and facilitates to expand new business opportunities (Dosi, 1982). Moreover, these technology acquisitions help firms to focus on their resources and capabilities for building core technological competencies (Tiwana & Keil, 2007). Technology imports can be in the form of embodied, through imports of capital goods or disembodied through the royalties, licensing, and technical fees paid by domestic firms for using the technology of foreign firms. The absorption capacity building hypothesis suggests a complementary relationship between in-house innovation and technology imports (Cohen & Levinthal, 1989). In contrast, the transaction cost theory states the existence of a substitute relationship between these two (Pisano, 1990). In the case of India, the literature provides mixed evidence on technology imports and innovation. Katrak (1989), Siddharthan (1992), and Aggarwal (2000) find a complementary relationship between innovation and disembodied technology imports, whereas Basant (1997) find a positive relationship between embodied technology imports and innovation.

Leverage:

The capital market imperfections affect adversely on the investment decisions of the firm (Hubbard, 1998). Moreover, the issue of financing is more predominant in the case of financing in R&D activities due to the higher risk and uncertainties associated with it. Hall and Lerner (2010) point out that the riskiness, uncertainty, and absence of collateral together act as a barrier for financing R&D projects. Brown et al. (2012) outlines the potential challenges associated with financing R&D and pointed out that financing constraints are a major barrier for innovative firms. Moreover, procurement of external finance is a major obstacle for financing innovation activities due to the information asymmetries (Harhoff & Korting, 1998) In India, less leveraged firms invest more in R&D (Ghosh, 2009), and are likely to participate more in incentive support schemes. Sasidharan et al. (2014) examine the role of financing constraints on the R&D expenditure of Indian manufacturing firms and find a significant positive relationship between a firm's R&D expenditure and internal cash flow during the period 1991–2011. Feldman and Kelley (2006) study the US firms that applied for the US Advanced Technology program and find that the R&D subsidy increased the external funding possibilities of the recipients. These funding possibilities reduce the financial constraints of financing innovation, especially for small and medium firms. Similarly, Meuelman and Maeseneire (2008) confirm that the R&D grant has a positive effect on access to external finance in small and medium-sized firms in Belgium. To account for the relevance of firm's financial constraints, we control for leverage, which is measured as the ratio of the firm's total borrowings to total assets.

HHI:

The Schumpeterian school of thought emphasizes the relationship between market concentration and innovation, where few firms dominate the market conducive for innovative activities. Schumpeter (1942) suggests that in a competitive industry, the increased market competition declines R&D activities. On the other hand, studies like Arrow (1972), Blundell et al. (1999) and, Raymond and Plotnikova (2015) advocate the positive the relationship between competition and innovation. In the case of a competitive industry, a firm may need to become more innovative to survive the competition. In the Indian context, Kumar (1987) find that market concentration had an adverse effect on R&D activities of manufacturing firms. Whereas Dhanora et al. (2020) find an inverted-U shaped relationship between innovation and competition in high and medium technology firms in India. Hirschman- Herfindahl index (HHI) is a commonly used measure of market concentration. HHI is measured as the sum of the square of the sales' share of each firm in a year. Especially in the case of India, considering the legacy of regulation, HHI reflects the industry-level competition with the understanding that, to survive in a competitive industry firm would participate in an incentive scheme to reduce the cost of R&D.

Firm Size:

Firm's size is one of the major determinants of the innovation ability of the firm. Due to the availability of external financing and economies of scale, larger firms tend to be more innovative and productive (Cohen & Levinthal 1989). The Schumpeterian notion of innovation supports the view that larger firms would spend more on R&D relative to their size than small firms (Shumpeter, 1942). Similarly, Galbraith (1952) argued that large firms would find R&D investments less risky than small firms and tend to invest more. However, there are empirical studies that have brought out various other patterns between firm size and innovation. For instance, studies like Acs and Audretsch (1988), Kumar and Saqib (1996), Pradhan (2002), Kumar and Aggarwal, (2005) find a U-shaped relationship between firm size and innovation. Katrak (1990) argued that the insulation of large firms due to their domination, coupled with diseconomies and mismanagement of R&D activities could lead to fewer innovations. In the case of R&D tax credit, firms avail the tax credit from the taxable portion of the profit and may vary among the firms due to their different tax positions and size. Hence, larger firms are more likely to use the R&D tax incentives due to their higher R&D investment and tax positions. Oh et al. (2009) find that the credit guarantee policy in South Korea influenced significantly on the firms' ability to maintain their size and increase their survival rate. Hence, we use the gross fixed asset as a measure of the firm size. To address the possible non-linear relationship, we have included a square term of the firm size.

Table 4.2: Outcome and control variables

Outcome variables	**Definition**	**Source of Data**
R&D expenditure	log (R&D exp+1), where R&D exp is deflated R&D expenditure (in M)	CMIE (Prowess)
R&D intensity	100×log (R&D exp/Sales+1)	CMIE (Prowess)
IPO patents	log (PatIPO +1), where PatIPO is the number of IPO patent applications	CGPDT
USPTO patents	log (PatUSPTO +1), where PatUSPTO is the number of USPTO	USPTO Patent Assignment database
Control variables		
Location	A dummy variable = 1 if a firm is located in the industrial cluster	CMIE (Prowess)
Foreign ownership	A dummy variable = 1 if a firm has foreign affiliation	CMIE (Prowess)
Age	Number of years since firm incorporation	CMIE (Prowess)
Exporter	A dummy variable = 1 if a firm is an exporter	CMIE (Prowess)
Raw material imports	Raw material imports as a proportion of sales turnover	CMIE (Prowess)
Technology imports	The sum of capital goods imports and paid royalties and technical fees as a proportion of sales turnover	CMIE (Prowess)
Leverage	Total borrowings divided by total assets of the firm	CMIE (Prowess)
HHI	Hirschman-Herfindhal index	CMIE (Prowess)
Firm size	Log of the gross value of fixed assets	CMIE (Prowess)
Firm size squared	Firm size^2	CMIE (Prowess)

CHAPTER 5

EMPIRICAL EVIDENCE ON THE IMPACT OF R&D TAX CREDIT SCHEME AND ITS 2010-11 REFORM ON INNOVATION ACTIVITY OF THE FIRMS[9]

5.1. Introduction

In this chapter, we present the results of the evaluation regarding the impact of R&D tax credit scheme and its 2010-11 reform, that increased the weighted tax deduction to 200%, on innovation activity of the firms during 2001-2016. From 2001–2010, an R&D tax credit of 150 % provided to firms engaged in manufacturing and production in the following eight industries: drugs and pharmaceuticals, electronic equipment, computers, telecommunications equipment, chemicals, manufacture of aircraft and helicopters, automobiles, and auto parts. In the fiscal year 2010-11, the provision of weighted tax deduction of 150% has increased to 200%.

Using firm-level data from 2001 to 2016, we evaluate the impact of R&D tax credit scheme and its 2010-11 reform on innovation activity of the firms. In a PSM and DID, we evaluate the change in innovation activity following the reform in DSIR-registered firms relative to non-DSIR-registered firms. In PSM framework, we examine the counterfactual situation, where how the innovation activity of the DSIR-registered firms changed if they would not be registered with DSIR. The DID framework considers the timing of DSIR registration and examines how the 2010-11 reform has impacted the firm innovation activity following registration. As

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per the discussions in the previous chapter, we estimate the impact of reform on outcome variables such as R&D expenditure, R&D intensity, IPO patent applications, and USPTO patent applications.

The rest of the chapter is organized as follows: Section 5.2 provides estimation results of the propensity score (PSM). Section 5.3 provides the estimation results of Difference-in-Difference (DID).

5.2. Estimation results of Propensity Score Matching (PSM)

We estimate the average treatment effect on the treated (ATT), which is given by the difference between expected outcome values with and without DSIR registration for firms that received DSIR recognition. We construct a panel dataset which contains firm-level observations of DSIR and non-DSIR firms during the period 2001-2016. The firm-level data is suitable to compare continuity of participation in the tax credit scheme throughout the period. In India, only those firms with one or more functional in-house R&D units are eligible for DSIR recognition. To account this policy framework, we consider only the non-DSIR firms that invest in R&D, thereby can eliminate the potential section bias in the sample selection.

To capture the R&D tax policy reform, we use two time periods- i.e., 2001-2010 and 2011-2016. The literature suggests that R&D behaviour of the firm is industry specific. To capture such effects of the R&D tax credit, we classify the sample firms into four major industry groups namely, *Motor vehicles & transport equipment, Chemicals & chemical products, Computer, electronic & optical products, and Pharmaceuticals & botanical products*. The NIC-2008 classification of firms and their industry-wise distribution is presented in Table 5.1. The firm coverage, by sector and DSIR recognition status of sample firms, are shown in Table 5.2. The dataset contains 788 firms during 2001-10 and 857 firms during 2011-16.

Table 5.1: Industry classification of the sample firms

Manufacture of:	NIC classification	Number of firms (2001-10)	Number of firms (2011-16)
Motor vehicles & transport equipment	2910,3091,3092, 2211, 3099, 2930	151	186
Chemicals & chemical products	2011,2012, 2013, 2021, 2022, 2023, 2029,2030	299	285
Computer, electronic & optical products	2610, 2620, 2630, 2640, 2651, 2652, 2660	99	105
Pharmaceuticals & botanical products	2100	239	281
Total		788	857

Note: Authors' calculations.

Table 5.2: Firm coverage, by sector and DSIR recognition status over 2001-2016

	2001-2010			2011-2016		
Manufacture of:	DSIR not recognized firms (%)	DSIR recognized firms (%)	Total number of firms	DSIR not recognized firms (%)	DSIR recognized firms (%)	Total number of firms
Motor vehicles & transport equipment	80 (21.39)	71 (17.14)	151	84 (24.70)	102 (19.72)	186
Chemicals & chemical products	153 (40.90)	146 (35.26)	299	120 (35.29)	165 (31.91)	285
Computer, electronic & optical products	45 (12.03)	54 (13.04)	99	42 (12.35)	63 (12.18)	105
Pharmaceuticals & botanical products	96 (25.66)	143 (34.54)	239	94 (27.64)	187 (36.17)	281
Total	374	414	788	340	517	857

Note: Authors' calculation.

Table 5.3 lists the outcome and control variables and their definitions. The control variables are used for the probit estimation to calculate propensity scores. The outcome variables are defined as follows: Deflated R&D expenditure; R&D intensity *(R&D exp/Sales);* IPO and USPTO patent application numbers, respectively.

Table 5.3: Summary of variables

Outcome variables:	Definition
R&D expenditure	Deflated R&D expenditure (in Million)
R&D intensity	R&D expenditure as a proportion of sales (R&D exp/Sales)
IPO patents	Number of IPO patent applications
USPTO patents	Number of USPTO patent applications
Control variables:	
Location	A dummy variable = 1 if a firm is located in the industrial cluster
Foreign ownership	A dummy variable = 1 if a firm has foreign affiliation
Age	Number of years since firm incorporation
Exporter	A dummy variable = 1 if a firm is an exporter
Raw material imports	Raw material imports as a proportion of sales turnover
Technology imports	The sum of capital goods imports and paid royalties and technical fees as a proportion of sales turnover
Leverage	Total borrowings divided by total assets of the firm
HHI	Hirschman-Herfindhal index
Firm size	Log of the gross value of fixed assets
Firm size squared	Firm size^2

Table 5.4 presents the mean statistics of the treated group of DSIR-registered firms and the potential control group of non-DSIR firms before matching. The t-test indicates the systematic difference between the covariates of DSIR and non-DSIR-registered firms. The DSIR registered firms in the sample are more likely to be foreign-owned firms and are exporters. Moreover, the affiliated firms on an average are less leveraged indicating good financial health. Table 5.5 also shows that the tax credit participants have a better performance in terms of outcome variables such as R&D expenditure, R&D intensity, IPO and USPTO patent applications during the study period. It is indeed intriguing that firms having the capability in terms of R&D do not participate in the tax credit scheme. A possible explanation is that the red tape associated with the procedure is cumbersome, and firms are likely to invest in R&D for their long-term survival in the industry irrespective of the credit scheme. This issue is worth academic exploration that is not within the scope of current work.

Table 5.4: Descriptive statistics: Mean comparison of treated and control firms, before matching

	2001-2010					2011-2016				
Variable	Non-DSIR firms		DSIR firms		t-test	Non-DSIR firms		DSIR firms		t-test
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Covariates										
Location	0.688	0.008	0.693	0.009		0.729	0.010	.697	0.009	**
Foreign ownership	0.060	0.004	0.085	0.005	***	0.042	0.004	0.079	0.005	***
Age	23.831	0.298	29.774	0.353	***	25.581	0.407	31.175	0.355	***
Exporter	0.584	0.008	0.874	0.006	***	0.577	0.011	0.827	0.007	***
Raw material imports	0.106	0.013	0.142	0.005	**	0.127	0.030	0.188	0.006	**
Technology imports	0.026	0.006	0.015	0.002		0.093	0.077	0.014	0.002	
Leverage	0.401	0.064	0.286	0.005		0.240	0.015	0.247	0.006	
HHI	0.053	0.001	0.052	0.001		0.065	0.002	0.062	0.002	
Firm size	4.861	0.051	6.89	0.032	***	5.414	0.068	7.428	0.033	***
Firm size squared	32.669	0.437	50.171	0.461	***	38.570	0.627	58.021	0.486	***
Outcome variables										
R&D expenditure	15.107	1.538	145.420	12.612	***	26.649	2.292	391.155	30.630	***
R&D intensity	0.091	0.043	0.033	0.002		0.016	0.005	0.047	0.003	***
IPO Patent applications	0.261	0.047	3.008	0.266	***	0.590	0.116	3.121	0.292	***
USPTO Patent applications	0.046	0.513	0.760	3.315	***	0.0564	0.562	0.911	4.412	***
Number of observations	6047					4681				

Notes: t-tests are comparisons of means of two sub-samples (DSIR and non-DSIR firms). The null hypothesis states that there is no difference between the DSIR and DSIR and non-DSIR firms. Here ***, ** and * denote that coefficients are statistically significant at 1%, 5% and 10%, respectively using a two-tailed test.

Score calculation and validity

To estimate the propensity score (predicted probability of registering with DSIR conditional on firms' observed characteristics), we employ a probit model, where the outcome variable equals one if a firm *i* is registered with the DSIR in year *t,* and zero otherwise. The covariates are selected based on the literature review, which identified the R&D characteristics of firms in India. The propensity score is defined as the conditional probability of receiving a treatment given pre-treatment characteristics in equation (1), Chapter 4.

We separately consider the periods before and after the 2010-11 reform. Table 5.5 shows the probit model estimation results. It appears that all covariates, except for *Raw material imports* and *HHI*, are important determinants of DSIR registration. The probability of firm registration with the DSIR rises with firm's age and size and falls with leverage. Exporting firms are also more likely to be registered with the DSIR.

Table 5.5: The propensity of affiliating with DSIR-Probit model

Variables	2001-10		2011-16	
	Coef.	Std. Err.	Coef.	Std. Err.
Location	0.046	0.039	-.088**	0.045
Foreign ownership	-0.184***	0.067	0.027	0.085
Age	0.009***	0.001	0.007***	0.001
Firm size	0.471***	0.034	0.434***	0.037
Firm size squared	-0.023***	0.003	-0.018***	0.003
Exporter	0.331***	0.050	0.202**	0.051
HHI	0.473	2.17	-0.368	2.513
Raw material imports	0.006	0.029	0.004	0.019
Leverage	-0.371***	0.063	-0.112**	0.046
Technology imports	-0.385**	0.168	-0.179	0.195
constant	-2.189***	0.139	-1.869***	0.147
Time dummies	yes		yes	
Industry dummies	yes		yes	
LR chi2(22)	1471.44		1024.85	
Prob > chi2	0.000		0.000	
Log likelihood	-3404.024		-2687.617	
Pseudo R2	0.1777		0.1601	
Observations	6045		4681	

Notes: This table presents results of probit estimation. Here affiliation with the DSIR as the dependent variable. Here ***, ** and * denote that coefficients are statistically significant at 1%, 5% and 10%, respectively.

The distribution of estimated propensity score of DSIR and non-DSIR registered firms are presented in Figures 5.1 and 5.2. As the figures illustrates, the distribution of treated observations shows a higher probability of affiliating with DSIR.

Figure 5.1: Estimated propensity score- Kernal distribution before matching-2001-10

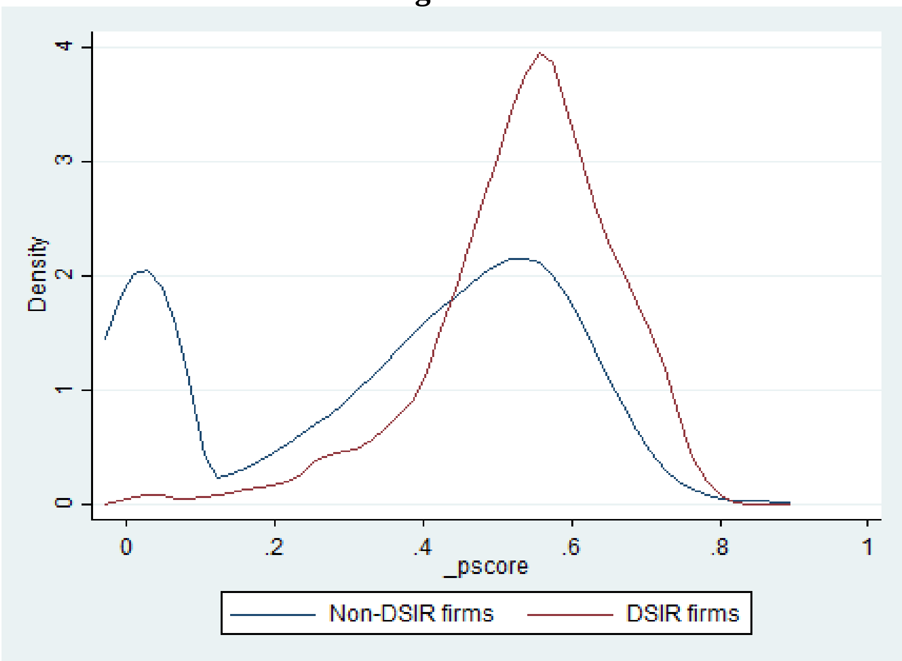
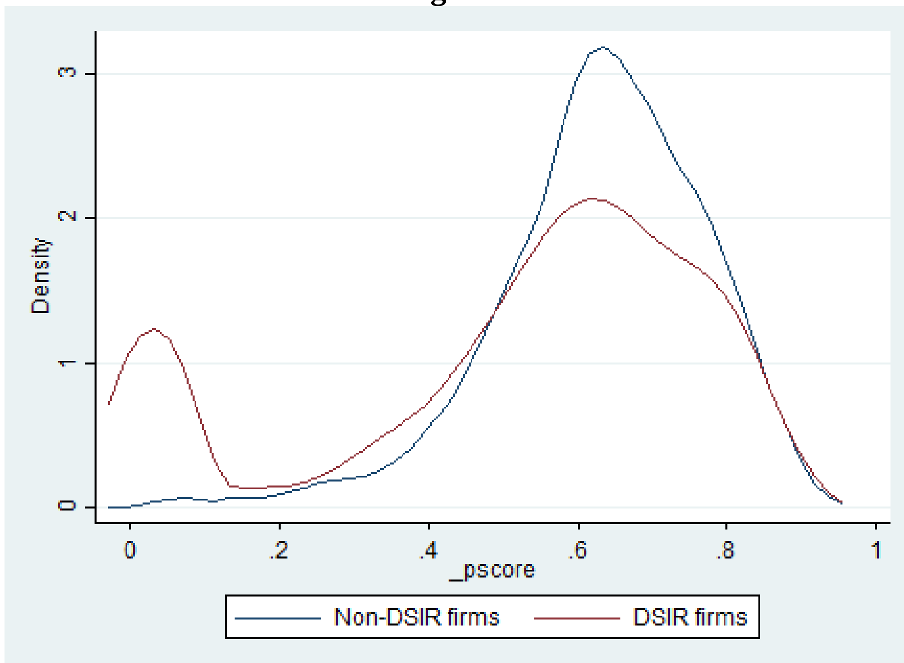


Figure 5.2: Estimated propensity score- Kernal distribution before matching- 2011-2016



Assessing the Quality of Matching

Our estimation procedure is based on the predicted average outcomes in the treated group of DSIR firms compared to the control group of non-DSIR firms. The propensity score matching procedure balances the distribution of observable variables between the treated and the control observations. In such a case, the common support should be assessed to confirm the success of matching between these two groups of observations (Imbens, 2004; Austin, 2011). The common support ensures that the mean propensity score is equivalent in the treatment and control group within each of its quintiles.

Table 5.6 shows the t-test statistic and the corresponding p-value between the covariates of the treated group and the control group after matching. Compared to table 5.4, there is no significant difference between the treated and untreated at the 5% level. This implies the success of matching (Snedecor & Cochran, 1989). We also calculate the mean standardised bias (MSB) of variables, as suggested by Caliendo and Kopeinig (2008). The MSB indicates that the distance in marginal distribution of variable. Most of the empirical studies considers an MSB value as a sufficient indication of the success of matching (Liu et al. 2016). The values of MSB of the variables before and after matching presented in Table 5.7. The percentage of bias is reduced for most of the covariates after matching, that is seen as a sufficient indication of successful matching. We present the distribution of estimated propensity scores after matching in Figure 5.3 and 5.4. It shows the precision in the estimated propensity score. The Figure illustrates that the treated and control observations have the same probability of participating in the R&D tax credit scheme after matching. The two groups' distributions are symmetric, and thus the common support assumption is satisfied.

