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A Learning Perspective

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BY
YUCHEN GAO

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Yuchen Gao

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Abstract

Public research and development (R&D) subsidy is one of the most important policy instruments to tackle R&D-related market failure of firms. Studies based on neoclassical economics have substantially discussed the effects of R&D subsidy on firm-level R&D input and output. Recently, academic studies have focused increasingly on the effect of R&D subsidy on the behavioral additionality of firm-level R&D processes to further describe and analyze the contents of the complicated "black box" between R&D subsidy and firms' R&D activities.

Combining the knowledge-based view with an organizational learning perspective, this dissertation explores and analyzes empirically the interactions between R&D subsidy, organizational learning behaviors, and firm-level R&D outputs in the context of China, from an evolutionary and systemic perspective. A set of panel data were applied to the empirical analysis, covering 7,928 manufacturing firms in Jiangsu Province observed from 2010 to 2014. The main econometric methods are comprised of propensity score matching, instrumental variables, Tobit regression model, Logit regression model, and Cox regression model based on the specific research questions for each chapter.

According to the empirical results, this dissertation reveals the following findings. First, the R&D subsidy promotes the firms' investment in R&D collaborations with universities, and it also promotes firms' citations of knowledge from universities in their invention patent applications. At the same time, firm-level higher educational R&D human resources, conceptualized as higher absorptive capacities, and are found to moderate R&D subsidy positively to promote the firms' citations of knowledge from universities in invention patents. Surprisingly, antagonistic effects exist between the science parks and R&D subsidy due to the overlapping of public support in China. Second, no impact of the R&D subsidy is detected in the novel knowledge exploration of firms in all stages, yet public funds significantly inhibit firms in the decline stage from adopting novel knowledge in innovation. Third, firms' learning behaviors in novel knowledge adoption of core technological focus change at the firm level can be significantly facilitated by participating in R&D subsidy programs. However, this effect differs between local and central R&D subsidy programs. More specifically, this facilitating effect on firm-level core technological focus change is significant in local R&D subsidy programs, while no similar effect can be found in central R&D subsidy programs.

This is arguably the first study that explores and discusses the effect of public R&D subsidy on firms' learning behaviors of novel knowledge exploration based on the knowledge-based view and organizational learning perspective in the context of China, in which the Chinese government has placed more emphasis on enhancing firm-level R&D capabilities by learning. Empirical evidence is also provided for validating relevant theoretical hypotheses. This dissertation extends understanding beyond previous studies, which focused mainly on the effect of R&D subsidy on firm-level R&D input and output within the logic of neoclassical economics. By extending the application of organizational learning theory, this dissertation strengthens the theoretical depth in the research field of public R&D subsidy. At the same time, it is the first study to differentiate various effects of R&D subsidy from central and local governments on firms' R&D behaviors. This provides a new perspective for related studies and expands the strategy research related to the government-industry dynamics. This dissertation also explores the interactions between public R&D subsidy, firms' learning behavior, and R&D output in the context of China from a more comprehensive perspective, and further contributes to the aforementioned process of understanding what is happening inside the "black box" between public R&D subsidy and firm-level R&D activities. In addition, the dissertation adopts Cox regression to explore the effect of R&D subsidy on firms' learning behaviors of new knowledge exploitation, which is a methodological innovation in respect of current related studies.

Furthermore, the policy and management implications based on this study are provided. For example, the focus of R&D subsidy policy is required to change from a result-based focus to process-orientation in China, and the Chinese government should carefully consider the timing of R&D subsidy allocation. At the same time, the government should also help shape the external learning environment of firms. More importantly, the central government needs to decentralize the authority of allocating R&D subsidy investment to local governments to enable the technological upgrading of local firms. For managers, this study provides implications on strategic decisions on when and how to participate proactively in governmental projects in relation to the exploration of new knowledge for the enhancement of their own innovative capabilities and technological upgrading.