Table 5.6: Descriptive statistics: Mean comparison of treated and control firms after matching

	2001-2010					2011-2016				
Variable	Non-DSIR firms		DSIR firms		t-test	Non-DSIR firms		DSIR firms		t-test
	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std. Dev.	Mean	Std. Dev.	
Covariates										
Location	0.695	0.461	0.693	0.461		0.708	0.442	0.697	0.459	
Foreign ownership	0.089	0.285	0.085	0.280		0.076	0.160	0.079	0.270	
Age	30.817	19.688	29.774	18.118		30.210	16.340	31.175	18.333	
Exporter	0.857	0.429	0.874	0.332		0.806	0.489	0.827	0.379	
Raw material imports	0.119	0.709	0.142	0.253		0.174	2.232	0.188	0.329	
Technology imports	0.018	0.067	0.015	0.096		0.013	0.080	0.014	0.108	
Leverage	0.266	0.273	0.286	0.244		0.239	0.220	0.247	0.293	
HHI	0.052	0.039	0.052	0.039		0.062	0.082	0.062	0.082	
Firm size	6.586	2.693	6.715	1.702		7.100	2.915	7.383	1.690	
Firm size squared	46.723	25.969	47.993	23.300		57.502	26.886	57.358	24.958	
Outcome variables										
R&D expenditure	34.763	145.898	145.402	647.184	***	22.969	90.366	391.153	1580.658	***
R&D intensity	0.010	0.103	0.031	0.144	***	0.015	0.263	0.047	0.201	***
IPO patent applications	0.263	1.412	3.008	13.645	***	0.438	1.877	3.121	15.085	***
USPTO patent applications	0.039	0.392	0.839	3.845	***	0.074	0.513	0.826	4.162	***
Observations	2633		2633			2663		2663		

Notes: T-tests are comparisons of means of two sub-samples (DSIR and non-DSIR firms). The null hypothesis states that there is no difference between the DSIR and DSIR and non-DSIR firms. Here ***, ** and * denote that coefficients are statistically significant at 1%, 5% and 10%, respectively using a two-tailed test

Table 5.7: Mean standardized bias (MSB) - before and after matching

Variables	2001-10		2011-16	
	% bias-Before matching	% bias-After matching	% bias-Before matching	% bias-After matching
Location	9.2	6.9	-7.8	3.7
Foreign ownership	-0.4	1.2	5.8	2.0
Age	7.1	11.2	-6.0	-2.2
Firm size	0.7	9.5	-8.2	0.0
Firm size squared	0.7	8.9	-3.7	0.5
Exporter	1.7	14.6	34.1	-7.9
HHI	-24.5	-2.4	4.3	40.1
Raw material imports	-5.6	6.9	1.0	-0.2
Leverage	-0.0	1.1	5.0	-2.6
Technology imports	-0.6	-4.2	0.1	-7.2
Observations	6045	5266	4681	5326

Note: % bias is the standardized bias as suggested by Rosenbaum and Rubin (1985).

Figure 5.3: Estimated propensity score- Kernal distribution after matching-2001-10

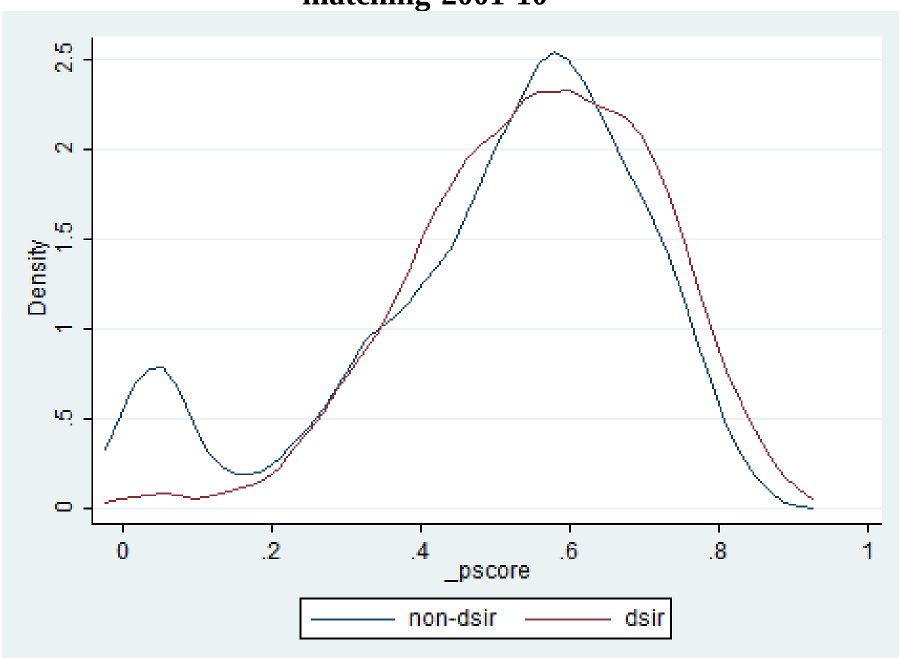
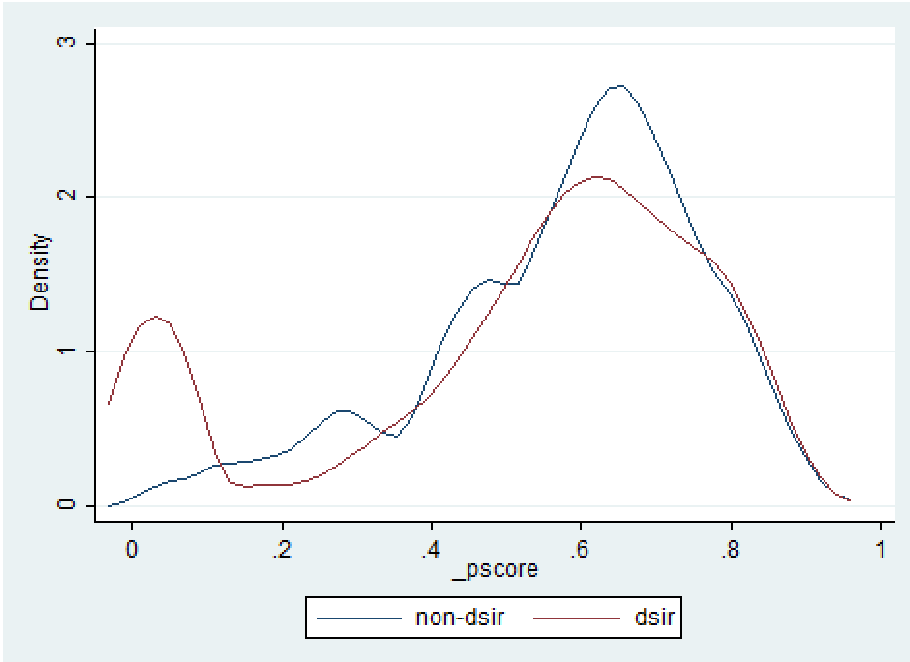


Figure 5.4: Estimated propensity score- Kernal distribution after matching-2011-16



5.2.1. Estimation Results of the average treatment effect on treated (ATT)

In this section, we discuss the estimation results of the average treatment effect (ATT) of the matched sample of DSIR and non-DSIR affiliated firms defined by equation (2). We use 1-1 nearest neighbour matching (NNM 1-1) as suggested by Liu et al. (2016) to estimate the ATT. We also include other matching methods such as 1-3 nearest neighbour matching (NNM 1-3), 1-5 nearest neighbor matching (NNM 1-5) and kernel matching as robustness checks. We respectively identify the impact of R&D tax credit on innovation four outcome variables. The outcome variables are defined as follows: R&D expenditure (in million); R&D intensity measured as R&D expenditure as a proportion of sales; and the number of IPO and USPTO patent applications.

To have a comprehensive evaluation, we estimate the results based on two periods (i.e. 2001-2010 and 2011-2016). The estimation results of ATT on innovation input and innovation output of the firm are presented in the next section. We have also estimated heterogeneity of ATT with respect to year, industry, size, ownership and export status. The Sub-section 5.2.2 provides the summary of the results.

R&D expenditure and R&D intensity

The average treatment effect on treated (ATT) of tax credits on investment (both levels and intensity of R&D) using the full sample are presented in Tables 5.8 and 5.9.

Columns (1) and (5) in Table 5.8 reports the ATT using 1-1 NNM. The results suggest that the treatment yields a positive and significant impact on the R&D expenditure during both the period. We have measured the R&D expenditure in a million Indian rupees and find an average of Rs 139.12 million and Rs 356.06 difference in the R&D investment of treated firms compared to control firms during 2001-10 and 2011-16 respectively. In columns (2)-(4) and (6)-(8), we also employ other matching methods as robustness checks. The ATT estimation results of NNM 1-3, NNM-1-5 and kernel matching indicate a similar positive effect of R&D tax credits on R&D investment in both periods.

Table 5.9 reports the effect of the R&D tax credit on R&D intensity of the firm. Based on the results of 1-1 NNM, the R&D intensity of the participating firms is significantly high by 0.0139 during the period 2001-10 compared to the non-participants of the tax credit scheme. It shows that registration with DSIR increases the R&D intensity by 0.0139 compared to firms not registered. Results of NNM 1-3, NNM-1-5 and kernel matching also indicate similar significant and positive effects of R&D tax credits on R&D intensity. The estimates during 2011-16 show that the difference in the R&D intensity is positive, but not significant. However, the results of NNM 1-3, NNM-1-5 and kernel matching shows a positive and significant effect of the R&D tax credit on R&D intensity of the firms.

While comparing the average treatment of the outcome during both periods, it is observed that the ATT of R&D expenditure is Rs 356.069 million in 2011-16, which is significantly higher than the treatment effect of Rs 139.126 million during 2001-10. It indicates that the policy reform that increased the weighted tax deduction rate from 150% to 200% has positively influenced the R&D spending of the firms.

Table 5.8: The ATT of the tax credit on R&D Expenditure –Full Sample

	2001-2010				2011-16			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NNM 1-1	NNM 1-3	NNM 1-5	Kernel	NNM 1-1	NNM 1-3	NNM 1-5	Kernel
ATT	139.126***	113.6464***	115.962***	119.010***	356.069***	354.236***	354.825***	301.884***
Std. Err.	19.509	18.790	18.535	14.253	31.844	31.519	31.553	27.168
Observations	5266	5266	5266	5266	5,326	5,326	5,326	5,326

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5.9: The ATT of the tax credit on R&D Intensity –Full Sample

	2001-2010				2011-16			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NNM 1-1	NNM 1-3	NNM 1-5	Kernel	NNM 1-1	NNM 1-3	NNM 1-5	Kernel
ATT	0.013**	0.019***	0.019***	0.015***	0.003	0.015**	0.024***	0.028***
Std. Err.	0.006	0.002	0.0028515	0.001	0.010	.007	0.005	0.004
Observations	5266	5266	5266	5266	5,326	5,326	5,326	5,326

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

IPO and USPTO Patent applications

In Tables 5.10 and 5.11, we report the results of the innovation outcome measured by IPO and USPTO patent applications. The estimation results in table 5.10 show the ATT of innovation outcome measured using IPO patent applications. Columns (1) and (5) in Table 5.10 report the ATT using 1-1 NNM. The results reveal a positive and significant difference of 2.71 and 2.45 during 2001-10 and 2011-16 respectively between the treated and non-treated firms. It indicates that the IPO patent applications of a firm rise by 2.71 and 2.45 times during 2001-10, and 2011-16 if the firm register with DSIR. Results of NNM 1-3 and NNM-1-5 in columns (2)-(4) and (6)-(8) also indicate similar significant and positive effects of R&D tax credits on the IPO patent application. The ATT of USPTO patent applications shown in Table 5.11 is positive and significant by 0.797 and 0.689 during 2001-10 and 2011-16, respectively. It indicates that the USPTO patent applications of a firm will rise by 0.797 and 0.689 times during 2001-10, and 2011-16 if the firm recognizes with DSIR.

The treatment effect of IPO and USPTO patent applications are higher during the pre-reform compared to the post-reform. One probable explanation given for this is that due to the changes in IPR policies to comply with the Agreement on Trade-related intellectual property rights (TRIPs) under the World Trade Organization (WTO). These policy changes limit the space for imitation goods and encouraged firms to file patents.

While comparing the estimation results of R&D and patents, the ATT of patent outcome falls short during both the periods. Such results are justified, in view of the legacy of Indian firms that are still involved in adoption, absorption, and imitation of the technologies available at the international level.

Table 5.10: The ATT of the tax credit on IPO Patent Applications –Full Sample

	2001-2010				2011-16			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NNM 1-1	NNM 1-3	NNM 1-5	Kernel	NNM 1-1	NNM 1-3	NNM 1-5	Kernel
ATT	2.712***	2.653***	2.659***	2.495	2.455***	2.450***	2.464***	2.072***
Std. Err.	0.270	0.268	0.267	0.288	0.303	0.294	0.294	0.277
Observations	5266	5266	5266	5266	5,326	5326	5326	5326

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5.11: The ATT of the tax credit on USPTO Patent Applications –Full Sample

	2001-2010				2011-16			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NNM 1-1	NNM 1-3	NNM 1-5	Kernel	NNM 1-1	NNM 1-3	NNM 1-5	Kernel
ATT	0.797***	0.794***	0.796***	0.800***	0.689***	0.661***	0.661***	0.702***
Std. Err.	0.075	0.075	0.074	0.064	0.083	0.083	0.082	0.100
Observations	5266	5266	5266	5266	5326	5326	5326	5326

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Different policy regime

Table 5.12 presents the year wise estimates of ATT of the R&D tax credit. The year-by-year ATT effects on R&D expenditure in columns (1)-(2) are positive and significant throughout the study period. The estimates suggest that the average treatment effect of R&D expenditure exhibit an increasing trend during the study period. Moreover, the growth rate is slightly higher during 2011-16, that is mainly attributed to the tax credit policy reform. It indicates that the policy changes in R&D tax credit resulted in encouraging R&D investment of the firms. The year-wise average treatment effect measured through R&D intensity in column (3)-(4) shows that the policy has a positive and significant effect throughout the study period.

In columns (5)-(8), ATT of IPO and USPTO patent applications show a positive and significant effect throughout the period. It is interesting to note that 2001-2005 was an important time-period during which patent policy-related changes were made in India to comply with TRIPS. Considering that such exogenous changes are applicable for both treated and non-treated firms, the difference here cannot be attributed to policy changes. Thus, once again, it is the efficiency with which R&D funds are utilized, and the type of activities (adoption and absorption) as explained above are the major reasons for the difference in the patent applications of participating and non-participating firms.

Table 5.12: The average treatment effect of R&D tax credits on innovation - year wise

	R&D expenditure		R&D intensity		IPO patent applications		USPTO patent applications	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.
2001	35.311***	8.409	0.008***	0.003	0.511***	0.139	0.310**	0.131
2002	48.027***	9.762	0.023***	0.008	1.098	0.346	0.409**	0.162
2003	58.790***	14.480	0.014***	0.002	1.500***	0.388	0.720***	0.211
2004	83.085***	19.865	0.024***	0.006	2.761***	0.680	0.829***	0.284
2005	98.620***	28.106	0.023***	0.003	3.192***	1.118	1.169***	0.388
2006	124.181***	34.708	0.022***	0.004	3.228***	1.033	0.758***	0.220
2007	138.965***	35.606	0.025***	0.009	4.082***	0.947	0.798***	0.159
2008	147.598***	43.194	0.017***	0.005	2.975***	0.635	0.951***	0.289
2009	153.227***	46.975	0.030***	0.015	3.026***	0.711	0.832***	0.198
2010	139.473***	42.871	0.021***	0.009	3.453***	0.901	0.901***	0.290
2011	210.340***	47.918	0.002***	0.030	3.000***	0.728	0.853***	0.153
2012	265.678***	59.607	0.033***	0.008	2.890***	0.685	0.719***	0.161
2013	314.290***	62.549	0.024***	0.011	2.057***	0.589	0.774***	0.193
2014	338.405***	74.520	0.036***	0.014	2.547***	0.744	0.747***	0.194
2015	424.664***	85.088	0.034***	0.008	2.746***	0.827	0.793***	0.231
2016	478.587***	97.670	0.019***	0.008	2.234***	0.768	0.618***	0.186

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Industry specific estimation results

To examine the impact of the tax credit at the sector level, we separately estimate the ATT for firms from all the sectors. We have classified the sample firms into four industries: *Chemicals*, *Pharmaceuticals*, *Computer*, and *Transport*. Table 5.13 reports the effect of R&D tax credit on R&D expenditure and R&D intensity of the firms. Columns (1)-(4) report positive and significant ATT of the tax credit on firms' R&D expenditure in all sectors. The effect is pronounced for the *Transport* and *Pharmaceuticals* sector, with 228.946 million and 150.369 million respectively during 2001-10 and 591.14 and 414.648 during 2011-16. The results also suggest that the ATT R&D expenditure of all industries are significantly higher during 2011-10 than 2001-10, which indicate that the policy reform has resulted in increasing the participating firm's R&D spending.

Columns (5)-(6), the ATT of R&D intensity is positive and significant for all four sectors during 2001-10. In columns (7)-(8), ATT is significant and positive only in *Chemicals* and *Computer* sectors. This indicates that the policy reform is reflected only for chemical and electrical industries in terms of firm innovation input intensity.

From columns (1)-(2) and (5)-(6) in Table 5.14, the ATT of the innovation outcome measured through IPO and USPTO patent applications show a positive and significant effect for *Transport* and *Pharmaceutical* sectors during 2001-10. The results are not significant for *Chemical* and *Computer* sectors. During 2011-16, the ATT of *Transport*, *Chemical* and *Pharmaceutical* sectors are positive and significant, indicating that the policy reform positively influenced the IPO patent filings of the treated firms. In the case of USPTO patent applications, the positive effect of reform is driven by *Chemical* and *Pharmaceutical* sectors.

The positive effect of the policy reform is reflected in the *Chemical* and *Pharmaceutical* sectors in terms of patent outcome. It is interesting to note that the treatment effect of *Chemical* sector is positive and significant during the post-reform period, indicating that the positive impact of policy reform in the form of patent outcome mainly driven from the *Chemical* sector.

Table 5.13: The average treatment effect of R&D tax credits on innovation R&D – Based on industry classification

	R&D expenditure				R&D intensity			
	2001-10		2011-16		2001-10		2011-16	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Manufacture of	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.
Transport	228.947***	49.60	591.143***	120.251	0.008***	0.001	-0.037	0.042
Chemicals	14.018***	03.60	73.754***	12.723	0.022***	0.007	0.016***	0.004
Computer	84.524***	15.80	165.349***	45.106	0.028***	0.006	0.072***	0.013
Pharmaceuticals	150.369***	20.40	414.648***	50.233	0.025***	0.004	-0.017	0.024

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5.14: The average treatment effect of R&D tax credits on Patenting – Based on industry classification

	IPO Patent applications				USPTO patent applications			
	2001-10		2011-16		2001-10		2011-16	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Manufacture of	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.
Transport	2.992***	0.783	6.733***	1.189	0.048**	0.024	0.004	0.040
Chemicals	0.462	0.296	1.016***	0.373	0.018	0.024	0.078***	0.019
Computer	-0.237	0.236	-0.367	0.570	0.050	0.039	0.260	0.218
Pharmaceuticals	5.864***	0.565	2.473***	0.306	2.259***	0.183	1.737***	0.229

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Heterogeneity in treatment effects

In this subsection, we further explore the effect of heterogeneity by classifying firms into different groups. The literature on innovation activities by firms in India has revealed heterogenous results among firms. It is shown that innovation activities of the firm considerably vary with the firm size, ownership category and export status. Thus, we also attempt to study if the effect of tax credits varies with such specific firm characteristics. Accordingly, we explore the heterogeneity effect by classifying firms into different groups. The results of kernel matching are presented in Tables 5.15 and 5.16. We used kernel matching in this context due to relatively small sub-sample size for each category.

As discussed earlier, a firm's size is associated with its innovation activities, which may further influence the firm's utilisation of R&D tax credit. We estimated whether the treatment effect is different among firms with varying size. We divided our sample firms into three groups in terms of gross fixed assets: small, medium, and larger firms. The results presented in Table 5.14, shows that the effect of R&D tax credit seems to increase with the firm size. The ATT of larger firms are significant and higher than medium and smaller firms in terms of R&D and patenting. The results suggest that R&D tax credit have the most significant influence on the larger firm's innovation activities and the treatment effects of small and medium firms are smaller than the large firms. We also estimate the ATT based on the ownership status of the firm on utilizing the R&D tax credit. Firms are classified into two domestic and foreign firms. Our estimates suggest that foreign firms have a higher ATT compared to the domestic firms in terms of R&D and patenting. In the Indian context, it has already been established that foreign firms are patenting extensively that may not be supported by the in-house R&D that these firms conduct in India (Ambrammal & Sharma, 2014). One probable explanation given for this is that foreign firms have access to R&D conducted at the headquarters and in the rest of the world by its parent company and subsidiaries. The ATT is also estimated with respect to the export status of the firm. The ATT of exporting firms that registered with DSIR are higher than non-exporting firms in terms of both R&D and patenting activities. Non-exporting firms tend to invest less in innovation activities due to less global exposure.

Table 5.15: Heterogeneity in ATT of R&D expenditure and R&D Intensity -Estimates using Kernel Matching- Classification by Size of the firm, Ownership and Export status

		2001-2010				2011-16			
Variables		R&D expenditure		R&D Intensity		R&D expenditure		R&D Intensity	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.
Size of the firm	Small	9.122	32.672	0.099	0.069	33.424	37.582	0.155***	0.053
	Medium	18.463***	03.270	.0195***	0.001	34.912***	5.379	0.030***	0.004
	Large	480.261***	60.021	0.015***	0.001	947.036***	82.617	0.022***	0.003
Ownership	Domestic	100.444***	14.597	0.015***	0.001	283.577***	23.683	0.030***	0.004
	Foreign	223.689***	52.173	0.021***	0.006	490.796***	153.169	0.016***	0.004
Export status	Exporters	138.180***	20.226	0.016***	0.001	349.118***	32.497	0.030***	0.003
	Non-Exporters	-8.553	9.797	0.010*	0.006	84.429***	25.283	0.059***	0.014

Notes: This table presents the treatment effect of the DSIR registration. Classifications are based on the sample firms. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5.16: Heterogeneity in ATT of IPO and USPTO Patent Applications -Estimates using Kernel Matching- Classification by Size of the firm, Ownership and Export status

		2001-2010				2011-16			
Variables		IPO patent Applications		USPTO patent Applications		IPO patent Applications		USPTO patent Applications	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.
Size of the firm	Small	-0.582***	0.215	15.863	13.437	-0.684	0.589	0.113**	0.049
	Medium	1.010***	0.159	0.328***	0.050	0.394***	0.138	0.169***	0.053
	Large	6.852***	0.688	2.326***	0.288	6.361***	0.711	1.797***	0.254
Ownership	Domestic	1.959***	0.250	0.745***	0.067	1.664***	0.238	0.716***	0.083
	Foreign	7.555***	1.731	1.554***	0.438	4.953***	1.559	0.918***	0.238
Export status	Exporters	2.832***	0.346	0.851***	0.080	2.291***	0.286	0.771***	0.0942
	Non-Exporters	0.212*	0.126	0.407	0.148**	1.096***	0.316	0.281***	0.059

Notes: This table presents the treatment effect of the DSIR registration. Classifications are based on the sample firms. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

5.2.2 Summary of results

The estimation results of ATT find that the R&D tax credit is significantly enhancing the R&D and patenting activities at the firm level. The DSIR affiliated firms realise higher R&D expenditure and patenting during the study period compared to the non-affiliated firms. We find that the R&D expenditure of the DSIR registered firms raised 139.126 million during the pre-reform and 354.069 million in the post-reform period. The R&D intensity has increased by 0.013 and 0.003, respectively, during the pre and post-reform. Innovation outcome in the form of patenting, IPO patent applications raised by 2.712 and 2.455 during both the periods. The USPTO patents raised by 0.712 and 0.689 during the pre and post-reform period for DSIR registered firms.

The industry-wise estimates show that the R&D expenditure has increased for DSIR registered firms compared to the non-participants in all four industries. The R&D intensity also indicates a positive increase in the case of all sectors except the pharmaceutical sector during 2011-16. The chemical and pharmaceutical sectors mainly drive the positive effect of the tax credit scheme on innovation outcome in the form of patent applications. The heterogeneities with respect to the firm characteristics reveal that the large firms benefit more from the tax incentive as compared to relatively small firms in terms of both R&D and patents. Mani and Nabar (2016) point out that the mostly small and medium firms benefit from the tax incentive scheme in India. Our sample firms skewed towards larger firms in India, that implies invariably, we focus on large firms that are affiliated with DSIR. The effect of the scheme is more for the exporting firms compared to non-exporters. Other interesting findings with respect to the ownership of the firm reveal that the impact of the tax credit scheme is more for foreign-owned firms. Such results highlight the need for policy initiatives for small and domestic firms.

5.3. Estimation results of Difference-in-difference (DID)

As discussed earlier, we consider the fact that not all firms have registered with DSIR by 2016, and that did vary by year of registration. In a DID framework, we evaluate the change in innovation activity following the 2010-11 reform in DSIR registered firms relative to non-DSIR firms. We also study the timing of DSIR registration and examine how the 2010-11 reform impacted the changes in firm innovation activity following the registration.

Out of 804 firms in our sample, 385 firms were never registered with DSIR, and 174 firms were always registered with DSIR during the sample period. The remaining 245 firms changed their DSIR registration status during the 2001-2016 period. Table 5.17 shows the breakdown of these 245 firms by years of initial DSIR recognition. Of these 245 firms, 174 (71%) firms received DSIR recognition during the pre-reform years of 2001-2010, and 71 (29%) firms received DSIR recognition during the post-reform years of 2011-2016. Most of these firms (217 out of 245) maintained their registration with the DSIR every year following initial recognition, but 28 firms “exited” the DSIR registration in some years. Table 5.18 further details on firm coverage, by sector and DSIR recognition status over the 2001-2016 period. From column 2, it appears that the firms in our sample are largely concentrated in two sectors: *Chemical and chemical products* (311 or 39% of firms) and *Pharmaceuticals and botanical products* (234 or 29%). In column 2, we further divide the firms in each sector into two groups: firms registered by the DSIR during 2001-2016 and firms not registered by the DSIR this period. The percentage of DSIR-recognized firms is highest in Pharmaceuticals and botanical products (62.0%), followed by *Computer, electronic and optical products* (50.5%) and *Motor vehicles and transport equipment* (50.6%), while it is noticeably lower in Chemicals and chemical products (46.0%).

Table 5.19 shows the list of the outcome and control variables and their definitions. The outcome variables are defined as follows: R&D expenditure as log *(R&D exp+1)*; R&D intensity as *100×log (R&D exp/Sales+1);* IPO and USPTO patent application numbers as log *(PatIPO +1)* and log *(PatUSPTO +1),* respectively. Table 5.20 provides the summary statistics of the variables.

Table 5.17: Firm coverage by DSIR recognition year

DSIR recognition	Number of firms with $D_{ijt} = D_{ij}$
2001	25
2002	2
2003	1
2004	2
2005	33
2006	19
2007	11
2008	32
2009	26
2010	23
2011	29
2012	6
2013	14
2014	9
2015	8
2016	5
Total	245

Note: Authors' calculations.

Table 5.18: Firm coverage, by sector and DSIR recognition status over 2001-2016

	Number of firms	DSIR firms recognized (% of total)	DSIR not recognized firms (% of total)
Manufacture of:			
Chemicals & chemical products	311	143 (46.0%)	168 (54.0%)
Pharmaceuticals & botanical products	234	145 (62.0%)	89 (38.0%)
Computer, electronic & optical products	99	50 (50.5%)	49 (49.5%)
Motor vehicles & transport equipment	160	81 (50.6%)	79 (49.4%)
Total:	804	419 (52.1%)	385 (47.4%)

Note: Authors' calculations.

Table 5.19: Outcome and control variables

Outcome variables:	Definition of variables
R&D expenditure	log (R&D exp+1), where R&D exp is deflated R&D expenditure (in M)
R&D intensity	100×log (R&D exp/Sales+1)
IPO patents	log (PatIPO +1), where PatIPO is the number of IPO patent applications
USPTO patents	log (PatUSPTO +1), where PatUSPTO is the number of USPTO patent applications
Control variables:	
Location	A dummy variable = 1 if a firm is located in the industrial cluster
Foreign ownership	A dummy variable = 1 if a firm has foreign affiliation
Age	Number of years since firm incorporation
Exporter	A dummy variable = 1 if a firm is an exporter
Raw material imports	Raw material imports as a proportion of sales turnover
Technology imports	The sum of capital goods imports and paid royalties and technical fees as a proportion of sales turnover
Leverage	Total borrowings divided by total assets of the firm
HHI	Hirschman-Herfindhal index
Firm size	Log of the gross value of fixed assets
Firm size squared	Firm size^2

Table 5.20: Summary statistics

Variables	Mean	Std. Dev.	Min	Max
R&D expenditure	109.9	783.2	0	22346
R&D intensity	0.024	0.408	0	34.94
Number of IPO patent applications	1.459	9.743	0	253
Number of USPTO patent applications	0.342	2.436	0	51
Location	0.718	0.45	0	1
Foreign ownership	0.066	0.249	0	1
Age	27.93	17.86	1	137
Exporter	0.62	0.485	0	1
Raw material imports	0.1	0.627	0	57.61
Technology imports	0.012	0.106	0	6.509
Leverage	0.022	0.12	0	6.194
HHI	0.518	0.297	0.003	0.818
Firm size	6.613	1.877	0.132	12.88
Firm size squared	47.26	25.2	0.018	165.9

Note: Authors’ calculations.

To have a comprehensive evaluation, we limit the sample to firms with constant DSIR registration status in sub-section 5.3.1 and 5.3.2 study the timing of DSIR registration. Sub-section 5.3.3 probe the common trends assumption. We conduct additional sensitivity analysis in sub-section 5.3.4. The section 5.3.5 provides summary of the results.

5.3.1. Constant DSIR registration status

The results in this sub-section are from the sample of 559 firms, of which 174 were always registered with the DSIR and 385 were never registered with the DSIR during the 2001-2016 period. We evaluate how innovation activity changed after the 2010-11 reform in the group of DSIR-registered firms as compared to firms not so registered.

Table 5.21 shows the results of estimating the model (4). The outcome variables are: R&D expenditure in columns (1)-(2); R&D intensity in columns (3)-(4); the number of IPO patent applications in columns (5)-(6); and the number of the USPTO patent applications in columns (7)-(8). The key variables of interest are the DSIR registration status dummy variable by itself (D_{ij}) and interacted with the post-reform dummy variable *(D_{ij} R_t)*. All specifications include fixed effects for each year and industry, while the specifications in columns (2), (4), (6), and (8) also include the vector of industry-specific time trends. Robust standard errors are clustered at the firm level in all regressions.

In column (1), the coefficient φ on the variable Dij and the coefficient γ on the term $D_{ij}R_t$ are both positive ($\varphi\hat{}$ = 0.665 and $\gamma\hat{}$ = 0.580) and highly statistically significant. The estimates remain largely unchanged when we also control for the industry-specific time trends in column (2). The results of this statistically more demanding specification imply that compared to the average R&D expenditure in the control group of non-DSIR-registered firms, the average R&D expenditure in the treatment group of DSIR-registered firms was *exp*(0.674) = 1.96 times greater in the pre-reform years and *exp*(0.674 + 0.552) = 3.41 times greater in the post-reform years. The estimate of the multiplicative treatment effect thus equals *exp* (0.552) = 3.41/1.96 = 1.74. It implies that the impact of DSIR registration on firm R&D expenditure has increased by 1.74 times after the reform. In other words, the treatment effect of the reform equals [*exp* (0.552) − 1]100 = 74%.

The results in columns (3)-(4) further show that the increase in R&D expenditure after the reform was accompanied by an increase in R&D intensity. The coefficient on $D_{ij}R_t$ is positive in both columns (1.661 and 1.605), although only marginally statistically significant. The estimate of $\gamma\hat{}$ = 1.605 implies that the impact of DSIR registration on firm R&D intensity has increased by a factor of *exp* (1.605/100) = 1.02 after the reform. Further from column (6), the number of IPO patent applications was *exp*(−0.162) = 0.85 times greater (or 15% lower) in the group of DSIR-registered firms (relative to the non-DSIR-registered firms) in the pre-reform years, and this cross-group difference did not change after the reform. Last from column (8), while the number of USPTO patent applications was *exp*(−0.106) = 0.90 times greater (or 10% lower) in the group of DSIR-registered firms in the pre-reform years, it was only *exp*(−0.106 + 0.050) = 0.95 times lower in the post-reform years. The treatment effect of the reform on the USPTO patent applications is thus positive and equals [*exp* (0.050) − 1]100 = 5.13%.

To allow for firm selection on individual characteristics, we redo the above analysis with controls for firm fixed effects. Table 5.22 shows the results of estimating the model (9). In addition to firm fixed effects, all specifications include year fixed effects, while those in columns (2), (4), (6), and (8) also include the vector of industry-specific time trends. The dummy variable D_{ij} is omitted in these regressions since it does not vary over time.

It is instructive to compare the results in Table 5.21 with the corresponding results in Table 5.20. We see that while the inclusion of firm fixed effects leaves the estimates of γ in columns (1)-(4) and (7)-(8) largely unchanged, it greatly affects the estimates of γ in columns (5)-(6), which are now larger in magnitude (0.097 and 0.100) and more precisely estimated. Thus, when the number of IPO patent applications is the outcome variable, unobserved cross-firm heterogeneity drives the results in Table 5.20 and must be accounted for. The estimates of γ in columns (2) and (6) imply that after the reform, the impact of DSIR registration on firm R&D expenditure has increased by a factor of *exp* (0.575) = 1.78, while that on the number of IPO and USPTO patent applications has respectively increased by a factor of *exp* (0.100) = 1.11 and *exp* (0.059) = 1.06; all three estimates are highly statistically significant. The estimate of γ in column (4) is also positive (1.592) but, again, only marginally significant.

Table 5.21: Constant DSIR registration status, without firm effects

Outcome variables (in logs):	R&D expenditure		R&D intensity		IPO Patents		USPTO Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group dummy (D_{ij})	0.665***	0.674***	1.176	1.188	-0.164***	-0.162***	-0.110***	-0.106***
	[0.149]	[0.149]	[0.911]	[0.902]	[0.057]	[0.057]	[0.035]	[0.035]
Treatment ×Reform dummy ($D_{ij}R_t$)	0.580***	0.552***	1.661*	1.605*	0.072*	0.06	0.061**	0.050**
	[0.085]	[0.081]	[0.927]	[0.873]	[0.042]	[0.040]	[0.025]	[0.023]
Location	-0.021	-0.02	0.281	0.278	0.025	0.026	0.028	0.029
	[0.086]	[0.086]	[0.340]	[0.341]	[0.041]	[0.041]	[0.032]	[0.032]
Foreign ownership	0.177	0.18	-0.342	-0.329	0.226	0.227	0.087	0.088
	[0.209]	[0.210]	[0.422]	[0.419]	[0.150]	[0.150]	[0.086]	[0.086]
Age	-0.001	-0.001	0.001	0.001	-0.001	-0.001	-0.002**	-0.002**
	[0.002]	[0.002]	[0.019]	[0.019]	[0.001]	[0.001]	[0.001]	[0.001]
Exporter	0.741***	0.738***	-0.158	-0.155	0.028	0.029	0.009	0.009
	[0.065]	[0.065]	[0.547]	[0.550]	[0.020]	[0.020]	[0.012]	[0.012]
Raw material imports	0.024	0.02	0.537	0.543	-0.005	-0.005	0	0
	[0.035]	[0.032]	[0.552]	[0.557]	[0.005]	[0.004]	[0.003]	[0.003]
Technology imports	0.253	0.251	0.51	0.52	-0.034	-0.033	0.048	0.045
	[0.232]	[0.232]	[0.663]	[0.677]	[0.060]	[0.060]	[0.046]	[0.046]
Leverage	-0.137*	-0.126*	-0.108	-0.083	-0.063*	-0.064*	-0.007	-0.007
	[0.073]	[0.074]	[0.453]	[0.450]	[0.032]	[0.034]	[0.018]	[0.019]
HHI	-1.745***	-1.761***	-2.321	-2.378	-1.071***	-1.078***	-0.570***	-0.574***
	[0.295]	[0.296]	[2.050]	[2.084]	[0.142]	[0.142]	[0.107]	[0.107]
Firm size	-0.626***	-0.633***	-0.872	-0.906	-0.266***	-0.266***	-0.157***	-0.158***
	[0.099]	[0.099]	[1.190]	[1.198]	[0.053]	[0.053]	[0.045]	[0.045]
Firm size squared	0.080***	0.080***	0.054	0.056	0.028***	0.028***	0.016***	0.016***
	[0.009]	[0.009]	[0.085]	[0.086]	[0.005]	[0.005]	[0.004]	[0.004]
Constant	1.858***	2.002	5.262*	-186.983	1.195***	-38.228***	0.705***	-21.269***
	[0.339]	[14.139]	[3.088]	[159.948]	[0.181]	[6.633]	[0.157]	[5.535]
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry-specific time trends		yes		yes		yes		yes
Observations	8,944	8,944	8,944	8,944	8,944	8,944	8,944	8,944
R-squared	0.643	0.646	0.042	0.044	0.343	0.347	0.246	0.249

Notes: OLS estimation of model (4) for the sample of 559 firms, of which 174 firms were always registered with the DSIR and 385 firms were never registered with the DSIR during 2001- 2016. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(2); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (3)-(4); the number of IPO patent applications, defined as log(PatIPO +1) in columns (5)-(6); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (7)-(8). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5.22: Constant DSIR registration status, with firm effects

Outcome variables (in logs):	R&D expenditure		R&D intensity		IPO Patents		USPTO Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Reform dummy ($D_{ij} R_t$)	0.573***	0.575***	1.557*	1.592*	0.097***	0.100***	0.063***	0.059***
	[0.082]	[0.078]	[0.910]	[0.892]	[0.035]	[0.035]	[0.023]	[0.022]
Location	0.425	0.569*	0.109	-0.121	0.178*	0.289	-0.087	-0.063
	[0.312]	[0.345]	[0.189]	[0.584]	[0.092]	[0.183]	[0.105]	[0.094]
Age	0.019***	0.019**	-0.024	-0.083	-0.004	-0.021***	-0.001	-0.008***
	[0.007]	[0.008]	[0.039]	[0.051]	[0.003]	[0.004]	[0.001]	[0.002]
Exporter	0.682***	0.676***	-0.11	-0.1	-0.003	-0.002	0.01	0.01
	[0.059]	[0.059]	[0.530]	[0.533]	[0.016]	[0.015]	[0.008]	[0.008]
Raw material imports	0.04	0.035	0.569	0.575	0.008	0.008	0.003	0.003
	[0.054]	[0.049]	[0.590]	[0.594]	[0.008]	[0.008]	[0.004]	[0.004]
Technology imports	0.211	0.204	-0.253	-0.239	0.005	0.005	0.021	0.017
	[0.178]	[0.174]	[0.382]	[0.403]	[0.023]	[0.023]	[0.014]	[0.013]
Leverage	-0.013	-0.003	0.321	0.326	-0.024	-0.025	-0.003	-0.005
	[0.059]	[0.057]	[0.338]	[0.352]	[0.018]	[0.019]	[0.007]	[0.008]
HHI	-1.318**	-1.745***	0.473	-0.832	-1.272***	-1.542***	-0.426**	-0.518***
	[0.666]	[0.650]	[3.773]	[3.492]	[0.426]	[0.412]	[0.172]	[0.190]
Firm size	-0.511***	-0.515***	-0.18	-0.247	-0.175***	-0.172***	-0.088***	-0.089***
	[0.093]	[0.088]	[0.361]	[0.397]	[0.036]	[0.033]	[0.024]	[0.024]
Firm size squared	0.069***	0.067***	0.011	0.01	0.020***	0.020***	0.010***	0.009***
	[0.010]	[0.009]	[0.036]	[0.041]	[0.004]	[0.003]	[0.003]	[0.003]
Constant	0.871	3.296	2.207	-106.360*	0.990***	-29.846***	0.495***	-13.620***
	[0.572]	[14.828]	[3.631]	[55.987]	[0.318]	[4.802]	[0.149]	[3.370]
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry-specific time trends		yes		yes		yes		yes
Observations	8,944	8,944	8,944	8,944	8,944	8,944	8,944	8,944
R-squared	0.842	0.845	0.342	0.344	0.738	0.741	0.746	0.749

Notes: OLS estimation of model (4) for the sample of 559 firms, of which 174 firms were always registered with the DSIR and 385 firms were never registered with the DSIR during 2001-2016. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(2); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (3)-(4); the number of IPO patent applications, defined as log(PatIPO +1) in columns (5)-(6); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (7)-(8). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Next, we confirm that our decision to focus on all four sectors together does not drive our results. To show this, we consider four distinct sectors: *Chemicals and chemical products; Pharmaceuticals and botanical products; Computer, electronic and optical products; and Motor vehicles and transport equipment*. We create four dummy variables: *Chemicals, Pharmaceuticals, Computer, and Transport* (one for each sector in that order) and interact each sector dummy variable with D_{ij} and *DijRt*. We then re-estimate the models (4) and (9) with the extended set of regressors. Tables 5.22 and 5.23 show the results.

From columns (1)-(2) in Table 5.23, the coefficient γ on the term DijRt is positive and highly statistically significant in the *Chemicals*, *Pharmaceuticals* and *Transport* sectors. The estimates imply that the impact of DSIR registration on firm R&D expenditure has increased after the reform by *exp*(0.489) = 1.63 times in Chemicals, by *exp*(0.724) = 2.06 times in *Pharmaceuticals* and by *exp*(0.633) = 1.88 times in Transport. In the Computer sector, the reform did not change the impact of DSIR registration on firm R&D expenditure; meanwhile, the impact on firm R&D intensity increased by *exp*(2.196/100) = 1.02 times after the reform, although this effect is statistically significant, it is economically very small. It is further apparent from columns (5)-(6) that the observed post-reform increase in the impact of DSIR registration on the number of IPO patent applications is driven by the *Computer* and *Transport* sectors, where the impact has risen after the reform by *exp*(0.406) = 1.50 and *exp*(0.279) = 1.32 times, respectively. At the same time, the estimate of γ in the *Chemicals* and *Pharmaceuticals* sectors in columns (5)-(6) is not statistically different from zero at the 10% level. Further from column (8), the impact of DSIR registration on the number of USPTO patent applications in the *Computer* sector has risen by *exp*(0.085) = 1.09 times after the reform. The positive and statistically significant at the 5% level coefficient on *Pharmaceuticals* x $D_{ij}R_t$ in column (7) further implies that the impact of DSIR registration on the number of USPTO patent applications in the Pharmaceuticals sector has risen after the reform by *exp*(0.135) = 1.14 times, but this coefficient is not statistically different from zero in column (8), where we also control for industry-specific time trends. These findings remain much the same when we also include firm fixed effects in Table 5.24.