KEYWORDS: R&D subsidy; behavioral additionality; R&D output; organizational learning perspective; novel knowledge exploration; China

Resumé (Summary in Danish)

Offentlige tilskud til virksomheders forsknings- og udviklingsudgifter (F&U) er et af de væsentligste politikinstrumenter i forhold til at adressere F&U-relaterede markedsfejl. Studier baseret på neoklassisk Økonomi har udfoldede diskussioner af effekterne af F&U tilskud på virksomheders F&U input og output. I den seneste tid har akademiske studier i stigende grad fokuseret på de adfærdsmæssige effekter af F&U tilskud for derigennem at afdække den komplicerede "black box" i sammenhængen mellem F&U tilskud og virksomheders F&U aktiviteter.

Ved at kombinere et vidensperspektiv med et organisatorisk læringsperspektiv udforsker og analyserer denne afhandling empirisk sammenhængene mellem F&U tilskud, adfærd i forbindelse med organisatorisk læring, og virksomhedernes F&U aktiviteter. Det sker i en empirisk kontekst som er Kina. Der anlægges et evolutionært og systemisk perspektiv. Et panel datasæt anvendes i den empiriske analyse. Det dækker 7,928 fremstillingsvirksomheder i Jiangsu Provinsen og dækker perioden 2010 til 2014. De primære økonometriske metoder er propensity score matching, instrumentielle variable, Tobit regressionsmodel, Logit regressionsmodel, og Cox regressionsmodel.

De empirisk analyser i denne afhandling giver de følgende resultater: For det første viser det sig, at F&U tilskud fremmer virksomheders investeringer i F&U samarbejder med universiteter og det fremmer virksomheders citeringer af viden fra universiteter, når de ansøger om patenter. På samme tid influerer det på resultaterne om virksomhederne har højt uddannet arbejdskraft, idet dette udgør en ressource i forhold til at indoptage viden fra universiteter, og dermed påvirker tendensen til at citere universitetsbaseret viden positivt. Det er overraskende, at der er modsatrettede effekter af forskerparker og F&U tilskud, men det kan skyldes overlappende subsidier i den kinesiske kontekst. For det andet viser det sig, at der er ikke effekter af F&U tilskud i fald virksomhederne er i en explorativ, udforskende fase. Dog er det sådan at F&U tilskud gør virksomheder i tilbagegang bedre i stand til at indoptage ny viden for innovation. For det tredie giver deltagelse i F&U programmer en positiv effekt på virksomheders evner til at optage ny viden, særligt i forbindelse med tilpasning af deres kerneteknologier. Imidlertid er denne effekt forskellig i henholdsvis lokale og centrale F&U tilskudsprogrammer, idet den er klart positiv i lokale programmer, men denne effekt genfindes ikke i centralt organiserede programmer.

Dette er sandsynligvis det første studie som udforsker effekterne af kinesiske, offentlige F&U tilskud på virksomhedernes læringsadfærd med hensyn til anvendelse af ny viden og som samtidigt anvender et vidensbaseret og organisatorisk læringsperspektiv. Den kinesiske regering har haft mere focus på at styrke virksomheders F&U kapacitet gennem læring. Der gives i afhandlingen desuden empirisk belæg for relevante teoretiske hypoteser. Afhandlingen udvider den eksisterende forståelse af emnet, eftersom tidligere studier primært har fokuseret på effekterne af F&U tilskud på virksomhedernes F&U input og output set i lyset af et neoklassisk økonmisk rationale. Ved at anvende organisatorisk læringsteorier styrker afhandlingen den teoretiske dybde i studier af F&U tilskud. Samtidigt er det det første studie som skelner mellem forskellige adfærdseffekter af F&U tilskud fra henholdsvis lokale og centrale offentlige aktører. Dette giver et nyt perspektiv for relaterede studier og udvider dagsordenen for studier af dynamikkerne i offentlig-privat samspil. Afhandlingen udforsker også sammenhængene mellem offentlige F&U tilskud, virksomheders læringsadfærd, og F&U output i en kinesisk kontekts med anvendelse af et mere holistisk perspektiv, og dermed udfoldes indholdet i den "black-box", som er mellem offentlig F&U tilskud og virksomheders F&U aktiviteter. Yderligere anvender afhandlingen Cox regressioner til at udforske effekter af F&U tilskud på virksomheders læringsadfærd med hensyn til at udnytte ny viden. Dette er en metodemæssig nyskabelse af relevans for lignende studier.