Table 5.23: Constant DSIR registration status by sector, without firm effects

Outcome variables (in logs):	R&D expenditure		R&D intensity		IPO Patents		USPTO Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chemicals × D_{ij}	0.763***	0.737***	1.516**	1.489**	-0.087	-0.095*	-0.038	-0.042
	[0.155]	[0.152]	[0.676]	[0.679]	[0.057]	[0.056]	[0.030]	[0.029]
Pharmaceuticals × D_{ij}	1.044**	0.998**	1.499	1.409	-0.418	-0.426	0.059	0.068
	[0.427]	[0.431]	[2.536]	[2.537]	[0.279]	[0.279]	[0.146]	[0.148]
Computer × D_{ij}	0.873**	0.892**	1.054	1.136	-0.976***	-0.987***	-0.339***	-0.355***
	[0.409]	[0.407]	[2.120]	[2.156]	[0.219]	[0.220]	[0.118]	[0.119]
Transport × D_{ij}	0.679	0.575	-1.025	-1.03	-1.024***	-1.058***	-0.447***	-0.475***
	[0.436]	[0.438]	[2.502]	[2.528]	[0.283]	[0.287]	[0.144]	[0.147]
Chemicals × $D_{ij}R_t$	0.428***	0.489***	1.002	1.08	0.037	0.057	0.007	0.016
	[0.107]	[0.108]	[0.799]	[0.761]	[0.037]	[0.039]	[0.014]	[0.015]
Pharmaceuticals × $D_{ij}R_t$	0.803***	0.724***	2.707	2.811	-0.033	-0.086	0.135**	0.08
	[0.142]	[0.144]	[2.384]	[2.283]	[0.071]	[0.071]	[0.062]	[0.060]
Computer × $D_{ij}R_t$	0.253	0.087	2.460**	2.196**	0.429***	0.406***	0.070**	0.085***
	[0.187]	[0.187]	[1.106]	[1.021]	[0.122]	[0.116]	[0.030]	[0.031]
Transport × $D_{ij}R_t$	0.560***	0.633***	0.195	0.104	0.265***	0.279***	0.013	0.048
	[0.153]	[0.159]	[0.468]	[0.582]	[0.101]	[0.095]	[0.036]	[0.039]
Control variables	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry-specific time trends		yes		yes		yes		yes
Observations	8,944	8,944	8,944	8,944	8,944	8,944	8,944	8,944
R-squared	0.645	0.648	0.047	0.049	0.369	0.372	0.295	0.297

Notes: OLS estimation for the sample of 559 firms, of which 174 firms were always registered with the DSIR and 385 firms were never registered with the DSIR during 2001-2016. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(2); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (3)-(4); the number of IPO patent applications, defined as log(PatIPO +1) in columns (5)-(6); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (7)-(8). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The regressions include the same control variables as in Table 5.20

Table 5.24: Constant DSIR registration status by sector, with firm effects

Outcome variables (in logs):	R&D expenditure		R&D intensity		IPO Patents		USPTO Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chemicals × $D_{ij}R_t$	0.433***	0.502***	1.057	1.131	0.042	0.064	0.011	0.021
	[0.111]	[0.112]	[0.832]	[0.792]	[0.038]	[0.040]	[0.013]	[0.014]
Pharmaceuticals × $D_{ij}R_t$	0.865***	0.796***	2.847	3.039	-0.013	-0.059	0.164**	0.112*
	[0.146]	[0.145]	[2.484]	[2.376]	[0.072]	[0.071]	[0.064]	[0.062]
Computer × $D_{ij}R_t$	0.255	0.112	2.474**	2.165**	0.430***	0.413***	0.071**	0.086***
	[0.196]	[0.195]	[1.137]	[1.060]	[0.126]	[0.121]	[0.030]	[0.031]
Transport × $D_{ij}R_t$	0.592***	0.640***	0.316	0.212	0.280***	0.285***	0.03	0.06
	[0.161]	[0.168]	[0.422]	[0.562]	[0.106]	[0.096]	[0.037]	[0.039]
Control variables	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firms fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry-specific time trends		yes		yes		yes		yes
Observations	8,944	8,944	8,944	8,944	8,944	8,944	8,944	8,944
R-squared	0.843	0.846	0.343	0.344	0.742	0.745	0.748	0.75

Notes: OLS estimation for the sample of 559 firms, of which 174 firms were always registered with the DSIR and 385 firms were never registered with the DSIR during 2001-2016. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(2); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (3)-(4); the number of IPO patent applications, defined as log(PatIPO +1) in columns (5)-(6); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (7)-(8). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The regressions include the same control variables as in Table 5.21.

5.3.2 Time-varying DSIR registration status

In this section, the results are from the sample of 245 firms with over time variation in the DSIR registration status. Out of 245 firms, 174 firms received initial recognition from the DSIR during the pre-reform period of 2001-2010, and 71 firms received initial recognition from the DSIR during the post-reform period of 2011-2016. We evaluate how the changes in firm innovation activity following DSIR registration were impacted by the 2010-11 reform.

Table 5.25 shows the results of estimating the model (10). All specifications include fixed effects for each year and firm. We also include the vector of industry-specific time trends in columns (2), (4), (6), and (8). In these regressions, the coefficients on D_{ijt} and $D_{ijt}R_t$ are identified purely from the within-firm over time variation in the data.

In columns (1)-(6) in Table 5.25, the coefficient φ on the variable D_{ijt} is positive and statistically significant at the 5% level. The estimates of ϕ in columns (2), (4) and (6) imply that following DSIR registration in the pre-reform years, firm R&D expenditure increased by $[e^{0.756} - 1]100 =$ 113%, R&D intensity increased by $[e^{1.058/100} - 1]100 = 1.06\%$, and the number of IPO patent applications increased by $[e^{0.181} - 1]100 =$ 20%.The coefficient ϕ is also positive in column (7) but only marginally significant. Furthermore, the coefficient ψ on the term $D_{ijt}R_t$ (which measures the differential effect of DSIR recognition in the post-reform years) is not statistically significant at the 5% level in any columns. This result implies that there is no statistically significant difference in the impact between firms initially recognized by the DSIR prior to the reform, on the one hand, and firms initially recognized by the DSIR after the reform, on the other hand.

Next, we examine individual sectors. We estimate the augmented model (10), where D_{ij} and $D_{ij}R_t$ are now interacted with the four sector dummy variables, *Chemicals*, *Pharmaceuticals*, *Computer*, and *Transport*. Table 5.26 shows the results. In all four sectors, firm R&D expenditure increased following DSIR recognition in the pre-reform years. R&D intensity also increased in the *Pharmaceuticals* sector, and the number of IPO patent applications increased in the *Pharmaceuticals* and *Transport* sectors. The data do not provide evidence that the number of USPTO patent applications changed following DSIR recognition in any of the sectors. For firms that received initial DSIR recognition during the post-reform years, we find no differential effect with one exception: in *Pharmaceuticals,* the impact of DSIR recognition on the number of IPO patent applications weakened after the reform.

Table 5.25: Time-varying DSIR registration status

Outcome variables (in logs):	R&D expenditure		R&D intensity		IPO Patents		USPTO Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group (D_{ijt})	0.831***	0.756***	1.214***	1.058**	0.186***	0.181***	0.032*	0.024
	[0.106]	[0.099]	[0.456]	[0.466]	[0.046]	[0.048]	[0.019]	[0.020]
Treatment × Reform ($D_{ijt}R_t$)	0.102	0.154	-0.12	-0.024	-0.115*	-0.082	-0.014	-0.01
	[0.139]	[0.138]	[0.654]	[0.629]	[0.065]	[0.054]	[0.024]	[0.024]
Location	-0.866***	-1.201***	-1.818***	-2.313***	0.035	-0.09	0.016	-0.012
	[0.170]	[0.253]	[0.653]	[0.610]	[0.049]	[0.057]	[0.025]	[0.025]
Age	0.048***	0.107***	0.056	0.04	0.011**	0.273***	0.003	-0.005
	[0.014]	[0.026]	[0.041]	[0.113]	[0.005]	[0.028]	[0.003]	[0.008]
Exporter	0.796***	0.810***	1.013**	0.941**	-0.01	-0.015	-0.015	-0.02
	[0.121]	[0.119]	[0.456]	[0.418]	[0.027]	[0.028]	[0.013]	[0.013]
Raw material imports	0.115	0.121	0.611	0.708	0.014	0.029	0.01	0.015
	[0.231]	[0.240]	[0.834]	[0.882]	[0.041]	[0.049]	[0.018]	[0.020]
Technology imports	0.038	0.069	3.584	3.67	-0.029	-0.026	-0.005	-0.005
	[0.104]	[0.104]	[3.199]	[3.258]	[0.043]	[0.041]	[0.020]	[0.017]
Leverage	-0.107	-0.099	-0.727	-0.321	-0.092	-0.115	-0.029	-0.009
	[0.232]	[0.225]	[0.887]	[0.972]	[0.097]	[0.094]	[0.032]	[0.044]
HHI	-0.351	-1.848	10.549	4.223	-0.023	-0.501	0.001	-0.364
	[1.098]	[1.229]	[7.393]	[6.613]	[0.461]	[0.394]	[0.317]	[0.293]
Firm size	-0.572***	-0.636***	1.15	0.78	-0.286***	-0.179***	-0.067	-0.087*
	[0.160]	[0.134]	[0.846]	[0.932]	[0.089]	[0.063]	[0.045]	[0.050]
Firm size squared	0.075***	0.078***	-0.053	-0.031	0.028***	0.018**	0.007	0.009*
	[0.017]	[0.014]	[0.068]	[0.077]	[0.008]	[0.007]	[0.005]	[0.005]
Constant	0.651	123.863**	-8.978**	-18.183	0.43	522.100***	0.075	-14.299
	[0.681]	[49.214]	[3.696]	[236.374]	[0.263]	[52.883]	[0.214]	[13.863]
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry-specific time trends		yes		yes		yes		yes
Observations	3,878	3,878	3,878	3,878	3,878	3,878	3,878	3,878
R-squared	0.739	0.746	0.385	0.396	0.58	0.609	0.465	0.477

Notes: OLS estimation of model (8) for the sample of 245 firms with over time variation in the DSIR registration status during 2001-2016. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(2); R&D intensity, defined as100×log(R&D exp/Sales+1), in columns (3)-(4); the number of IPO patent applications, defined as log(PatIPO +1) in columns (5)-(6); and the number of USPTO patent applications, defined as log(PatUSPTO +1), in columns (7)-(8). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 5.26: Time-varying DSIR registration status, by sector

	R&D expenditure		R&D intensity		IPO Patents		USPTO Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chemicals × D_{ijt}	0.673***	0.618***	0.35	0.312	0.085	0.105*	0.009	0.005
	[0.149]	[0.137]	[0.299]	[0.267]	[0.053]	[0.060]	[0.020]	[0.023]
Pharmaceuticals ×D_{ijt}	0.936***	0.931***	2.552**	2.330**	0.259***	0.259***	0.055	0.036
	[0.168]	[0.171]	[1.163]	[1.169]	[0.085]	[0.089]	[0.047]	[0.048]
Computer × D_{ijt}	1.196***	1.060***	1.73	1.874	0.359*	0.372	0.134	0.165
	[0.325]	[0.340]	[1.299]	[1.574]	[0.195]	[0.226]	[0.110]	[0.129]
Transport × D_{ijt}	0.690***	0.672***	-0.122	0.073	0.193**	0.144**	-0.018	-0.003
	[0.258]	[0.252]	[0.359]	[0.406]	[0.094]	[0.072]	[0.019]	[0.017]
Chemicals × $D_{ijt}R_t$	0.027	0.19	0.011	0.174	-0.039	0.007	-0.039	-0.021
	[0.187]	[0.179]	[0.521]	[0.360]	[0.079]	[0.069]	[0.026]	[0.025]
Pharmaceuticals × $D_{ijt}R_t$	0.042	0.06	-0.798	-1.072	-0.231**	-0.188**	0.019	-0.007
	[0.182]	[0.190]	[1.307]	[1.240]	[0.094]	[0.084]	[0.049]	[0.052]
Computer × $D_{ijt}R_t$	0.22	-0.11	3.354	2.72	-0.25	-0.293	-0.01	-0.05
	[0.388]	[0.410]	[3.510]	[4.121]	[0.177]	[0.202]	[0.101]	[0.094]
Transport × D_{ijt} R_t	0.463*	0.356	-0.159	0.399	0.031	0.008	-0.017	0.015
	[0.260]	[0.265]	[0.586]	[0.477]	[0.071]	[0.079]	[0.029]	[0.021]
Control variables	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry-specific time trends		yes		yes		yes		yes
Observations	3,878	3,878	3,878	3,878	3,878	3,878	3,878	3,878
R-squared	0.741	0.747	0.394	0.399	0.584	0.611	0.47	0.478

Notes: OLS estimation of model (10) for the sample of 245 firms with over time variation in the DSIR registration status during 2001-2016. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(2); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (3)-(4); the number of IPO patent applications, defined as log(PatIPO +1) in columns (5)-(6); and the number of USPTO patent applications, defined as log(PatUSPTO +1), in columns (7)-(8). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The regressions include the same control variables as in Table 5.25

5.3.3 Probing the common trends assumption

By including firm fixed effects (α_i) in the model (10), we address the concern of endogeneity due to selection of firm-specific characteristics. But selection could also be based on firm time-varying characteristics related to firm innovation performance. The common trends assumption, which is key for the causal attribution, would fail in the presence of such selection. To address this concern, we add firm-specific parametric time trends (α_{it}) to the controls in the model (10). This approach allows us to introduce a degree of nonparallel changes in the outcome between firms in the absence of the treatment and in doing so, relax the common trends assumption and perform a check on the causal interpretation (Angrist and Pischke, 2014). The identification in this model hinges on there being sharp deviations in the outcome around the DSIR registration year from otherwise smooth trends.

Table 5.27 shows the results. The estimates of φ remain largely unchanged, as compared to the estimates in Table 5.25. Quantitatively, the estimate of the impact on firm R&D expenditure falls from 113% to 109%, and the estimate of the impact on R&D intensity rises from 1.06% to 1.37%, while the estimate of the impact on the number of IPO patent applications stays at 20%. The level of statistical significance stays at 1%, 5% and 1% in columns (1), (2) and (3), respectively, and rises to 10% in column (4). The robustness of the estimates suggests that our results are not driven by selection on firm characteristics that vary over time. The results continue to hold even when we allow for the fact that innovation activity in different firms was on different trajectories from the start, which supports their causal interpretation. And the fact that we are still able to pick up the impact of DSIR registration when we control for firm-specific trends suggests that the treatment effects do not emerge gradually but rather, firm innovation activity changes sharply around the DSIR registration year.

Table 5.27: Probing the common trends assumption

Outcome variables (in logs):	R&D expenditure	R&D intensity	IPO Patents	USPTO Patents
	(1)	(2)	(3)	(4)
Treatment group (D_{ijt})	0.739***	1.356**	0.184***	0.040*
	[0.124]	[0.575]	[0.050]	[0.022]
Treatment × Reform (Dijt Rt)	0.062	-0.433	-0.108*	-0.016
	[0.156]	[0.686]	[0.058]	[0.027]
Control variables	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
Firm-specific time trends	yes	yes	yes	yes
Observations	3,878	3,878	3,878	3,878
R-squared	0.812	0.514	0.725	0.598

Notes: OLS estimation of model (10) with firm-specific time trends for the sample of 245 firms with over time variation in the DSIR registration status during 2001-2016. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in column (1); R&D intensity, defined as 100×log(R&D exp/Sales+1), in column (2); the number of IPO patent applications, defined as log(PatIPO +1) in column (3); and the number of USPTO patent applications, defined as log(PatUSPTO +1), in column (4). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The regressions include the same control variables as in Table 5.24.

5.3.4 Additional sensitivity analysis

One concern with our analysis is that the DSIR registration status variable is noisy, in that it does not effectively capture the R&D tax credit treatment. This concern is valid, since we cannot be confident that all DSIR-registered firms in our sample have utilized the R&D tax credit scheme annually. But there are three important mitigating considerations. First, our sample is skewed towards large companies, which are large R&D spenders. These companies benefit significantly from the R&D tax credit and are thus highly likely to utilize it. Secondly, our empirical strategy serves to minimize the impact of the noise in the DSIR registration variable on our estimates. The controls for firm-specific effects absorb much of the noise, since they account for permanent differences in the outcomes not only across the two groups of firms (DSIR-registered and non-DSIR registered) but also across individual firms within each group. The controls for firm-specific trends further absorb some of the time-varying noise. The analysis of the timing of DSIR registration reveals that the treatment effects do not emerge gradually but rather, firm innovation activity changes sharply around the registration year. This finding reaffirms that the estimate of the coefficient of the DSIR registration status variable is picking up the causal effect of the R&D tax credit, given that firms were required to have functional R&D units with well-defined R&D programs prior to registration and that the R&D tax credit scheme is the only benefit of DSIR registration for 99% of firms in our sample. Last, as discussed in Section 2, initial recognition with the DSIR and subsequent maintenance of the DSIR status is costly for a firm. Faced with such costs, a firm that does not reap sufficient benefits from the DSIR registration would choose to "exit" the registration. But a vast majority of firms in our sample maintained their DSIR status in all years. This last point is important and deserves more detail, which we provide next.

As many as 28 firms (out of 245 firms initially recognized by the DSIR during 2001-2016) exited the DSIR registration in some years. Despite being eligible, these firms most likely failed to utilize the R&D tax credit. By excluding these firms from our data and re-estimating the model (10), we can check if our results are robust to the noise in the DSIR registration status variable. Table 5.27 shows the new set of estimates, from the smaller sample. It is apparent that our results remain qualitatively unchanged but compared to the respective estimates in Tables 5.25 and 5.27, the estimates in Table 5.28 are slightly larger in magnitude (more so for R&D intensity) and more precisely estimated. This suggests that the noise in our treatment variable does lead to a slight downward bias in our estimates and a loss of precision, but it does not have a significant impact on our results.

Table 5.28: Excluding the “exiting” firms

Outcome variables (in logs):	R&D expenditure			R&D intensity			IPO Patents			USPTO Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment group (D_{ij})	0.829***	0.806***	0.863***	1.549***	1.396**	1.756***	0.195***	0.191***	0.198***	0.043	0.035	0.041*
	[0.125]	[0.121]	[0.132]	[0.576]	[0.571]	[0.631]	[0.060]	[0.057]	[0.057]	[0.026]	[0.025]	[0.025]
Treatment×Reform (D_{ijt} R_t)	-0.026	0.03	-0.136	-0.518	-0.495	-1.089	-0.092	-0.045	-0.077	0.007	0.005	0.007
	[0.158]	[0.158]	[0.172]	[0.739]	[0.694]	[0.775]	[0.083]	[0.066]	[0.071]	[0.027]	[0.027]	[0.032]
Age	0.061***	0.113***	-0.094***	0.05	0.025	0.001	0.008	0.269***	-0.022**	-0.001	-0.009	-0.010*
	[0.019]	[0.031]	[0.025]	[0.061]	[0.130]	[0.116]	[0.007]	[0.029]	[0.010]	[0.003]	[0.009]	[0.005]
Exporter	0.729***	0.750***	0.644***	0.986*	0.894*	0.625	-0.016	-0.018	0.025	-0.019	-0.027*	-0.012
	[0.136]	[0.133]	[0.130]	[0.524]	[0.467]	[0.416]	[0.031]	[0.033]	[0.032]	[0.015]	[0.016]	[0.016]
Raw material imports	0.123	0.141	-0.044	0.595	0.707	0.349	0.013	0.032	-0.032	0.012	0.015	-0.008
	[0.240]	[0.257]	[0.175]	[0.838]	[0.895]	[0.688]	[0.040]	[0.051]	[0.033]	[0.018]	[0.020]	[0.012]
Technology imports	0.037	0.061	0.024	3.564	3.638	2.339	-0.028	-0.027	-0.033	-0.005	-0.004	-0.002
	[0.104]	[0.102]	[0.060]	[3.201]	[3.255]	[2.143]	[0.044]	[0.042]	[0.036]	[0.020]	[0.017]	[0.016]
Leverage	-0.129	-0.1	-0.279	-1.856*	-1.14	-2.406**	-0.17	-0.179	-0.110*	-0.054	-0.02	-0.058
	[0.237]	[0.239]	[0.276]	[1.067]	[1.288]	[1.106]	[0.133]	[0.131]	[0.060]	[0.045]	[0.063]	[0.035]
HHI	-1.107	-2.493*	-2.560**	11.668	4.99	3.954	-0.017	-0.475	-0.317	-0.015	-0.379	-0.26
	[1.198]	[1.321]	[1.201]	[8.373]	[7.376]	[6.775]	[0.523]	[0.434]	[0.474]	[0.359]	[0.320]	[0.224]
Firm size	-0.527***	-0.568***	-0.221	1.264	0.89	4.372	-0.318***	-0.188**	-0.04	-0.078	-0.104*	-0.046
	[0.180]	[0.151]	[0.268]	[0.919]	[1.031]	[3.500]	[0.100]	[0.075]	[0.095]	[0.051]	[0.056]	[0.063]
Firm size squared	0.070***	0.073***	0.043*	-0.055	-0.031	-0.315	0.031***	0.019**	0.008	0.009*	0.011*	0.006
	[0.020]	[0.016]	[0.023]	[0.076]	[0.087]	[0.274]	[0.010]	[0.008]	[0.010]	[0.005]	[0.006]	[0.006]
Constant	0.172	116.572**	-318.868***	-10.834**	-47.642	-129.797	0.605**	522.073***	-53.394***	0.173	-16.721	-16.589***
	[0.749]	[52.646]	[18.309]	[4.289]	[266.825]	[175.444]	[0.307]	[52.819]	[7.243]	[0.241]	[15.620]	[4.538]
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-specific time trends		yes			yes			yes			yes	
Firm-specific time trends			yes			yes			yes			yes
Observations	3,430	3,430	3,430	3,430	3,430	3,430	3,430	3,430	3,430	3,430	3,430	3,430
R-squared	0.737	0.744	0.812	0.386	0.399	0.519	0.572	0.603	0.72	0.47	0.484	0.603

Notes: OLS estimation of model (10) for the sample of 217 firms which registered with the DSIR during 2001-2016 and maintained their registration thereafter. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(3); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (4)-(6); the number of IPO patent applications, defined as log(PatIPO +1) in columns (7)-(9); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (10)-(12). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

5.3.5. Summary of results

In a DID framework, we find that the 2010-11 reform has spurred firm innovation activity at both margins. First, the reform has lowered the user cost of R&D by 33% for firms that were long registered with the DSIR. Such firms became more innovative and more productive as a result. Specifically, the impact of DSIR registration on their R&D expenditure has increased by 78% after the reform while the impact on their number of IPO and USPTO patent applications has increased by 11% and 6%, respectively. These impacts are both statistically and economically significant.

Secondly, the reform has incentivized new firms to register with the DSIR, to become eligible for the 200% R&D tax credit. Following DSIR registration, these firms' R&D expenditure, R&D intensity, and the number of IPO patent applications increased by 113%, 1.06%, and 20% respectively.

We do not find strong evidence that the number of USPTO patent applications increased following DSIR registration in the pre-reform years; the relevant coefficient lacks precision. Furthermore statistically, there is no difference in the impact between firms initially recognized by the DSIR before 2011 and those initially recognized by the DSIR in or after 2011. Interestingly, we also find that for smaller firms in our sample, an increase in size over time is associated with a reduction in R&D expenditure. Policy initiatives aimed at promoting R&D activity of small firms are thus needed to ensure that firms continually innovate for the market.

CHAPTER 6

EMPIRICAL EVIDENCE ON THE IMPACT OF R&D TAX CREDIT SCHEME AND ITS 2009-10 REFORM ON INNOVATION ACTIVITY OF THE FIRMS

6.1 Introduction

In this chapter, using PSM and DID framework, we examine the impact of R&D tax credit scheme and its 2009-10 reform, that extended the provision of the tax credit scheme to all manufacturing industries. Till 2009-10, the R&D tax credit was available only to the companies engaged in the production of selected industries, but during 2009-2010, the scope of the current provision of weighted deduction on in-house R&D is extended to all manufacturing businesses except for a small negative list. The firms involved solely in the manufacturing or production of items under Schedule 11 of the Income-tax act 1961[10].

The rest of the chapter is organized as follows: Section 5.2 provides estimation results of the Propensity Score Matching (PSM). Section 5.3 provides the estimation results of Difference-in-Difference (DID).

6.2. Estimation results of Propensity Score Matching (PSM)

We construct a panel dataset which contains firm-level observations of DSIR and non-DSIR firms from newly eligible industries during the period 2011-2016. The firm-level data is suitable to compare continuity of participation in the tax credit scheme throughout the period. In India, only those firms with active in-house R&D units are eligible for DSIR

[10] Firms involved solely in manufacturing or production of items under Schedule 11 of the Income tax act 1961 are not eligible for claiming the weighted tax credit. https://www.incometaxindia.gov.in/Acts/Income-tax%20Act,%201961/2008/102120000000022829.htm

recognition. To account this policy framework, we consider only the non-DSIR firms that invest in R&D.

Till 2009-10, R&D tax credit was provided to firms from selected industries such as drugs and pharmaceuticals, electronic equipment, computers, telecommunications equipment, chemicals, manufacture of aircraft and helicopters, automobiles, and auto parts industries. We refer these industries as the "original industries". The 200-10 policy reform extended the current provision of tax credit to all manufacturing industries in India. We refer those industries as the "new industries".

The literature suggests that R&D behaviour of the firm is industry-specific and to capture such effects of the R&D tax credit, we classify the "new industries" sample firms into eleven major industries namely; *Architecture and civil engineering; Beverages, and food products; Electrical equipment; Leather, textiles and wearing; Machinery and equipment; Metals; Non-metallic mineral products; Rubber and plastics products; Wood products and paper; Retail and wholesale trade; and Other manufacturing sector.*

To estimate the effect of new DSIR registration following the policy reform, we use the sample of newly added eligible industries for the tax credit. These industries are matched with three-digit National Industrial Classification (NIC) 2008 to categorize the firms on industry groups. The NIC classification of firms and their industry-wise distribution is presented in Table 6.1. The industry-wise distribution of DSIR and non-DSIR recognized firms are shown in Table 6.2. As mentioned earlier, firms should own an in-house R&D unit to register with DSIR; thus, we consider only the R&D performing firms in our sample. The dataset contains firm-level data of 1173 firms from during 2011-2016.

Table 6.1: Industry classification of the sample firms

Manufacture of:	NIC classification	Number of firms
Architecture and Civil engineering	7110, 7120 4210, 4220, 4290 8110, 8121, 8129, 8130	33
Beverages and food products	1910, 1920, 1101, 1102, 1103, 1104, 1010, 1020, 1030, 1040, 1050, 1061, 1062, 1071, 1072, 1073, 1074, 1075, 1079, 1080	178
Electrical equipment	2710, 2720, 2731, 2732, 2733, 2740, 2750, 2790	89
Leather, textiles and wearing	1311, 1312, 1313, 1391, 1392, 1393, 1394, 1399, 1410, 1420, 1430, 1511, 1512, 1520	108
Machinery and equipment	2811, 2812, 2813, 2814, 2815, 2816, 2817, 2818, 2819, 2821, 2822, 2823, 2824, 2825, 2826, 2829	119
Metals	2410, 2420, 2431, 2432, 2511, 2512, 2513, 2520, 2591, 2592, 2593, 2599,	106
Non-metallic mineral products	2310, 2391, 2392, 2393, 2394, 2395, 2396, 2399	54
Rubber and plastics products	2211, 2219, 2220	76
Wood products and paper	1610, 1621, 1622, 1623, 1629, 1701, 1702, 1709	29
Retail and wholesale trade	4510, 4520, 4530, 4540, 4610, 4620, 4630, 4641, 4649, 4651, 4652, 4653, 4659, 4661, 4662, 4663, 4669, 4690 4711, 4719, 4721, 4722, 4723, 4730, 4741, 4742, 4751, 4752, 4753, 4759, 4761, 4762, 4763, 4764, 4771, 4772, 4773, 4774, 4781, 4782, 4789, 4791, 4799	180
Other manufacturing	0810, 0891, 0892, 0893, 0899, 3510, 3520, 3530, 6110, 6120, 6130, 6190, 7210, 7220, 7710, 7721, 7722, 7729, 7730, 7740, 8211, 8219, 8220, 8230, 8291, 8292, 8299 3211, 3212, 3220, 3230, 3240, 3250, 3290, 6411, 6419, 6420, 6430, 6491, 6492, 6499, 6201, 6209	201
Total		1173

Table 6.2: Firm coverage, by sector and DSIR recognition status over 2011-2016

Industry	Total number of firms	DSIR not recognized firms (%)	DSIR recognized firms (%)
Architecture and Civil engineering	33	25 (75.76)	8 (24.24)
Beverages and food products	178	168 (94.38)	10 (5.62)
Electrical equipment	89	75 (84.27)	14 (15.73)
Leather, textiles and wearing	108	102 (94.44)	6 (5.56)
Machinery and equipment	119	89 (74.79)	30 (25.21)
Metals	106	89 (74.79)	17 (16.03)
Non-metallic mineral products	54	44 (81.48)	10 (18.52)
Rubber and plastics products	76	61 (80.26)	15 (19.74)
Wood products and paper	29	24 (82.75)	5 (17.25)
Retail and wholesale trade	180	155 (86.11)	25 (13.89)
Other manufacturing	201	162 (80.58)	39 (19.42)
Total	1173	994 (84.74)	179 (15.26)

Note: Authors' calculation

Table 6.3 presents the mean statistics of the treated group of DSIR-registered firms and the potential control group of non-DSIR firms before matching. The t-test indicates the systematic difference between the covariates of DSIR and non-DSIR-registered firms. The DSIR registered firms are more likely to be foreign-owned and export. In terms of firm size, DSIR firms are smaller in size than non-DSIR firms. Moreover, the affiliated firms on an average are less leveraged indicating good financial health. It also shows that the firms registered with DSIR have better innovation performance in terms of outcome variables such as R&D expenditure, R&D intensity, and number of IPO and USPTO patent applications during the study period.

Table 6.3: Descriptive statistics: Mean comparison of treated and control firms, before matching

	2011-2016				
Variable	Non-DSIR firms		DSIR firms		t-test
	Mean	SD	Mean	SD	
Covariates:					
Location	0.840	0.366	0.893	0.309	***
Foreign ownership	0.051	0.220	0.094	0.292	***
Age	33.992	19.732	32.489	16.287	*
Exporter	0.484	0.500	0.764	0.425	***
Raw material imports	0.047	0.124	0.195	3.089	****
Technology imports	0.008	0.043	0.015	0.043	***
Leverage	0.040	0.413	0.020	0.055	
HHI	0.144	0.145	0.175	0.183	***
Firm size	6.556	2.031	7.395	2.011	***
Firm size squared	47.110	27.718	58.721	31.533	***
Outcome variables:					
R&D expenditure	23.914	327.642	178.719	810.356	***
R&D intensity	0.008	0.286	0.029	0.116	*
IPO Patent applications	0.198	2.148	0.501	1.620	***
USPTO Patent applications	0.052	1.449	0.057	0.383	
Number of observations	6429	609			

Notes: t-tests are comparisons of means of two sub-samples (DSIR and non-DSIR firms). The null hypothesis states that there is no difference between the DSIR and DSIR and non-DSIR firms. Here ***, ** and * denote that coefficients are statistically significant at 1%, 5% and 10%, respectively using a two-tailed test.

Score calculation and validity

To estimate the propensity score (i.e., the predicted probability of registering with DSIR conditional on firms' observed characteristics), we employ a probit model, where the outcome variable equals one if a firm i

is registered with the DSIR in year *t*, and zero otherwise. The covariates are selected based on the literature review, which identified the R&D characteristics of firms in India. The propensity score is defined as the conditional probability of receiving a treatment given pre-treatment characteristics in equation (1) in Chapter 4.

Table 6.4 shows the probit model estimation results. It appears that all covariates, except for Foreign *ownership, Raw material imports, Leverage and Technology imports*, are important determinants of DSIR registration. The probability of firm registration with the DSIR increases with firm's age and export status and *HHI* and falls with firm size.

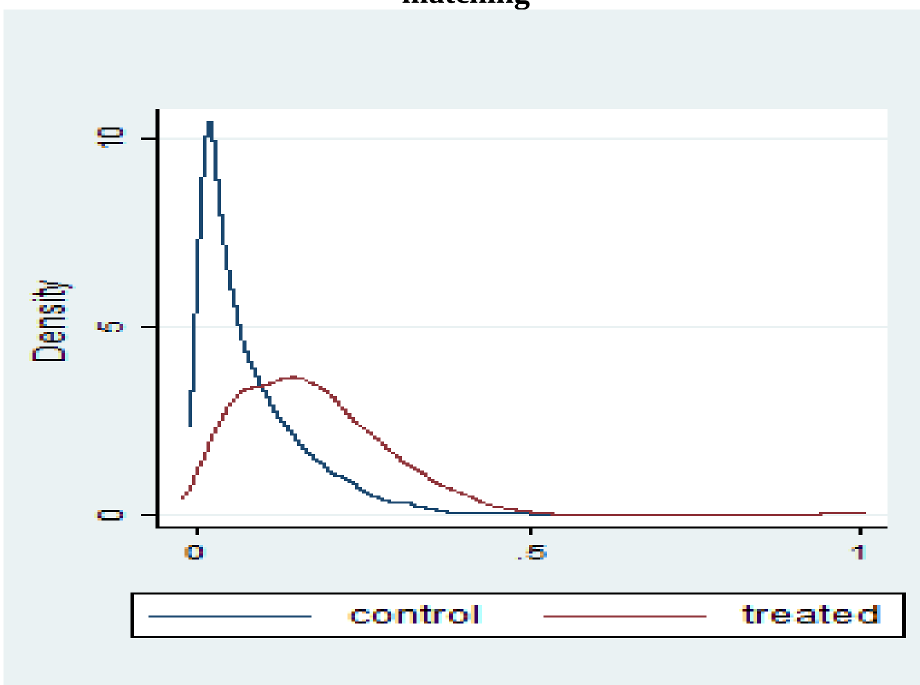
Table 6.4: The propensity of affiliating with DSIR-Probit model

Variables	Coeff.	Std. Err.
Location	0.489*	0.273
Foreign ownership	0.501	0.362
Age	0.013***	0.004
Firm size	-0.436***	0.149
Firm size squared	0.043***	0.011
Exporter	0.379***	0.131
HHI	2.390***	0.554
Raw material imports	0.162	0.500
Leverage	-0.166	0.290
Technology imports	-1.319	1.756
constant	-5.209***	0.582
Time dummies	yes	
Industry dummies	yes	
Wald chi2(10)	59.49	
Prob > chi2	0.00	
Log likelihood	-1504.619	
Pseudo R2	0.230	
Observations	7038	

Notes: This table presents estimations of probit estimation. Here affiliation with the DSIR is the dependent variable. Here ***, ** and * denote that coefficients are statistically significant at 1%, 5% and 10%, respectively

The distribution of the estimated propensity score of DSIR and non-DSIR registered firms are presented in Figure 6.1. It illustrates that the distribution of treated and control observations have the same probability of participating in the R&D tax credit scheme after matching. The two groups' distributions are symmetric, and thus the common support assumption is satisfied.

Figure 6.1: Estimated propensity score- Kernel distribution before matching



Assessing the Quality of Matching

The propensity score matching procedure balances the distribution of observable variables between the treated and the control observations. In such a case, the common support should be assessed to confirm the success of matching between these two groups of observations (Imbens, 2004; Austin, 2011). The common support ensures that the mean propensity score is equivalent in the treatment and control group within each of its quintiles.

Table 6.5 shows the t-test statistic and the corresponding p-value between the covariates of the treated group and the control group after matching. Compared to Table 6.3, there is no significant difference between the treated and untreated at the 5% level. It implies the success of matching procedure (Snedecor & Cochran, 1989). Also, we calculate the mean standardised bias (MSB) of variables, as suggested by Caliendo and Kopeinig (2008), to indicate the distance in the marginal distribution of variables. Most of the empirical studies consider MSB value as a sufficient indication of the success of matching (Liu et al. 2016). The values of MSB of the variables before and after matching are presented in Table 6.6. The percentage of bias is reduced for most of the covariates after matching, that is seen as a sufficient indication of successful matching. We present the distribution of estimated propensity scores after matching in Figure 6.2. As the figure illustrates the distribution of treated and control observations have the same probability of participating in the R&D tax credit scheme after matching. The two groups' distributions are symmetric, and thus the common support assumption is satisfied.

Table 6.5: Descriptive statistics: Mean comparison treated and control firms, after matching

	2011-2016				
Variable	Non-DSIR firms		DSIR firms		t-test
	Mean	Std. Dev.	Mean	Std. Dev.	
Covariates:					
Location	0.913	0.282	0.893	0.309	
Foreign ownership	0.089	0.285	0.094	0.292	
Age	32.723	17.521	32.489	16.287	
Exporter	0.621	0.486	0.764	0.425	
Raw material imports	0.080	0.124	0.195	3.089	
Technology imports	0.013	0.058	0.015	0.043	
Leverage	0.032	0.231	0.020	0.055	
HHI	0.174	0.183	0.175	0.183	
Firm size	7.384	2.065	7.395	2.011	
Firm size squared	58.776	31.801	58.721	31.533	
Outcome variables:					
R&D expenditure	18.918	131.181	178.719	810.356	***
R&D intensity	0.005	0.022	0.029	0.116	***
IPO Patent applications	0.097	0.479	0.501	1.620	***
USPTO Patent applications	0.016	0.190	0.057	0.383	***
Number of observations	609		609		

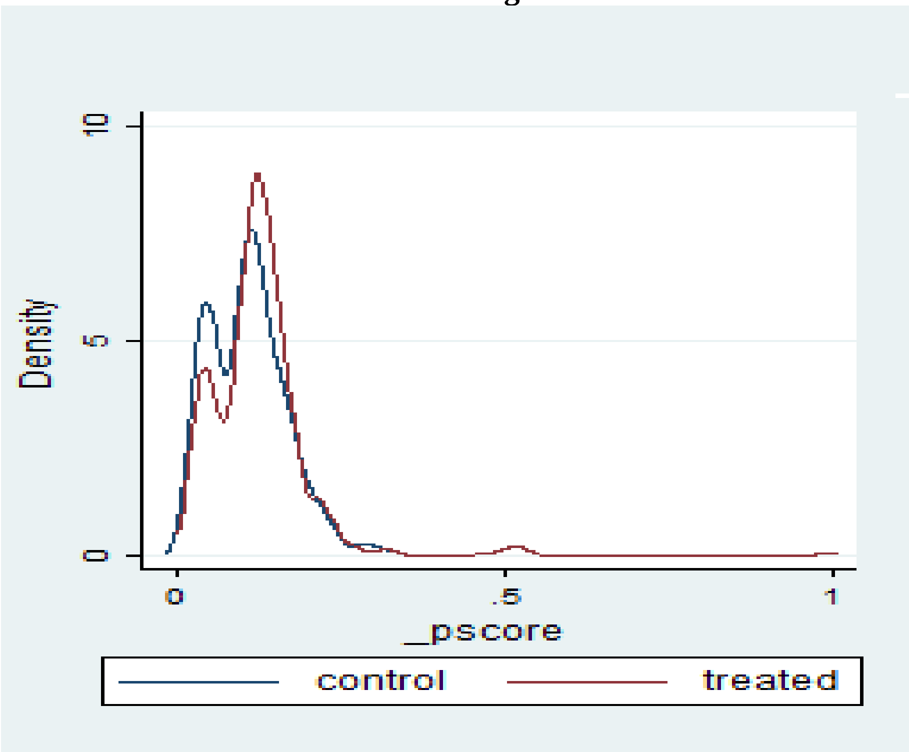
Notes: t-tests are comparisons of means of two sub-samples (DSIR and non-DSIR firms). The null hypothesis states that there is no difference between the DSIR and DSIR and non-DSIR firms. Here ***, ** and * denote that coefficients are statistically significant at 1%, 5% and 10%, respectively using a two-tailed test.

Table 6.6: Mean standardized bias (MSB) - before and after matching

Variables	2011-16	
	% bias-before matching	% bias-after matching
Location	1.90	-2.80
Foreign ownership	-6.40	-1.10
Age	-0.80	-7.00
Firm size	3.70	3.70
Firm size squared	4.50	4.00
Exporter	1.80	-1.10
HHI	-5.70	-11.00
Raw material imports	5.20	5.60
Leverage	-0.20	3.60
Technology imports	-4.30	5.20
Observations	7038	1218

Note: % bias is the standardized bias as suggested by Rosenbaum and Rubin (1985).

Figure 6.2: Estimated propensity score- Kernel distribution after matching



6.2.1. Estimation Results of the average treatment effect on treated (ATT)

In this section, we discuss the estimation results of the average treatment effect on treated (ATT) of the matched sample of DSIR and non-DSIR affiliated firms defined by equation (2). We use 1-1 nearest neighbour matching (NNM 1-1) as suggested by Liu et al. (2016) to estimate the ATT. We also include other matching methods such as 1-3 nearest neighbour matching (NNM 1-3), 1-5 nearest neighbour matching (NNM 1-5) and kernel matching as robustness checks.

The estimation results of ATT on innovation input and innovation output of the firm are presented in the following sub-sections.

R&D expenditure and R&D intensity

The average treatment effect on treated (ATT) of tax credits on investment (both levels and intensity of R&D) using the full sample is presented in Table 6.7. Column (1) in Table 6.7 reports the ATT using 1-1 NNM. The results suggest that the treatment yields a positive and significant impact on the R&D expenditure during the period. We have measured the R&D expenditure in a million Indian rupees and find an average of Rs 166.234 million difference in the R&D investment of treated firms compared to control firms during 2011-16. In columns (2)-(4), we also employ other matching methods as robustness checks. The ATT estimation results of NNM 1-3, NNM-1-5 and kernel matching indicate a similar positive effect of R&D tax credits on R&D investment.

Based on the results of 1-1 NNM in column (5), the R&D intensity of the participating firms is significant and positive by 0.027 during the period 2011-16 compared to the non-participants of the tax credit scheme. It shows that registration with DSIR increases the R&D intensity by 0.027 compared to firms not registered. Results of NNM 1-3, NNM-1-5 and kernel matching also indicate similar significant and positive effects of

R&D tax credits on R&D intensity. The results imply that the policy reform increased the R&D expenditure and R&D intensity of the newly registered firms with DSIR compared to the firms that are not registered.