Endelig giver afhandlingen såvel politik- som ledelsesmæssige implikatoner. For eksempel bør fokus i F&U tilskudspolitik ændres fra resultatbaseret til procesbaseret politik i Kina, og den kinesiske regering bør overveje nøje hvordan timingen af F&U tilskud skal ske. Desuden bør regeringen hjælpe med at skabe et læringsmiljø for virksomhederne. Endnu mere vigtigt bør den centrale regering decentralisere kompetenceen til at foretage allkokering af F&U tilskud møntet på teknologisk udvikling af virksomhederne. For virksomhedsledere peger studierne på den strategiske betydning af hvornår og hvordan virksomheder skal deltage proaktivt i offentlige programmer for at udnytte ny viden til teknologisk og innovative evner.

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1. Introduction

1.1 Research Background

1.1.1 Public R&D Subsidy: A policy tool for Coping with Market Failure of R&D

Public research and development (R&D) subsidy is a series of policy instruments, including a variety of economic incentives, designed to promote and encourage the participation of the private sector in R&D activities and innovation (Becker, 2015; David, Hall, & Toole, 2000; Dimos & Pugh, 2016; Garcia-Quevedo, 2004). By eliminating market failures related to R&D and innovation, and motivating R&D activities of firms, R&D subsidy is regarded as having positive externalities on economic development with less distortionary effects on the market (David et al., 2000; Klette, Moen, & Griliches, 2000; Martin & Scott, 2000). In the *Agreement on Subsidies and Countervailing Measures* (SCM Agreement)[1] promulgated by the World Trade Organization (WTO), R&D subsidy is classified as Non-Actionable Subsidies. Consequently, R&D subsidy is one of the widely adopted, effective policy instruments for the facilitation of firms' R&D activities, such as the Small Business Innovation Research Program (SBIR) of the United States and Horizon 2020 of the European Union.

Innovation-related market failures come about for three main well-understood reasons: first, the characteristics of public goods in R&D. R&D activities have non-competitive and non-exclusive characteristics (Arrow, 1962; Bush, 1945; Nelson, 1959). Second, firms undertaking R&D may fail to attract external financial support because of information asymmetry from the institutional theory, which results in a situation where the value of R&D cannot be anticipated by external investors (Arrow, 1962). Third, from the perspective of innovation literature, due to the liability of newness, innovation, especially radical innovation, usually suffers a high level of uncertainty and high risk of failure, as the financial returns of R&D investment are usually long term (Hall & Lerner, 2010).

Market failures of R&D would lead to under-investment in R&D, resulting in the inhibition of the enhancement of firm-level innovation-related capabilities and, subsequently, innovation performance (Jourdan & Kivleniece, 2017). Thus, market failures are invoked in arguments that government intervention is necessary for

1 Agreement on Subsidies and Countervailing Measures, SCM Agreement https://www.wto.org/english/docs_e/legal_e/24-scm_01_e.htm

supporting the R&D of firms (Stiglitz, 1988). Public R&D subsidy, as one of the government interventions at firm-level R&D, is considered to cope with market failures by buffering the financial capital shortage, reducing the cost of R&D, jointly undertaking the risk of R&D and providing endorsement to firms (Amezcua et al., 2013; Dimos & Pugh, 2016; Jourdan & Kivleniece, 2017; Lee & Cin, 2010). R&D subsidy is not only expected to promote firms' own R&D investment, but to attract external financing (Gonzalez & Pazo, 2008; Lerner, 1999; Marino et al., 2016; Toole & Turvey, 2009). R&D subsidy is also expected to enhance the innovation-related capabilities of firms and subsequently facilitate firm-level innovation performance in areas such as patent application and new product sales (Hussinger, 2008; Jourdan & Kivleniece, 2017).