IPO and USPTO Patent applications

In Tables 6.8, we report the results of the innovation outcome measured by IPO and USPTO patent applications. Columns (1) and (5) in Table 6.8 reports the ATT using 1-1 NNM. The results reveal a positive and significant effect of patent applications during 2011-16 between the treated and non-treated firms. It indicates that the IPO patent applications of a firm increased by 0.422 times during 2011-16 if the firm register with DSIR. Results of NNM 1-3 and NNM-1-5 in columns (2)-(4) also indicate similar significant and positive effects of R&D tax credits on the IPO patent application. The ATT of USPTO patent applications is positive and significant by 0.041 during 2011-16. It shows that the USPTO patent applications of a firm increased by 0.041 times during 2011-16 if the firm recognizes with DSIR. The treatment effect on the number of IPO patent applications (0.422) is higher than the USPTO patent applications (0.041) during the period. One probable explanation is the territorial nature of the patents, where firms prefer to file patents in India. Moreover, the cost associated with filing patents at USPTO is higher as compared to IPO.

Table 6.7: The ATT of the tax credit on R&D Expenditure and R&D intensity–Full Sample

	R&D Expenditure				R&D intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NNM 1-1	NNM 1-3	NNM 1-5	Kernel	NNM 1-1	NNM 1-3	NNM 1-5	Kernel
ATT	166.234***	167.624***	165.153***	108.829***	0.027***	0.026***	0.026***	0.024***
Std. Err.	32.428	30.745	30.756	29.554	0.005	0.005	0.005	0.004
Observations	1218	1218	1218	1218	1218	1218	1218	1218

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 6.8: The ATT of the tax credit on IPO and USPTO Patent Applications –Full Sample

	IPO Patent applications				USPTO Patent applications			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NNM 1-1	NNM 1-3	NNM 1-5	Kernel	NNM 1-1	NNM 1-3	NNM 1-5	Kernel
ATT	0.422***	0.416***	0.043***	0.358***	0.041***	0.045***	0.043***	0.027**
Std. Err.	0.069	0.066	0.016	0.056	0.017	0.016	0.016	0.020
Observations	1218	1218	1218	1218	1218	1218	1218	1218

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Different policy regime

Table 6.9 presents the year wise estimated ATT of the R&D tax credit. The year-by-year average treatment effect measured through R&D expenditure in column (1)-(2) is positive and significant throughout the study period, except during 2011. The estimates suggest that the treatment effect of R&D expenditure exhibit, on average an increasing trend during the study period. The year-wise average treatment effects measured through R&D intensity in column (3)-(4) show that the average treatment effect is positive and significant throughout the study period.

In columns (5)-(6), ATT of the number of IPO patent applications show a positive and significant effect throughout the period, except during 2012. The number of USPTO patent applications have a positive and significant treatment effect only in 2016. Thus, once again, it is the efficiency with which R&D funds are utilized, and the type of activities (adoption and absorption) as explained earlier are the major reasons for the difference in the R&D and patent applications of DSIR and non-DSIR registered firms.

Table 6.9: The average treatment effect of R&D tax credits on innovation - year wise

	R&D expenditure		R&D intensity		IPO patent applications		USPTO patent applications	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.
2011	129.236	94.506	0.008*	0.004	0.360**	0.159	0.040	0.039
2012	136.298**	64.148	0.017***	0.006	0.299	0.279	0.075	0.049
2013	120.330*	68.719	0.027***	0.009	0.348***	0.107	0.011	0.011
2014	199.438***	74.698	0.029***	0.011	0.287***	0.094	0.056	0.059
2015	183.263**	82.093	0.036***	0.013	0.238*	0.134	0.023	0.020
2016	167.514***	53.863	0.024***	0.009	0.753***	0.174	0.105**	0.047

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Industry specific estimation results

To examine the impact of the tax credit at the sector level, we separately estimate the ATT for firms from all sectors. We have classified the sample firms into eleven distinct sectors as mentioned above and table 6.10 reports the effect of R&D tax credit on innovation activity of the firm from those sectors. Columns (1)-(2) report positive and significant ATT of the tax credit on firms' R&D expenditure in all sectors except *Leather, textiles and wearing, Metals, and Retail and wholesale trade* sectors. The treatment effect is pronounced for the *Electrical equipment, and Rubber and plastics products* sectors, with 93.778 million and 78.469 million respectively during 2011-16. Columns (3)-(4), the ATT of R&D intensity is positive and significant for all sectors except Electrical equipment during 2011-16. It indicates that the policy reform reflected in almost all sectors in terms of firm innovation input intensity.

From columns (5)-(6) in Table 6.10, the ATT of the innovation outcome measured through IPO patent applications shows a positive and significant effect for *Electrical equipment, Machinery and equipment, Metals, Retail and wholesale trade and Other manufacturing during the study period.* In the case of USPTO patent applications in columns (7)-(8), the positive effect of reform-driven from *Retail and wholesale trade, and Other manufacturing* sectors.

Table 6.10: The average treatment effect of R&D tax credits on innovation – Based on industry classification

	R&D expenditure		R&D intensity		IPO patent applications		USPTO patent applications	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.
Architecture and Civil engineering	39.355**	15.929	0.073**	0.031	0.110	0.126	-	-
Beverages and food products	21.737**	8.996	0.009***	0.001	-	-	-	-
Electrical equipment	93.778***	17.976	0.003	0.004	0.446**	0.209	0.036	0.025
Leather, textiles and wearing	54.673	40.232	0.004***	0.001	0.791	0.776	0.437	0.417
Machinery and equipment	26.392**	11.580	0.006**	0.003	0.648***	0.165	0.030	0.025
Metals	10.200	9.475	0.007***	0.002	0.132**	0.057	-	-
Non-metallic mineral products	45.986***	9.777	0.003***	0.001	0.080	0.050	0.019	0.021
Rubber and plastics products	78.469***	29.659	0.029**	0.011	0.109	0.067	0.069	0.055
Wood products and paper	50.699***	12.569	0.061**	0.031	0.278	0.188	-	-
Retail and wholesale trade	207.739	136.280	0.026***	0.007	0.439**	0.218	0.037*	0.023
Other manufacturing	459.118***	144.066	0.060***	0.017	0.783***	0.185	0.107**	0.039

Notes: This table presents the treatment effect of the DSIR registration. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Heterogeneity in treatment effects

In this subsection, we further explore the effect of heterogeneity by classifying firms into different groups. The literature on innovation activities by firms in India has revealed heterogenous results among firms. The innovation activity of the firms considerably varies with the firm size, ownership category and export status. Thus, we also attempt to study if the effect of tax credits varies with such specific firm characteristics. Accordingly, we explore the effect of heterogeneity by classifying firms into different groups. The results of kernel matching are presented in Table 6.11.

As discussed earlier, a firm's size is associated with its innovation activities, which may further influence the firm's utilisation of R&D tax credit. We estimated whether the treatment effect is different among firm size. Sample firms are equally divided into three groups in terms of gross fixed assets: small, medium, and larger firms. The results presented in Table 6.11, shows that the effect of R&D tax credit seems to increase with the firm size. The ATT of larger firms are significant and higher than medium and smaller firms in terms of R&D expenditure, R&D intensity, and the number of IPO patent applications. However, the treatment effect on the number of USPTO patent applications does not yield any positive impact during the study period. The results suggest that R&D tax credit have the most significant influence on the larger firm's innovation activities and the treatment effects of small and medium firms are smaller than the large firms.

We next estimate the ATT based on the ownership status of the firm on utilizing the R&D tax credit. Firms are classified into two domestic and foreign firms. Our estimates suggest that domestic firms have a higher ATT compared to the foreign firms in terms of innovation input (i.e., R&D expenditure and R&D intensity). However, the innovation outputs (i.e., IPO and USPTO patent applications) are higher for foreign firms. In the Indian context, it has already been established that foreign firms are patenting extensively that may not be supported by the in-house R&D that these firms conduct in India (Ambrammal & Sharma, 2014). One probable explanation given for this is that foreign firms have access to R&D conducted at the headquarters and in the rest of the world by its parent company and subsidiaries.

The ATT of the firm's export status shows that exporting firms registered with DSIR are higher than non-exporting firms in terms of R&D expenditure, R&D intensity, and the number of IPO patent applications. An interesting finding with respect to the number of USPTO patent applications that the non-exporting firms tend to file more patent applications at USPTO.

Table 6.11: Heterogeneity in ATT of R&D tax credits on innovation -Estimates using Kernel Matching-Classification by Size of the firm, Ownership and Export status

Variables		R&D expenditure		R&D Intensity		IPO patent applications		USPTO patent applications	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.	ATT	Std. Err.
Size of the firm	Small	4.282***	1.469	0.051	0.033	0.001	0.073	-	-
	Medium	89.711***	25.591	0.024***	0.005	0.368***	0.080	0.011	0.023
	Large	1214.480***	413.469	0.001	0.002	1.225***	0.429	0.261	0.188
Ownership	Domestic	117.33***	27.450	0.023***	0.005	0.323***	0.074	0.017	0.019
	Foreign	100.463*	60.270	0.019***	0.007	0.594***	0.214	0.088**	0.042
Export status	Exporters	133.827***	32.003	0.015***	0.003	0.375***	0.104	0.025	0.025
	Non-Exporters	50.894***	11.677	0.055***	0.017	0.292***	0.084	0.029*	0.015

Notes: This table presents the treatment effect of the DSIR registration. Classifications are based on the sample firms. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

6.2.3. Summary of results

The estimation results of ATT find that the R&D tax credit is significantly enhancing the R&D and patenting activities at the firm level. The DSIR affiliated firms realise higher R&D expenditure and patenting during the study period compared to the non-affiliated firms. We find that the R&D expenditure of the firm DSIR registered firms was raised by 166.234 million during the post-reform period. The R&D intensity has increased by 0.027 times for the DSIR registered firms, during the post-reform. In case of innovation outcome in the form of patents, the number of IPO and USPTO patent applications raised by 0.422 and 0.045 times during the periods for DSIR registered firms.

The industry-wise estimates show that the R&D expenditure has increased for DSIR registered firms compared to the non-participants in most of the sectors. The R&D intensity also shows a positive increase except *Electrical equipment* sector during the period. The positive effect of the tax credit scheme on innovation outcome in the form of patent applications is mainly driven by the *Electrical equipment, Machinery and equipment, Metals, Retail and wholesale trade, and Other manufacturing* sectors. The heterogeneities with respect to the firm characteristics reveal that the large firms benefit more from the tax incentive as compared to relatively small firms in terms of both R&D and patents. Our sample firms are skewed towards larger firms in India, that implies invariably, we focus on large firms that are affiliated with DSIR. The impact of the scheme is more for the exporting firms compared to non-exporters. Other interesting findings with respect to the ownership of the firm reveal that the impact of R&D tax credit on innovation input in the form of R&D expenditure and R&D intensity is higher for domestic firms, while the innovation output in the form of patents is higher for foreign-owned firms.

As discussed earlier, a mere comparison of treated and control firms may not yield sufficient guidelines for appropriate policy recommendations.

For a complete evaluation policy, it is important to consider how the timing of DSIR affiliation and its overtime variation reflects the innovation activities of the firm. Also, it is necessary to account for the bias from the unobservable cross-firm heterogeneity and firm-specific time trends over the period. The ex-post analysis of the reform and its impact make further contributes to an effective valuation of the tax credit scheme. In the next section, we take advantage of the panel data and use a DID framework to examine the timing of DSIR affiliation and its variations over time to capture the effect of the policy reform.

6.3. Estimation results of Difference-in-difference (DID)

The results in this section are from the firms in the “new industries” group. Till 2009-2010, the tax credit is available only to firms in the selected industries; however, the 2009-2010 policy reform extended the provision of tax credit to all manufacturing industries in India. We refer these new additions of industries are “new industries”. The “new industries” include firms from *Architecture and civil engineering, Beverages, and food products, Electrical equipment, Leather, textiles and wearing, Machinery and equipment, metals, Non-metallic mineral products, Rubber and plastics products, Wood products and paper, Retail and wholesale trade, and Other manufacturing firms.*

Out of 461 firms from the new industries, 179 firms were registered with DSIR following the reform during 2010-2016. Table 6.12 shows the breakdown of these firms by year of initial DSIR recognition of multi-product firms.

Table 6.12: Firm coverage by DSIR recognition year

DSIR recognition year	Number of firms with $D_{ijt} \neq D_{ij}$
2010	15
2011	34
2012	17
2013	26
2014	19
2015	25
2016	43
Total	***179***

Note: Authors' calculations.

Table 6.13 shows the firm coverage by sector and DSIR recognition status over 2001-2016. Table 6.14 shows the summary statistics of the variables.

Table 6.13: Firm coverage by sector

Manufacture of	Number of DSIR firms recognized
Architecture and Civil engineering	23
Beverages, and food products	55
Electrical equipment	15
Leather, textiles and wearing	20
Machinery and equipment	77
Metals	67
Non-metallic mineral products	29
Rubber and plastics products	31
Wood products and paper	27
Retail and wholesale trade	44
Other manufacturing	73
Total	461

Note: Authors' calculations.

Table 6.14: Summary statistics

Variables	Mean	Std. Dev.	Min	Max
R&D expenditure	91.880	682.542	0	19489.50
R&D intensity	0.018	0.492	0	34.941
Number of IPO patent applications	1.159	10.842	0	558
Number of USPTO patent applications	0.121	1.752	0	96
Location	0.892	0.311	0	1
Foreign ownership	0.099	0.299	0	1
Age	36.882	22.968	1	153
Exporter	0.728	0.445	0	1
Raw material imports	0.082	0.895	0	76.25
Technology imports	0.016	0.111	0	8.795
Leverage	0.026	0.193	0	7.272
HHI	0.147	0.161	0.022	0.976
Firm size	6.942	2.278	0.062	14.876
Firm size squared	53.379	33.216	0.003	221.284

Note: Authors' calculations.

6.3.1 Firms with DSIR registration following the reform

The results in this section are from the sample of 179 firms which registered with DSIR following the reform on the tax credit eligibility. We evaluate how the innovation activity changed after the 2009-10 reform among the firms newly registered with DSIR.

Table 6.15 shows the results of estimating the model (12) can mention in which chapter and section. The outcome variables are: The outcome variables are: R&D expenditure in columns (1)-(2); R&D intensity in columns (3)-(4); the number of IPO patent applications in columns (5)-(6); and the number of the USPTO patent applications in columns (7)-(8). The key variables of interest are the DSIR registration status dummy variable by itself (D_{ijt}). All specifications include fixed effects for each year and industry, while the specifications in columns (2), (4), (6), and (8) also include the vector of industry-specific time trends. Robust standard errors are clustered at the firm level in all regressions.

In column (1), the coefficient ψ on the variable D_{ijt} positive ($\hat{\psi}$ = 1.135) and highly statistically significant. The estimates of ψ in column (1) imply that the DSIR recognition in the post-reform years following the policy reform, firm R&D expenditure increased by $[e^{1.135}-1]100$= 211.12 %. The estimates remain largely unchanged when we also control for the industry-specific time trends in column (2). The results in column (3) further show that the increase in R&D expenditure after the reform was accompanied by an increase in R&D intensity. The coefficient on D_{ijt} is positive ($\hat{\psi}$ = 0.007) and significant. The estimates of $\hat{\psi}$ imply that the impact of DSIR registration on firm R&D intensity has increased by a factor of $[e^{0.007/100}-1]100$ =0.007 %. Further, from column (5)-(8), the coefficient ψ is not statistically significant for IPO and USPTO patent applications.

To allow for firm selection on individual characteristics, we redo the above analysis with controls for firm fixed effects. Table 6.16 shows the results of estimating model (13). By including the fixed effects (α_t), in the specification (11), the endogeneity due to the selection on firm-specific characters will be considered. In addition to the firm fixed effects, all specifications include year fixed effects, while those in columns (2), (4), (6) and (8) also include the vector of industry-specific time trends.

As compared to Table 6.15 with the corresponding in Table 6.16, the inclusion of firm fixed effects leaves the estimates of ψ in columns (1)-(8) largely unchanged.

Table 6.15: Firms affiliated with DSIR following the reform, without firm fixed effects

Outcome variables (in logs):	R&D expenditure	R&D expenditure	R&D intensity	R&D intensity	IPO patents	IPO patents	USPTO Patents	USPTO Patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group (D_{ijt})	1.135***	1.046***	0.007**	0.007**	0.048	0.041	-0.005	-0.007
	[0.157]	[0.164]	[0.003]	[0.003]	[0.035]	[0.036]	[0.018]	[0.020]
Location	0.150	0.155	-0.005	-0.005	0.023	0.025	0.045	0.046
	[0.286]	[0.286]	[0.007]	[0.007]	[0.027]	[0.027]	[0.029]	[0.030]
Foreign ownership	0.172	0.162	-0.001	-0.001	0.021	0.020	0.009	0.009
	[0.374]	[0.380]	[0.003]	[0.003]	[0.053]	[0.055]	[0.038]	[0.037]
Age	0.003	0.003	-0.000	-0.000	-0.001	-0.001	0.000	0.000
	[0.006]	[0.006]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Exporter	0.513***	0.481***	0.005**	0.004	-0.013	-0.006	-0.016	-0.013
	[0.110]	[0.108]	[0.003]	[0.003]	[0.023]	[0.024]	[0.015]	[0.017]
Raw material imports	-0.009	0.002	-0.001	-0.001	-0.002**	-0.002**	-0.000	-0.000
	[0.008]	[0.013]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Technology imports	0.998	1.206	0.148	0.154	0.061	0.134	0.054	0.074
	[1.093]	[1.178]	[0.121]	[0.128]	[0.129]	[0.117]	[0.079]	[0.081]
Leverage	-0.051	0.004	0.001	0.001	0.002	-0.001	0.002	0.002
	[0.076]	[0.098]	[0.001]	[0.001]	[0.013]	[0.011]	[0.006]	[0.006]
HHI	0.372	-1.862*	0.022	0.022	0.476**	0.430*	0.012	0.081
	[0.811]	[0.964]	[0.021]	[0.040]	[0.197]	[0.241]	[0.057]	[0.100]
Firm size	-0.354***	-0.279**	0.005**	0.005**	-0.074***	-0.072**	-0.042	-0.048
	[0.112]	[0.124]	[0.002]	[0.003]	[0.028]	[0.031]	[0.035]	[0.042]
Firm size squared	0.053***	0.047***	-0.000**	-0.000**	0.010***	0.010**	0.006	0.006
	[0.013]	[0.014]	[0.000]	[0.000]	[0.003]	[0.004]	[0.004]	[0.005]
Constant	0.066	-127.636***	-0.011	-1.827***	0.005	-30.783***	-0.003	-5.627***
	[0.370]	[19.084]	[0.015]	[0.344]	[0.065]	[3.632]	[0.044]	[1.278]
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Sector fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Sector-specific time trends		yes		yes		yes		yes
Observations	2,864	2,864	2,864	2,864	2,864	2,864	2,864	2,864
R-squared	0.539	0.576	0.185	0.207	0.233	0.295	0.118	0.128

Note: OLS estimation of model (12) for the sample of 179 firms registered with DSIR following the reform. *The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(3); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (4)-(6); the number of IPO patent applications, defined as log(PatIPO +1) in columns (7)-(9); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (10)-(12). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.*

Table 6.16: Firms affiliated with DSIR following the reform, with firm fixed effects

Outcome variables (in logs):	R&D expenditure	R&D expenditure	R&D intensity	R&D intensity	IPO patents	IPO patents	USPTO patents	USPTO patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group (D_{ijt})	1.111***	1.009***	0.009***	0.009***	0.051	0.046	0.011	0.009
	[0.153]	[0.153]	[0.003]	[0.003]	[0.034]	[0.034]	[0.014]	[0.017]
Age	0.023*	-0.028*	0.000	-0.001**	0.007**	-0.006**	0.002	0.000
	[0.014]	[0.016]	[0.000]	[0.000]	[0.003]	[0.003]	[0.001]	[0.002]
Exporter	0.546***	0.492***	0.004	0.003	-0.017	-0.009	-0.003	0.002
	[0.112]	[0.103]	[0.003]	[0.003]	[0.022]	[0.021]	[0.007]	[0.009]
Raw material imports	-0.017***	-0.007	-0.001	-0.001	-0.002**	-0.001**	-0.000	-0.000
	[0.005]	[0.010]	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]
Technology imports	1.040	1.199	0.139	0.145	0.084	0.151	0.040	0.055
	[1.006]	[1.073]	[0.120]	[0.128]	[0.142]	[0.133]	[0.055]	[0.057]
Leverage	-0.116	-0.057	-0.000	0.000	-0.002	-0.005	-0.000	-0.001
	[0.098]	[0.111]	[0.002]	[0.001]	[0.014]	[0.012]	[0.004]	[0.003]
HHI	0.393	-1.772*	0.024	0.023	0.501**	0.448*	0.026	0.084
	[0.806]	[0.948]	[0.021]	[0.041]	[0.199]	[0.244]	[0.062]	[0.095]
Firm size	-0.342***	-0.119	0.007**	0.008**	-0.038	-0.015	-0.011	-0.008
	[0.106]	[0.112]	[0.003]	[0.003]	[0.029]	[0.029]	[0.014]	[0.020]
Firm size squared	0.052***	0.032***	-0.001**	-0.001***	0.007***	0.004**	0.001	0.001
	[0.011]	[0.011]	[0.000]	[0.000]	[0.002]	[0.002]	[0.002]	[0.002]
Constant	-0.204	-121.964***	-0.026	-1.845***	-0.213*	-29.259***	-0.020	-5.023***
	[0.366]	[19.219]	[0.017]	[0.323]	[0.116]	[3.973]	[0.034]	[1.330]
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Sector-specific time trends?		yes		yes		yes		yes
Observations	2,864	2,864	2,864	2,864	2,864	2,864	2,864	2,864
R-squared	0.686	0.723	0.326	0.349	0.380	0.443	0.407	0.417

Notes: OLS estimation of model (13) for the sample of 179 firms registered with DSIR following the reform. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(3); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (4)-(6); the number of IPO patent applications, defined as log(PatIPO +1) in columns (7)-(9); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (10)-(12). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Next, we consider the effect of the policy reform on the eleven broad sectors. We interact each sector dummy variable with D_{ijt}. We then re-estimate the models (12) and (13) with the extended set of regressors. Tables 6.17 and 6.18 show the estimated results.

From columns (1)-(2) in Table 6.17, the coefficient ψ on the term D_{ijt} is positive and significant for all the sectors, except *Beverages and Food products* sectors. The estimates imply that following the reform firm R&D expenditure has increased by exp (2.101) = 8.17 times in *Architecture and Civil engineering,* exp (1.122) = 3.07 times in *Leather, textiles and wearing,* exp (0.949)= 2.58 times in *Machinery and equipment, exp(1.235) = 3.44* times in *metals, exp (1.149) =3.15 times* in *Non-metallic mineral products,* exp (1.235) = 3.44 times in *Rubber and plastics products, exp (0.919) = 2.51* times in *Retail and wholesale trade, and exp (1.194) = 3.30 times* in *Other manufacturing sectors.* The reform did not change the impact of DSIR registration on firm R&D activities in the case of *Beverages and food products* sector.

The impact on firm R&D intensity has increased by $[e^{0.041/100}-1]100=$ 0.041 % in *Architecture and Civil engineering*, $[e^{0.003/100}-1]100$ = 0.003 % in *beverages and food products*, $[e^{0.007/100}-1]100$ = 0.007 % in *metals*, and $[e^{0.013/100}-1]100$ = 0.013 % in *rubber and plastics products.* The results are positive and significant while controlling the sector-specific time trend in the case of *Architecture and civil engineering, Beverages and food products, Metals, and Rubber and plastics products sectors*.

It is further apparent from columns (5)-(6) that the impact of DSIR registration on the number of IPO patent applications is negative and significant in the case of *Beverages, and food products, Non-metallic mineral products, and Rubber and plastics products sectors* but sensitive to inclusion of sector-specific time trend. At the same time, the estimate of ψ in the architecture and civil engineering sector is positive and significant while controlling the sector-specific time trends. There is no significant impact on the number of USPTO patent applications in any of these sectors. These findings were largely unchanged when we include firm fixed effects in Table 6.18.

Table 6.17: Firms affiliated with DSIR following the reform by sector, without firm fixed effects

Outcome variables (in logs):	R&D expenditure	R&D expenditure	R&D intensity	R&D intensity	IPO patents	IPO patents	USPTO patents	USPTO patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Architecture & Civil engineering x_D$_{ijt}$	1.501**	2.101***	0.039**	0.041**	0.038	0.133**	0.012	0.052
	[0.612]	[0.799]	[0.018]	[0.016]	[0.048]	[0.053]	[0.033]	[0.053]
Beverages & food products x_D$_{ijt}$	0.377	0.761	-0.001	0.003*	-0.125***	-0.038	-0.031	-0.020
	[0.524]	[0.557]	[0.002]	[0.002]	[0.036]	[0.040]	[0.022]	[0.028]
Electrical equipment x_D$_{ijt}$	0.936**	0.118	0.002	0.000	0.032	0.064	0.000	0.021
	[0.473]	[0.597]	[0.003]	[0.004]	[0.087]	[0.068]	[0.020]	[0.037]
Leather, textiles & wearing x_D$_{ijt}$	1.226*	1.122**	0.004	0.003	0.125	0.158	0.089	0.137
	[0.684]	[0.559]	[0.003]	[0.002]	[0.252]	[0.169]	[0.131]	[0.140]
Machinery & equipment x_D$_{ijt}$	1.459***	0.949***	0.006*	0.004	0.137	0.056	0.005	0.022
	[0.267]	[0.340]	[0.003]	[0.003]	[0.086]	[0.075]	[0.024]	[0.030]
Metals x D$_{ijt}$	1.109***	1.235***	0.005	0.007*	0.017	0.035	-0.000	0.025
	[0.398]	[0.468]	[0.004]	[0.004]	[0.056]	[0.062]	[0.020]	[0.035]
Non-metallic mineral products x_D$_{ijt}$	1.543***	1.149**	0.002	0.003	-0.091**	0.026	-0.025	-0.004
	[0.343]	[0.504]	[0.002]	[0.004]	[0.039]	[0.034]	[0.030]	[0.025]
Rubber & plastics products x_D$_{ijt}$	1.175***	1.234***	0.008**	0.013**	-0.070*	-0.046	0.017	-0.002
	[0.365]	[0.440]	[0.004]	[0.005]	[0.038]	[0.061]	[0.036]	[0.055]
Wood products & paper x_D$_{ijt}$	1.393*	1.017	0.029	0.039	0.042	0.090	-0.003	0.006
	[0.716]	[0.691]	[0.026]	[0.026]	[0.091]	[0.074]	[0.020]	[0.014]
Retail & wholesale trade x_D$_{ijt}$	0.735***	0.919***	0.010	0.008	0.151	0.145	0.005	0.011
	[0.271]	[0.236]	[0.011]	[0.009]	[0.114]	[0.116]	[0.028]	[0.022]
Other manufacturing x_D$_{ijt}$	1.125***	1.194***	0.002	-0.001	0.069	-0.031	-0.034	-0.104
	[0.373]	[0.422]	[0.005]	[0.006]	[0.105]	[0.134]	[0.072]	[0.109]
Control variables	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Sector fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Sector-specific time trends		yes		yes		yes		yes
Observations	2,864	2,864	2,864	2,864	2,864	2,864	2,864	2,864
R-squared	0.543	0.579	0.194	0.213	0.240	0.297	0.120	0.133

Notes: OLS estimation of model (11) for the sample of 179 firms registered with DSIR following the reform. The regressions include the same list of control variables as in Table 6.15. **** p <0.01, ** p <0.05, * p<0.1. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(3); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (4)-(6); the number of IPO patent applications, defined as log(PatIPO +1) in columns (7)-(9); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (10)-(12). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.*

Table 6.18: Firms affiliated with DSIR following the reform by sector, with firm fixed effects

Outcome variables (in logs):	R&D expenditure	R&D expenditure	R&D intensity	R&D intensity	IPO patents	IPO patents	USPTO patents	USPTO patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Architecture & Civil engineering x_D_{ijt}	1.209**	1.542**	0.035**	0.029**	0.022	0.110***	-0.005	0.017
	[0.543]	[0.719]	[0.017]	[0.013]	[0.050]	[0.041]	[0.011]	[0.024]
Beverages & food products x_D_{ijt}	0.211	0.561	-0.001	0.003**	-0.119***	-0.013	-0.009	0.009
	[0.435]	[0.364]	[0.002]	[0.001]	[0.032]	[0.021]	[0.009]	[0.013]
Electrical equipment x_D_{ijt}	1.178**	0.605	0.004	0.003	0.018	0.024	0.014	0.016
	[0.482]	[0.589]	[0.003]	[0.004]	[0.092]	[0.051]	[0.016]	[0.016]
Leather, textiles & wearing x_D_{ijt}	1.366**	1.345**	0.005	0.004	0.156	0.190	0.133	0.163
	[0.686]	[0.572]	[0.003]	[0.003]	[0.261]	[0.171]	[0.134]	[0.138]
Machinery & equipment x_D_{ijt}	1.427***	0.878**	0.007**	0.005	0.157*	0.085	0.015	0.043
	[0.288]	[0.369]	[0.003]	[0.004]	[0.084]	[0.076]	[0.023]	[0.032]
Metals x_D_{ijt}	1.015**	1.124**	0.006	0.009**	0.001	0.012	-0.003	0.018
	[0.430]	[0.500]	[0.004]	[0.004]	[0.044]	[0.058]	[0.009]	[0.015]
Non-metallic mineral products x_D_{ijt}	1.464***	0.919*	0.003	0.003	-0.067*	0.057**	0.002	0.015
	[0.364]	[0.536]	[0.003]	[0.004]	[0.039]	[0.029]	[0.016]	[0.019]
Rubber & plastics products x_D_{ijt}	1.303***	1.486***	0.011**	0.017**	-0.053	-0.016	0.046	0.031
	[0.381]	[0.438]	[0.005]	[0.007]	[0.043]	[0.058]	[0.036]	[0.051]
Wood products & paper x_D_{ijt}	1.332*	0.957	0.026	0.034	0.034	0.101	0.001	0.024
	[0.726]	[0.662]	[0.026]	[0.026]	[0.100]	[0.088]	[0.012]	[0.021]
Retail & wholesale trade x_D_{ijt}	0.646**	0.811***	0.011	0.009	0.137	0.118	0.014	0.016
	[0.282]	[0.222]	[0.011]	[0.008]	[0.120]	[0.117]	[0.023]	[0.020]
Other manufacturing x_D_{ijt}	1.075***	1.130***	0.006	0.005	0.089	-0.018	-0.005	-0.077
	[0.395]	[0.413]	[0.005]	[0.005]	[0.105]	[0.132]	[0.067]	[0.113]
Control variables	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Sector-specific time trends		yes		yes		yes		yes
Observations	2,864	2,864	2,864	2,864	2,864	2,864	2,864	2,864
R-squared	0.690	0.725	0.332	0.352	0.387	0.445	0.409	0.421

Notes: OLS estimation of model (12) for the sample of 179 firms registered with DSIR following the reform. The regressions include the same list of control variables as in Table 6.16. The outcome variables are: R&D expenditure, defined as log(R&D exp+1), in columns (1)-(3); R&D intensity, defined as 100×log(R&D exp/Sales+1), in columns (4)-(6); the number of IPO patent applications, defined as log(PatIPO +1) in columns (7)-(9); and the number of USPTO patent applications, defined as log(PatUSPTO +1) in columns (10)-(12). Robust standard errors in parentheses are clustered at the firm level. Here, *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

6.3.4 Summary of results

In a DID framework, we evaluate the effect of R&D tax credit reform that extended the provision of tax credit scheme to all industries in India. We find that the 2010-11 reform has spurred the firm innovation activity of the firms. First, the firms registered with the DSIR following the reform on extended provision of the tax credit, increased the R&D expenditure and R&D intensity by 211.12 % and 0.007% respectively. Most of the industries have increased the innovation input in the form of R&D expenditure and R&D intensity following the DSIR registration in the post-reform period. The industry-specific estimation results also show that most of the industries increased their R&D expenditure and R&D intensity following the DSIR affiliation in the post-reform period. However, the reform did not spur innovation activity in the form of innovation outcomes, such as the number of IPO and USPTO patent applications.

Our main findings suggest that R&D tax credit policy reform resulted in the increase of R&D expenditure of the firms, but not with other innovation measures such as the number of patent application in IPO and USPTO.

CHAPTER 7

SUMMARY AND CONCLUSION

7.1 Introduction

This thesis evaluates the impact of India's R&D tax credit scheme and its reforms on the innovation activity of the manufacturing firms in India. Using the firm-level data from 2001 to 2016, we evaluate the changes in the innovation activity of the DSIR recognized firms following the reforms. We use Propensity Score Matching (PSM) and Difference-in-difference (DID) framework to account for the issues of selection bias and endogeneity.

The thesis considers the effect of the R&D tax credit on innovation input measured through R&D expenditure and R&D intensity and innovation output proxied by the IPO and USPTO patent applications. It provides new insights into the relationship between R&D incentives and innovation in the context of emerging economies like India.

The thesis includes a general introduction, followed by the brief outline of the R&D incentive mechanism in India, literature review, methodology, two core chapters of empirical findings, and a conclusion chapter. This chapter summarizes the thesis, and its major findings, provides policy recommendations, discusses the contributions and limitations of the study undertaken. The rest of the chapter is organized as follows: Section 7.2 presents a summary of the thesis. Section 7.3 gives an overview of the key findings. Section 7.4 synthesizes the results. Section 7.5 offers policy implications, and Section 7.6 highlights the contribution of the work. Section 7.7 presents the key limitations and direction for future research.

7.2 Summary of the thesis

Private sector Research and Development (R&D) is an important driver of technology-led economic growth. Risky innovation projects increase the marginal cost of undertaking R&D activities causing, under-investment and market failure. Policymakers across countries devise a variety of schemes such as research grants, loans, venture capital and tax incentives to deal with market failure. The positive influence of such schemes in the developed countries has motivated developing countries to follow suit (Hall and Van Reenen, 2000). For instance, India has adopted a mix of industrial and innovation policies since the 1990s to promote the innovation activities of firms and to build the National Innovation System (NIS).

R&D tax credit scheme was introduced in India during 1999-2000 to promote private in-house R&D investment and firm innovation. During the 2001–2010 period, the policy offered weighted tax deductions of 150% for any capital and revenue expenditure incurred on in-house R&D by firms in select sectors. In the fiscal year 2010-11, the country's R&D tax deduction was increased to 200%, and the eligibility was extended to firms in all sectors in 2009-10, placing India among the select few countries providing "super deduction" for investment in R&D.

Several empirical studies already exist which examines the effectiveness of R&D tax incentive schemes on innovation. David et al. (2000) and Hall and Van Reenen (2000) provide an extensive review literature on the impact of R&D subsidy programs on firms' R&D expenditure. Most of these studies examine the crowding-out effect of R&D investment, where the substitution of private R&D investment with public R&D funding is examined. The aggregate empirical estimates on the impact of R&D tax incentives suggest that they increase private R&D of the firm (Bloom et al. 2002); however, the recent micro-level studies give more mixed results. Most of the previous empirical studies have considered R&D investment as an outcome measure while evaluating the effect of the R&D tax credit policy (Kasahara et al. 2014; Liu et al. 2016). There are only a few studies that examine the interaction between government innovation support schemes and the firm's innovation output in terms of patenting and new product development (Cappelen et al. 2012; Lee & Wong, 2009). However, empirical findings on the effectiveness of tax incentives on innovation output show mixed results.

Most of the literature examining the effectiveness of R&D tax incentives on innovation activity is based on the developed countries. More recently, attention has shifted to studying the effectiveness of the fiscal incentives for R&D on innovation in emerging economies. The effectiveness of R&D tax incentive schemes in emerging economies is expected to differ from the developed countries due to relatively ample financial constraints and distortions in financial markets, substantial challenges to effective administration, ineffective systems of intellectual property rights, and widespread corruption in such economies.

This thesis evaluates the impact of the R&D tax credit scheme and its reforms on the innovation activity in an emerging country context like India. Only the firms registered with the Department of Scientific and Industrial Research (DSIR) were eligible for the R&D tax credit. We exploit the fact that not all firms have registered with the DSIR by 2016 and those that did, vary by year of registration. This exogenous policy change provides us with a unique opportunity to study changes in firm innovation activity following these two reforms: (i) due to the increase in existing provision of R&D tax deduction from 150% to 200% and (ii) due to the change in new eligibility provision of the R&D tax credit for firms.

The empirical challenge is to reliably measure a causal effect of the R&D tax credit scheme and its reforms on firm innovation activity. One key concern in this respect is the potential endogeneity and the self-selection into DSIR registration. The company's decision to seek recognition from the DSIR might have been endogenous to its innovation performance or driven by the reform. A more financially constrained company, for example, might have had a smaller R&D budget and been more likely to seek the R&D tax credit, particularly after the reform. There is also the concern of endogeneity due to confounding policy changes implemented in India. The R&D tax credit reform could have coincided with other domestic policy changes that had a differential effect on DSIR-registered firms.

To address the selection bias and endogeneity concern, we adopt a PSM and DID setting and evaluate how innovation activity changed after the reforms among "DSIR-registered" firms. In the PSM framework, we use a non-parametric matching approach to control the possible selection bias and compared the innovation activities of the DSIR recognized firms to a matched control group of the non-DSIR firms. The PSM is based on the conditional assumption that there is no unobserved difference between the treated firms and the control firms of non-DSIR firms that are associated with the outcome of interest. In DID setting, we study the timing of DSIR registration and evaluate how the changes in firm innovation activity following registration were impacted by the policy change.

We measure the firm innovation activity using four different outcome variables: the level of R&D expenditures; the R&D intensity, measured as the ratio of R&D expenditures to sales; the number of patent applications filed at the IPO; and the number of patent applications filed at the USPTO. The level of R&D expenditures is a proxy for the firm innovation input. The R&D intensity is a proxy for the intensity of firm innovation input activities. The numbers of patent applications at the IPO and the USPTO are proxies for the firm innovation output.

The thesis begins with Meta-regression analysis of the existing empirical evidence on R&D incentives and innovation in Chapter 3. The meta-analysis reveals the heterogeneity of empirical studies with respect to the type of incentive, data and econometric methodology used. Furthermore, the effectiveness of R&D incentives varies with the measurement and definition of innovation indicators.

In PSM framework, we estimate the average treatment effect on the treated (ATT), which is given by the difference between the expected outcome values with and without DSIR recognition of firms that received DSIR recognition. The outcome values without DSIR recognition for firms that received DSIR recognition is the counterfactual, which is not observed. We employ the PSM to construct this counterfactual using observational data. The PSM uses the unit's observed characteristics to calculate the propensity score, which is the predicted probability of a unit receiving treatment and then matches each unit in the treatment group with one or more control units on the propensity score. To calculate the propensity score, we have identified the factors that contribute significantly to determine the firm's participation in the R&D incentive scheme. The selection of these covariates is made based on the existing empirical studies in India. Building on the literature, we use a number of firm and characteristics such as location, foreign ownership status, age of the firm, export status, raw material imports, technology imports, leverage, firm size and Hirschman-Herfindahl index (HHI).

The PSM balances the pre-treatment covariates between the treated and control units and in doing so, reduces the bias in the estimation of treatment effects. We use nearest neighbor matching, where the individual firm from the comparison group is chosen as a matching partner for a treated individual firm that is closest in terms of propensity score obtained from the covariates (Caliendo & Kopeinig, 2008). We also use other matching methods such as 1-1 Nearest Neighbour Matching (1-1 NNM), 1-3 Nearest neighbour matching (1-3 NNM), 1-5 Nearest neighbour matching (1-5 NNM), and Kernel matching as robustness checks to estimate the ATT.

As discussed earlier, a mere comparison of treated and control firms may not yield sufficient guidelines for appropriate policy recommendations. For a complete evaluation policy, it is important to consider how the timing of DSIR affiliation and its overtime variation reflects the innovation activities of the firm. Moreover, the bias from the unobservable cross-firm heterogeneity and firm-specific time trends over the period should be taken into consideration for policy evaluation. The ex-post analysis of the reform and its impact further contributes to an effective valuation of the tax credit scheme. We take advantage of the panel data to address the concern of endogeneity due to confounding policy changes.

In a DID setting, we examine how innovation activity changed after the reform in the group of DSIR-registered firms. The DID framework estimates the average effect of the policy reform on innovation outcomes of the firm while assuming that, in the absence of reform, the changes in innovation outcome between the pre and the post-reform would remain the same. We examine the timing of DSIR registration, exploiting the fact that firms vary by year of registration. Also, we control for the firm and industry fixed effect to deal with the endogeneity and self-selection issues. The industry variations are estimated with the sector dummy variables. Building on the literature, we control for a number of firm and industry characteristics in the estimation.

7.3 Key findings of the thesis

A short summary of the research findings of each objective is presented below:

Objective 1: To investigate the impact of R&D tax credit scheme and its 2010-11 reform, that increased the weighted tax deduction from 150 % to 200 % on innovation activity of the firms.

Key findings

Propensity Score Matching

- R&D expenditure of the DSIR recognized firms increased on average by 139.126 million during 2001-10 compared to the non-DSIR firms. During 2011-16, the R&D expenditure of DSIR recognized firms increased on average by 354.069 compared to non-DSIR firms.
- R&D intensity of the DSIR recognized firms increased on average by 0.013 during 2001-10 compared to non-DSIR firms. However, during 2011-16, the R&D intensity of DSIR recognized firms increased only on a marginal level compared to non-DSIR firms.
- The number of IPO patent applications of the DSIR recognized firms increased on average by 2.712 during 2001-10 compared to non-DSIR firms. During 2011-16, the IPO patent applications of DSIR recognized firms increased on average by 2.455 compared to non-DSIR firms.
- The number of USPTO patent applications of the DSIR recognized firms increased on average by 0.712 during 2001-10 compared to non-DSIR firms. During 2011-16, the USPTO patent applications of DSIR recognized firms increased on average by 0.689 compared to non-DSIR firms.

- Larger firms benefit more from the tax incentive scheme as compared to relatively small firms in terms of both R&D and patents.
- The effect of the tax credit scheme is more for exporting firms compared to non-exporters.
- The impact of tax credit on innovation is higher for domestic firms compared to foreign-owned firms.

Difference-in-difference

- The R&D expenditure of firms registered with DSIR throughout the period has increased by 77.71% after the reform.
- The IPO and USPTO patent applications of firms registered with DSIR throughout the period has increased by 11 % and 6 % respectively.
- The reform has incentivized new firms to registrar with the DSIR, in order to become eligible for the 200 % R&D tax credit.
- R&D expenditure, R&D intensity and the number of IPO patent applications of firms registered with DSIR following the reform have increased by 113 %, 1.06 % and 20 % respectively.
- We do not find strong evidence that the number of USPTO patent applications increased following DSIR registration in the pre-reform.
- We find that there is no difference in the impact between firms initially recognized by DSIR before 2011 and those initially recognized by the DSIR in or after 2011.