Present studies focus primarily on the effects of R&D subsidy on firm-level R&D input and output additionality (Cerulli, 2010; David et al., 2000; Garcia-Quevedo, 2004; Zuniga-Vicente et al., 2014). Additionality is a key factor in evaluating the effects of public R&D subsidy, which refers to the additional R&D input and output generated by public intervention beyond the counter-factual levels that firms would have achieved without such intervention (Dimos & Pugh, 2016; Georghiou & Clarysse, 2006; Gök & Edler, 2012). Input additionality, from a resource-based perspective, investigates whether and to what extent firms engage in greater R&D expenditure after receiving public support. In other words, input additionality justifies the capacity of public R&D subsidy to stimulate additional private R&D investment to reach the social optimum. The analysis of the input additionality is the most popular among present relevant studies on R&D subsidy, due to its straightforward consistency according to standard neoclassical theory (Colander, 2000). Output additionality is a result-based concept that considers the increase of R&D output generated by R&D subsidy (Falk, 2007; Guan & Yam, 2015). Based on the R&D process, R&D output is further classified into technological output and economic output and mainly measured by the creation of patents and sales of new products, respectively (Guan & Yam, 2015).

However, evaluating public subsidy from the input and output additionality perspective may run the risk of oversimplifying the innovation process, as it takes for granted that additional R&D input would inevitably result in increased firm-level R&D outputs (Falk, 2007; Gök & Edler, 2012). This leads to conflicting research results on how R&D subsidy generates output additionality (Dimos & Pugh, 2016). A possible explanation is that previous studies based on the input and output additionality perspective neglect how firms would have changed their R&D-related behaviors after receiving a given R&D subsidy (Chapman & Hewitt-Dundas, 2015; Gök & Edler, 2012). In line with that, the concept of behavioral additionality is introduced by Buisseret et al. (1995) and has attracted increasing research interest in recent years (Gök & Edler, 2012).

1.1.2 Behavioral Additionality: A New Perspective of Evaluation on Effects of R&D Subsidy

Behavioral additionality is defined as the firm's desirable behavioral changes during the innovation process, which can result in a more efficient transformation from R&D inputs to outputs caused by policy intervention (Buisseret, Cameron, & Georghiou, 1995; Falk, 2007). Thus, behavioral additionality can capture the essential enhancements generated by R&D subsidy on aspects such as: firm-level managerial capabilities, technological know-how, and networking skills (Falk, 2007; Knockaert, Spithoven, & Clarysse, 2014). It is also argued that behavioral additionality is associated with a change in the process of exploring, creating, learning, and exploiting new knowledge for innovation from the learning perspective (Clarysse, Wright, & Mustar, 2009). This conception of behavioral additionality potentially indicates the effect of R&D subsidy on firm-level R&D activities from a more comprehensive perspective (Georghiou & Clarysse, 2006). Furthermore, behavioral additionality goes beyond the basic intervention logic of R&D subsidy which stems from market failure. Behavioral additionality has roots in a broader range of failures, such as system and knowledge processing failures from evolutionary and structural views (Gök & Edler, 2012). Thus, an analysis of behavioral additionality, as the third type of additionality effect of R&D subsidy, essentially complements conventional R&D subsidy studies on input and output additionality (Knockaert et al., 2014; Wanzenboeck, Scherngell, & Fischer, 2013). It also enables us to further open up the "black box" of the mechanism of public R&D subsidy on firm-level R&D activities. The evaluation of behavioral additionality induced by R&D subsidy mainly focuses on both internal usage and external linkage for accessing, acquiring and exploiting innovation-related resources, such as knowledge (Chapman & Hewitt-Dundas, 2015; Clarysse et al., 2009; Gök & Edler, 2012). Looking at behavioral additionality helps us to understand better the exploitation of input additionality and the acquisition of output additionality generated by R&D subsidy.

Behavioral additionality can be further classified into several subcategories from different perspectives. From the perspective of sponsored projects implementation, behavioral additionality can be classified into scale, scope and acceleration additionality (Falk, 2007; Georghiou, 2002; Wanzenboeck et al., 2013). Scale additionality refers to the situation where R&D subsidy recipient firms may conduct R&D projects on a larger scale (Wanzenboeck et al., 2013). Scope additionality is the extension of firm-level R&D activities to a wider range of markets, applications or players (Knockaert et al., 2014) while acceleration additionality measures whether firms receiving R&D subsidies conduct their projects faster than they would have, had they not usually used external funding (Falk, 2007; Gök & Edler, 2012).

Cognitive capacity additionality, deriving from the perspective of the increasing cognitive capacity of R&D subsidy recipient firms, is defined as the positive effect on firms' capacities which are crucial for innovation activities and performance (Knockaert et al., 2014). Two key additionalities of cognitive capacity are networks and competence additionality (Alexander & Martin, 2013; Antonioli, Marzucchi, & Montresor, 2014). Network additionality occurs through external collaboration and network building with both individual and organizational learning, thereby enhancing the internal cognitive capacities of firms (Alexander & Martin, 2013; Falk, 2007). Competence additionality is conceptualized in terms of the positive impact that R&D subsidy has on the different kinds of internal individual abilities and organizational capabilities that are required in managing the innovation process (Antonioli et al., 2014).

As stressed by Clarysse et al. (2009), "*the distinctions between the different types of behavioral additionality are not always clear-cut*" (pp. 1519). Clarysse et al. (2009) elaborate behavioral additionality from a knowledge-based view combining it with a learning perspective. It is argued that firm-level behavioral additionality could be caused by changes in organizational learning processes. For example, the methods of acquisition and the search scope of firms on new technological knowledge may be changed after receiving R&D subsidies. More specifically, firms receiving R&D subsidies are more likely to obtain new knowledge via formal collaboration with external sources, such as universities and research institutes (Afcha Chavez, 2011). Behavioral additionality can also be derived from the attitude change of new knowledge usage within firms (Chapman & Hewitt-Dundas, 2015). For example, R&D subsidy recipient firms may have a higher motivation and risk-taking level for knowledge recombination with less previous experience and relevant knowledge stock, and this may lead to more innovative technology, even radical innovation (Beck, Lopes-Bento, & Schenker-Wicki, 2016; Clarysse et al., 2009; Zhao, Li, & Liu, 2016). Thus, it is suggested that behavioral additionality is directly and indirectly linked with organizational learning.

1.1.3 Development of R&D Subsidy in China

Transforming from a planned economy to a market-driven economy, the Chinese government assigns science and technology an important role in economic development (Benner, Liu, & Serger, 2012; OECD, 2008). During the early stages of economic reform, the Chinese government mainly adopted public intervention and national-level science and technology (S&T) programs, investing heavily to acquire and develop technologies to build S&T capabilities for catching up (Guan & Yam, 2015).

With fast economic growth, China has been increasingly emphasizing the importance of indigenous innovation and identifies innovation as the key driving force for economic development (Serger & Breidne, 2007). Central government sets the goal to make China a world-leading innovation country with the adoption of the National Medium- and Long-Term Plan for Science and Technology Development (2006–2020) in 2006 (Liu et al., 2017). The overall deployment of this plan focuses on indigenous innovation in high-tech industries. More specifically, the emphasis of this plan is to enhance technological capacities in several selected high-tech and strategic industries, strengthen the weak capacity of indigenous innovation, and overcome the issue of under-investment in S&T (Gao, 2015; Liu, Li, & Li, 2016). The relevant supports are provided via various types of R&D programs with substantial public R&D funding (Boeing, 2016).