Objective 2: To investigate the impact of 2009-10 R&D tax credit reform, that extended the provision of tax credit scheme to all manufacturing industries, on innovation activity of the firms.

Key findings

Propensity Score Matching

- R&D expenditure of the DSIR recognized firms increased on average by 166.234 million compared to the non-DSIR firms following the reform.
- R&D intensity of the DSIR recognized firms increased on average by 0.27 compared to the non-DSIR firms following the reform.
- The number of IPO patent applications of DSIR recognized firms increased on average by 0.442 times compared to non-DSIR firms following the reform.
- The number of USPTO patent applications of DSIR recognized firms increased on average by 0.045 times compared to the non-DSIR firms.
- Larger firms benefited more from the tax incentive scheme as compared to relatively small firms in terms of both R&D and patents.
- The effect of the tax credit scheme is more for exporting firms compared to non-exporters.
- The impact of tax credit on innovation input in the form of R&D and R&D intensity is higher for domestic firms, while innovation outcome in the form of patents is higher for foreign-owned firms.

Difference-in-difference

- R&D expenditure of the firms recognized by DSIR following the reform has increased by 174.28 %.

- R&D intensity of the firms recognized by DSIR following the reform has increased by 0.009 %.
- The reform did not spur innovation activity in the form of innovation outcomes, such as the number of IPO and USPTO patent applications.

7.4 Synthesis of the results

In this section, we synthesize the results as obtained from the empirical investigations performed and given in detail in Chapters 5 and 6.

In chapter 5, we examine the impact of R&D tax credit scheme and its 2010-11 reform, that increased the tax credit to 200 %, on innovation activity of the firms in India. We used the firm-level data of Original industries[11] and examined how the innovation activity changed following the DSIR registration were impacted by the scheme and its reform. Tables 7.1, 7.2 and 7.3 present the summary of PSM and Table 7.4 shows the summary of DID estimation.

The estimation results of ATT are presented in table 7.1, and table 7.2. The results show that the R&D tax credit is significantly enhancing the R&D and patenting activities at the firm level. The DSIR affiliated firms realise higher R&D expenditure and patenting during the study period compared to the non-affiliated firms. We find that the R&D expenditure of the DSIR recognized firms on average increased during the study period. The R&D intensity of the firms recognized by DSIR increased compared to the non-DSIR firms during the 2001-10. However, during 2011-16, compared to non-DSIR firms, R&D recognized firms increased the R&D intensity by a marginal level only. In the case of innovation outcome in the form of patents, the number of IPO and USPTO patent applications of DSIR recognized firms on average increased compared to non-DSIR firms

[11] The industries where tax credit was available till 2010. We classified these industries into *Chemicals, Pharmaceuticals, Computer and Transport* sectors

during the study period. The industry-wise estimates show that the R&D expenditure has increased for the DSIR registered firms compared to the non-participants in all four industries. The R&D intensity also indicates a positive increase in the case of all sectors except the pharmaceutical sector during 2011-16. The positive effect of the tax credit scheme on innovation outcome in the form of patent applications is mainly driven by the chemical and pharmaceutical sectors. The heterogeneities with respect to the firm characteristics reveal that the large firms benefit more from the tax incentive as compared to relatively small firms in terms of both R&D and patents. The effect of the scheme is more for the exporting firms compared to non-exporters. Other interesting findings with respect to the ownership of the firm reveal that the impact of the tax credit scheme is more for foreign-owned firms.

In Difference-in-difference framework, we investigated how innovation activity changed after the 2010-11 reform among "DSIR-registered" firms as compared to "non-DSIR-registered". We also study the timing of DSIR registration and evaluate how the changes in firm innovation activity following registration were impacted by the 2010-11 reform. Table 7.3 shows that that the 2010-11 reform has spurred firm innovation activity. The impact of DSIR registration on their R&D expenditure has increased by 78% after the reform while the impact on their number of IPO and USPTO patent applications has increased by 11% and 6%, respectively. These impacts are both statistically and economically significant. Secondly, the reform has incentivized new firms to register with the DSIR, in order to become eligible for the 200% R&D tax credit. Following DSIR registration, these firms' R&D expenditure, R&D intensity, and the number of IPO patent applications increased by 113%, 1.06%, and 20% respectively. At the same time, we do not find strong evidence that the number of USPTO patent applications increased following DSIR registration in the pre-reform years; the relevant coefficient lacks precision. Furthermore statistically, there is no difference in the impact between firms initially recognized by the DSIR before 2011 and those initially recognized by the DSIR in or after 2011. But it is important to keep in mind that some impacts (e.g., on firm innovative output) may take more time to be fully realized. Following David et al. (2000), tax credit induces firms to start short-term projects which reflect only in terms of R&D, but not necessarily with the other innovation measures such as patents. Firms' R&D budgets are typically small around the time of initial DSIR registration and gradually increase following registration. Also, firms initially recognized by the DSIR in 2011 or after, were not able to take advantage of the 200% R&D tax credit for a sufficiently long period, since we have only a few years of data after initial DSIR recognition for such firms.

In chapter 6, we examine the effect of R&D tax credit scheme and its 2009-10 reform, that extended the provision of the tax credit scheme to all manufacturing industries, on innovation activity of the firms in India. We used the firm-level data of newly added industries[12] and examined how the changes in firm innovation activity following the DSIR registration were impacted by the 2009-10 reform. Tables 7.5, 7.5 and 7.6 present the summary of PSM and Table 7.8 shows the summary of DID framework.

The estimation results of ATT find that the R&D tax credit is significantly enhancing the R&D and patenting activities at the firm level. The DSIR affiliated firms realise higher R&D expenditure and patenting during the study period compared to the non-affiliated firms. We find that the R&D expenditure of the DSIR registered firms on average increased compared to non-DSIR firms during the study period. Similarly, the R&D intensity

[12] The policy reform in 2009-2010 made new industries to register with DSIR, and these firms received initial recognition during post-reform years (i.e., they first affiliated with the DSIR in or after 2010). We classified these industries into *Architecture and civil engineering; Beverages, and food products; Electrical equipment; Leather, textiles and wearing; Machinery and equipment; Metals; Non-metallic mineral products; Rubber and plastics products; Wood products and paper; Retail and wholesale trade; and Other manufacturing sector*.

of the DSIR registered firms increased compared to non-DSIR firms. In case of innovation outcome in the form of patents, the number of IPO and USPTO patent applications of DSIR recognized firms on average increased during the period compared to non-DSIR registered firms. The effect of the scheme is more for the exporting firms compared to non-exporters. Other interesting findings with respect to the ownership of the firm reveal that the effect of the innovation input in the form of R&D expenditure and R&D intensity is higher for domestic firms, while the innovation output in the form of patents is higher for foreign-owned firms.

The industry-wise estimates show that the R&D expenditure has increased for DSIR registered firms compared to the non-participants in all most of the sectors. The R&D intensity also shows a positive increase in most of the industries except the *Electrical equipment* sector during the period. The positive effect of the tax credit scheme on innovation outcome in the form of patent applications is mainly driven by the *Electrical equipment, Machinery and equipment, Metals, Retail and wholesale trade, and Other manufacturing* sectors. The heterogeneities with respect to the firm characteristics reveal that the large firms benefit more from the tax incentive as compared to relatively small firms in terms of both R&D and patents

In DID framework, we examine the effect of the extended provision of R&D tax credit scheme on innovation activity of the DSIR recognized firms following the reform. We find that the 2009-10 reform has spurred the firm innovation activity of the firms. First, the firms that are registered with the DSIR following the change in the extended provision of the tax credit increased the R&D expenditure and R&D intensity by 174.28 % and 0.009 % respectively. Most of the industries have increased the innovation input in the form of R&D expenditure and R&D intensity following the DSIR registration in the post-reform period. The industry-specific estimation results also show that most of the industries increased their

R&D expenditure and R&D intensity following the DSIR affiliation in the post-reform period. However, the reform did not spur innovation activity in the form of innovation outcomes, such as the number of IPO and USPTO patent applications. It is noteworthy that the most newly added industries belong to the low technology sector that are not patent intensive. Moreover, the lack of qualified R&D to carry out innovation activities may not be immediately reflected on innovation outcome in the form of patents. Also, firms recognized by the DSIR after the reform were not able to take immediate advantage of the R&D tax credit. It is important to keep in mind that the impacts on patenting may take more time to be fully realized.

Our results imply that the tax credit scheme contributes to the innovation activities of the firms in the form of R&D. Tax credit participants realise higher R&D expenditure during the study period. At the same time, we find a mixed result with respect to the innovation outcomes proxied by the number of IPO and USPTO patent applications. A few studies that focus on the impact of tax incentives for Indian firms' R&D have argued that mostly small and medium firms (Mani and Nabar, 2016) benefit from the tax incentive. This argument is based on the amount of R&D expenditure incurred. In the sample firms that are used in this thesis, we focus on firms listed on Bombay Stock Exchange (BSE) as mentioned earlier. This implies invariably, we focus on large firms that are affiliated with DSIR. We further consider gross fixed assets of firms to capture their size as used in other studies on Indian firms' innovation activity (Sasidharan & Kathuria, 2011; Dhanora et al. 2019). Interestingly, here we find that with-in the sample firms, large firms benefit more from the tax incentive as compare to relatively small firms. Considering the firm size as a co-variable in the estimation, we find an inverted U-shaped relationship between firm size and innovation activity of the firm.

Other government institutions also play a significant role in building an environment conducive to innovative activity. The legal protection afforded to inventions through the patent system, for example, increases firms' ability to appropriate the rents accruing from their innovations. This, in turn, makes future market returns to innovation more certain, which can be a major influence in innovation investment decisions (Ivus and Wajda, 2018). Effective protection and enforcement of intellectual property rights can help attenuate the negative impact of uncertainty on business R&D spending and stimulates R&D investment (Czarnitzki & Toole, 2011). It is noteworthy in this respect that our data provide no evidence that the 2010-11 R&D tax credit reform increased the number of IPO patent applications in the Chemicals and Pharmaceuticals sectors, where patents are relatively effective means of appropriating rents from product innovations. In 2005, India extended its patent laws governing pharmaceuticals and agricultural chemicals to make patentable not only the process of manufacture but the products themselves. India's pharmaceutical industry that has established abilities in process patenting appears to be adjusting to the new developments. For pharmaceutical firms that were long registered with the DSIR, we do find evidence that the reform increased the number of USPTO patent applications, but the estimates are not precise.

In summary, our main findings suggest that R&D tax credit policy reforms mainly resulted in the increase of R&D expenditure of the firms, but not necessarily with other innovation measures such as the number of patent application in IPO and USPTO. Policymakers need to devise a strategy whereby firms are motivated to undertake risk and involve in researching new products and/or processes to compete domestically as well as worldwide. Based on the findings, we would also infer that the R&D tax credit reforms may not achieve its overall objective, though the reform has succeeded in increasing the firm R&D expenditure but not reflected on the innovation outcome in the form of patents. The findings also lead to the need for outcome-based incentive schemes such as patent box, where the incentive can be given on innovation outcome.

Summary of results for objective 1

Table 7.1: Summary of Average Treatment Effect (ATT)

	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications
2001-2010	Positive and significant	Positive and significant	Positive and significant	Positive and significant
2011-2016	Positive and significant	Insignificant	Positive and significant	Positive and significant

Table 7.2: Summary of Average Treatment Effect (ATT), by sector

	2001-10				*2001-10*			
	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications
Chemical	Positive and significant	Positive and significant	Insignificant	Insignificant	Positive and significant	Positive and significant	Positive and significant	Insignificant
Pharmaceuticals	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Insignificant	Positive and significant	Positive and significant
Computer	Positive and significant	Positive and significant	Insignificant	Insignificant	Positive and significant	Positive and significant	Insignificant	Insignificant
Transport	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Insignificant	Positive and significant	Positive and significant

Table 7.3: Summary of Average Treatment Effect (ATT), by size, ownership, and export status

	R&D expenditure		R&D intensity		IPO patent applications		USPTO patent applications	
	2001-2010	2011-2016	2001-2010	2011-2016	2001-2010	2011-2016	2001-2010	2011-2016
Small firms	Insignificant	Insignificant	Insignificant	Positive and significant	Negative and significant	Insignificant	Insignificant	Positive and significant
Medium firms	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant
Large firms	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant
Domestic firms	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant
Foreign firms	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant
Non-exporters	Insignificant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Insignificant	Positive and significant
Exporters	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant	Positive and significant

Table 7.4: Summary of Difference-in-difference (DID) Results

	R&D expenditure	R&D intensity	IPO patent applications	USPTO patent applications
Firms registered with DSIR throughout the period				
DSIR registration in the Pre-reform period	Positive and significant	Insignificant	15% lower	10 % lower
DSIR registration in the Post-reform period	Positive and significant	Positive and significant	Positive and significant	Positive and significant
Firms with variations in DSIR registration status				
DSIR registration in the Pre-reform period	Positive and significant	Positive and significant	Positive and significant	Marginally significant
DSIR registration in the Post-reform period	Insignificant	Insignificant	Insignificant	Insignificant

Summary of results for objective 2

Table 7.5: Summary of Average Treatment Effect (ATT)

	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications
Full Sample	Positive and significant	Positive and significant	Positive and significant	Positive and significant

Table 7.6: Summary of Average Treatment Effect (ATT), by sector

	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications
Architecture and Civil engineering	Positive and significant	Positive and significant	Insignificant	-
Beverages and food products	Positive and significant	Positive and significant	-	-
Electrical equipment	Positive and significant	Insignificant	Positive and significant	Insignificant
Leather, textiles and wearing	Insignificant	Positive and significant	Insignificant	Insignificant
Machinery and equipment	Positive and significant	Positive and significant	Positive and significant	Insignificant
Metals	Insignificant	Positive and significant	Positive and significant	-
Non-metallic mineral products	Positive and significant	Positive and significant	Insignificant	Insignificant
Rubber and plastics products	Positive and significant	Positive and significant	Insignificant	Insignificant
Wood products and paper	Positive and significant	Positive and significant	Insignificant	-
Retail and wholesale trade	Insignificant	Positive and significant	Positive and significant	Positive and significant
Other manufacturing	Positive and significant	Positive and significant	Positive and significant	Positive and significant

Table 7.7: Summary of Average Treatment Effect (ATT), by size, ownership, and export status

	R&D expenditure (in million)	R&D intensity	IPO patent applications	USPTO patent applications
Small firms	Positive and significant	Insignificant	Insignificant	Insignificant
Medium firms	Positive and significant	Positive and significant	Positive and significant	Insignificant
Large firms	Positive and significant	Insignificant	Positive and significant	Insignificant
Domestic firms	Positive and significant	Positive and significant	Positive and significant	Insignificant
Foreign firms	Marginally significant	Positive and significant	Positive and significant	Positive and significant
Non-exporters	Positive and significant	Positive and significant	Positive and significant	Insignificant
Exporters	Positive and significant	Positive and significant	Positive and significant	Marginally significant

Table 7.8: Summary of Difference-in-difference (DID)

	R&D expenditure	R&D intensity	IPO patent applications	USPTO patent applications
DSIR registration in the Post-reform period	Positive and significant	Positive and significant	Insignificant	Insignificant

7.5 Policy implications

Based on the analysis, this thesis derives following policy implications.

First, we find that the R&D tax credit scheme and its reforms spurred firm innovation activity. The overall results support increasing tax credit incentives in India. Encouraging R&D with "super deductions" has real and economically significant effects on firms' input into innovation as well as their innovative output. Our findings do not support the government's decision to reduce the tax incentives in corporate firms to just 100% of R&D from 2020-21. On the contrary, the evidence supports increasing R&D tax credit incentives in India. The tax incentives and its reforms were successful in promoting firm innovation, but the level and growth rate of private R&D spending in India is still not internationally comparable. If India aims to make business R&D a major driver of the national innovation system, policymakers must continue encouraging additional R&D with "super deductions."

Secondly, the innovation output measured through the number of IPO and USPTO patent applications shows a mixed effect of the R&D tax credit scheme. Considering that few DSIR-registered firms have patents registered with the USPTO, India's policymakers may consider designing an award mechanism for businesses seeking international patent protection. Additional benefits could be conferred when patent applications are from R&D undertaken because of R&D tax incentives. In the pharmaceutical sector, the road from product discovery to marketing is typically long (due to clinical trials, drug approvals, etc.). Also, India's pharmaceutical industry, which has established abilities in process patenting, appears to be adjusting to the new developments in the patent policy. For pharmaceutical firms that were registered with the DSIR, we do find evidence that the reforms increased the number of USPTO patent applications, but the estimates are not precise. Thus, the incentives also focusing on patent applications are worthwhile to consider. Policymakers need to devise a strategy whereby these firms are motivated to undertake risk and involve in researching new products and/or processes to compete domestically as well as worldwide. One example is the "Patent box" scheme introduced in 2016-17, which encourages innovative output, but applies only for firms that receive income in the form of royalties and technology licensing.

With TRIPs, the space for imitation goods has shrunk, and Indian firms need to spend R&D resources efficiently that result in new to the market innovations. Based on this, we would also infer that the R&D tax credit policy may not be fulfilling its overall objective. Though it may have succeeded in incentivizing firms to invest more in R&D these firms are not able to file for patents as the outcome of such investment. This highlights an important aspect about the Indian innovation by firms. Such firms need to focus more on the newer technologies and build niche to be competitive. To that effect, we can suggest that additional incentive as detailed above to be given if the registered firms file and are granted a patent based on the investment undertaken in a period of three years. Thus, there is a need to customize and strengthen the existing scheme per the innovation capabilities of firms. In such a scenario, if the government reduces the tax incentives as mentioned earlier in the text, it may adversely affect the incentives and the innovation ecosystem that India is trying to build.

It is important to underscore that the effectiveness of government programs aimed at stimulating R&D activity in the private sector depends on the sensitivity of economic agents to build conditions. This sensitivity varies greatly across firms, depending on their size, export orientation and market characteristics, etc. We find that larger firms benefit more from the R&D tax credit scheme compared to the relatively small and medium firms. Policy initiatives aimed at promoting R&D activity of small firms are thus needed to ensure that firms continually innovate for the market. In this respect, a more flexible approach to R&D incentives might be more effective, and policymakers might consider abandoning the current 'one size fits all' approach to firm R&D investment and re-designing the R&D tax credit scheme to better suit individual firm needs. Finally, the heterogeneous effect of the tax credit scheme also suggests a special policy focus on promoting innovation activities of small and medium firms.

7.6 Contributions of the thesis

This thesis contributes to the previous literature in four ways. First, we study the impact of the R&D tax credit scheme in an emerging country context. While previous work in this context has studied in China (Guo et al. 2016; Howell, 2016; Liu et al. 2016; Wang et al. 2017) and Taiwan (Yang et al. 2012). However, the market environment and regulatory framework of these economies are much different than in India. One study Mani (2010) estimated the elasticity of R&D expenditure with respect to tax foregone due to the R&D incentive scheme, but the data used for a short period (2000-2006) and did not address the selection into the R&D program concern.

Secondly, this thesis examines the R&D tax policy reforms on innovation activity of the firms in India. This exogenous policy changes providing us with a unique opportunity to study changes in firm innovation activity at two different sets of policy reforms: (i) change in the existing provision of weighted tax credit rate from 150% to 200% and (ii) change in the eligibility provision of the tax credit scheme to all industries.

Third, we account for the endogeneity and selection into the tax credit scheme by employing Propensity Score Matching (PSM) and Difference-indifference (DID) framework. Finally, we also examine if the increase in R&D by the private sector leads to new to world innovation proxied by the number of patent applications. The second part of the study gains relevance in view of the changes in IPRs regime made across countries to comply with the Agreement on Trade-related intellectual property rights (TRIPs) under World Trade Organization (WTO). These changes across countries limit the space for imitation goods. Thus, there is a need to innovate goods that not only cater to domestic demand but can have an international market.

7.7 Limitations and future directions for research

Mani and Nabar (2016) pointed out that the mostly small and medium firms benefit from the tax incentive. This argument is based on the amount of R&D expenditure incurred. In this thesis, we use the firm-level data collected from the CMIE Prowess database, which consists of the firms listed in stock exchanges and other larger companies. This implies, invariably, we focus on large firms and ignore the small firms due to the non-availability of data. These companies benefit significantly from the R&D tax credit and are thus likely to have a higher benefit. Therefore, it is not possible to discern the true impact of the weighted deduction policy on R&D spending in India and to see whether small and large firms respond differently to these incentives.

This thesis also raises several directions for future research. First, for a complete policy evaluation, it is important to consider the amount of weighted deduction that has been availed by each firm. It helps the policymakers to evaluate the proportion in which tax foregone is driven by each firm based on the industry and size. The policymakers could consider the differential rates depending on the size of the firm. Another important limitation of the work is that the elasticity of tax foregone is not considered for the study. The effect of the R&D tax credit may vary with firm’s R&D expenditure and profit generated. It will be interesting to see how the elasticity of tax foregone varies among the different category of firms. It is also necessary to investigate whether the positive effect of the R&D tax credit scheme leads to higher productivity of the DSIR recognized firms. As mentioned earlier, our sample is skewed towards large companies, which are large R&D spenders. It will be interesting to study the effect of the tax credit scheme among the small firms, especially the effect on overcoming the financing constraints of innovation.

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