In 2012, the Chinese government launched the Innovation-Driven Development Strategy and firms were identified as the core entities of innovation and economic growth (Liu et al., 2016). Following Neo-Schumpeterian Growth Theory, national economic growth depends highly on firm-level R&D capabilities of developing original innovation (Aghion, 2011; Aghion & Howitt, 1992). Consequently, central and regional governments of China launched various R&D subsidy programs and deployed a large amount of capital resource to support firms' R&D and innovation activities for enhancing firm-level R&D capabilities (Guan & Yam, 2015; Guo, Guo, & Jiang, 2016; Liu et al., 2016; Liu et al., 2017; Wang, Li, & Furman, 2017).

The Chinese government designed different types of R&D subsidies to provide financial capital for firms to carry out R&D and to encourage private-owned firms, in particular, to participate in national S&T programs (Larédo, Köhler, & Rammer, 2016). The three main R&D subsidy tools in China are direct grants, subsidized loans and tax incentives (Guan & Yam, 2015; Xin et al., 2016).

Direct R&D grants are the traditional and most prevalent tool of the Chinese government to support firms' innovation activities (Zheng, Singh, & Mitchell, 2015). Direct R&D grants can directly compensate for the resource shortage in the private sector with no interest and repayment required (Guan & Yam, 2015). The sponsored range of direct R&D grants depends on the technology level and market prospects of target projects applying for public support (Guan & Yam, 2015). The screening process is undertaken by government institutions (Xin et al., 2016). Moreover, to avoid the crowding-out on firms' own R&D investment by providing over-funded public money, the Chinese government in recent years in principle requires recipient firms' dollar-to-dollar matching for direct R&D grants (Guo et al., 2016). It is similar to an upper-limitation setting in providing direct R&D grants (Hsu & Hsueh, 2009).

Although some of the recent studies demonstrate the existence of an additionality effect on firm-level R&D expenditure of direct R&D grants (Liu et al., 2016), the efficiency of direct R&D grants still remains inconsistent conclusions in China (Boeing, 2016; Guan & Yam, 2015; Wang et al., 2017). The government failure issue associated with public R&D subsidies is exacerbated in China due to profound political interference, stronger public intervention and a sophisticated bureaucratic system with Chinese characteristics (Guan & Yam, 2015; Wang et al., 2017). According to Guan and Yam's research (2015), direct R&D grants from the Chinese government exert a negative effect on firm-level patent applications and new product sales.

Having noticed the failure of government intervention, the Chinese government introduced more market-orientated R&D subsidies, namely, R&D-subsidized or interest-reduced loans (贴息贷款 *Tiexi Daikuan*) and R&D tax incentives (加计扣除 *Jiaji Kouchu*). R&D subsidized loans are essentially a business loan with interest, where the government pays back a proportion of or all the interest to commercial banks on behalf of the subsidy recipients (Grau, Huo, & Neuhoff, 2012). R&D tax incentives are tax exemptions or reductions depending on the essential firm-level R&D expenditure (Guan & Yam, 2015). R&D subsidized loans and R&D tax incentives are usually used jointly with direct R&D grants by regional governments as a kind of innovation policy.

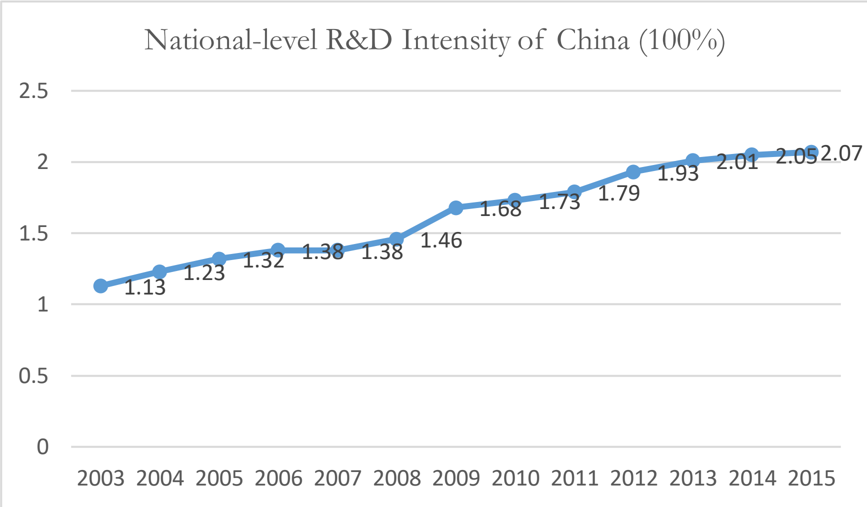

Figure 1.1 National-level R&D Intensity of China (100%)

From 2003 to 2015, the national-level R&D intensity of China was raised from 1.13% to 2.07%[2] (see Figure 1.1). Total R&D expenditure in China increased from 153.96 billion RMB in 2003 to 1416.988 billion RMB in 2015 (see Table 1.1), keeping the average growth rate at 20.47%. Particularly, R&D expenditure from government funds rose from 46.06 billion RMB to 301.32 billion RMB from 2003 to 2015, keeping the average growth rate at 17.09%. However, the ratio of public funds on total R&D expenditure dropped from 29.9% to 21.3% from 2003 to 2015, while the ratio of firm-level R&D funds increased yearly from 60.1% to 74.7% during the same period (see Figure 1.2). This implies that the R&D activities of Chinese firms become more active, and public funds may have more responsibility for leveraging resources from the private sector rather than directly bridging the resource gaps of firm-level R&D activities.

[2] China Statistical Yearbook on Science and Technology (2009-2016, in Chinese)

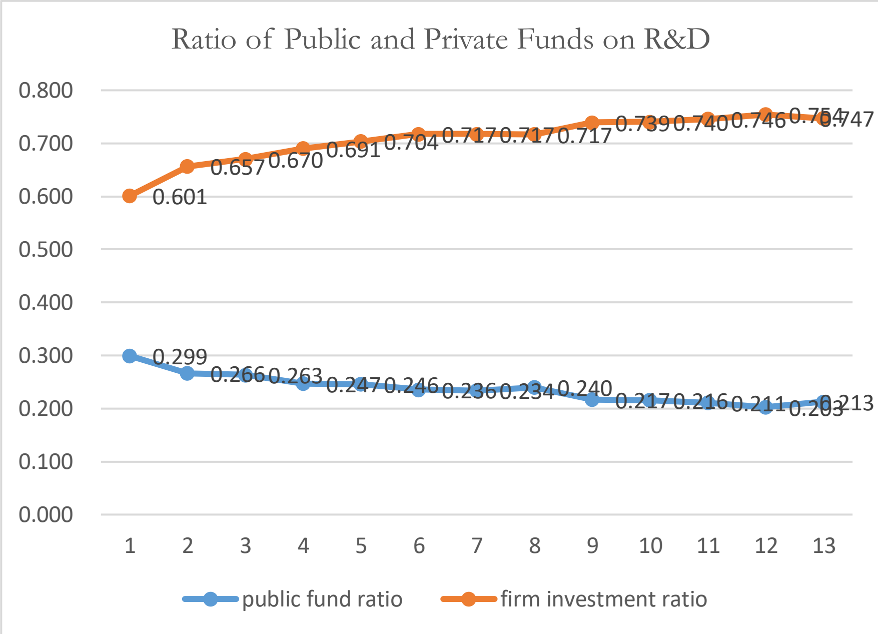

Figure 1.2 the Ratio of Public and Private Funds on R&D

Another tendency is that the Chinese government has increasingly emphasized the importance of using public intervention to facilitate firms' learning behaviors and enhance firm-level technological capabilities (Liu et al., 2017). In my pre-research interview in 2017, a key official from the provincial science and technology bureau stated that the main target of R&D subsidy now is to guide and motivate high-tech firms to acquire, create and apply the frontier S&T knowledge when undertaking R&D activities. The enhancement of firm-level technological capabilities is expected to improve innovation performance, thereby supporting regional innovation-driven development.

Table 1.1 R&D Expenditure of China by Sources (2003-2015, billion RMB)

Year	Total	Government R&D Funds	Firms Self-raised R&D Funds
2003	153.960	46.060	92.540
2004	196.630	52.360	129.130
2005	245.000	64.540	164.250
2006	300.310	74.210	207.370
2007	371.020	91.350	261.100
2008	461.600	108.890	331.150
2009	580.211	135.827	416.272
2010	706.258	169.630	506.314
2011	868.701	188.297	642.064
2012	1029.841	222.139	762.502
2013	1184.660	250.057	883.772
2014	1301.560	263.610	981.650
2015	1416.988	301.32	1058.860

For example, the formal industry-university R&D collaboration in China is maintaining a steady increase (see Figure 1.3). The number of R&D funds from firms to universities has been increasing yearly from 17.17 billion RMB in 2009 to 30.15 billion RMB in 2015. In recent years, from 2012 to 2014, the ratio of funds from firms to support R&D of universities on total R&D funds for universities stands at around 33%. Via formal industry-university R&D collaboration, firms are expected to use frontier S&T knowledge generated by universities.

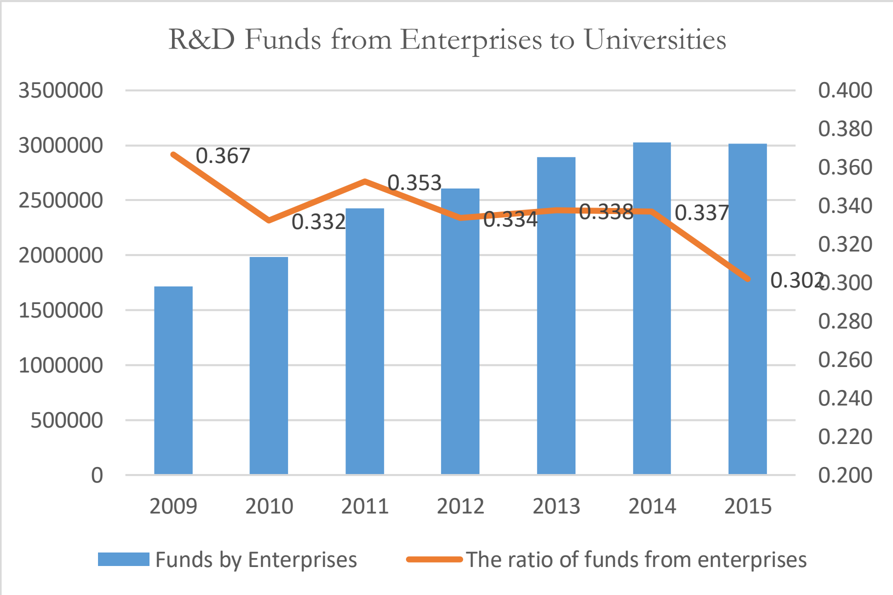

Figure 1.3 R&D Funds from Firms to Universities in China

1.2 Problem Formulation and Potential Contributions

1.2.1 Problem Formulation and Delimitation

Behavioral additionality is related to the behavioral changes of firms' R&D process resulting from a public intervention, which occurs during the innovation process (Clarysse et al., 2009). Research on the correlation between subsidies and firms' behavioral additionality has grown in recent years. Although present studies have contributed greatly to the understanding of behavioral additionality generated by R&D subsidy, relevant research still retains several gaps.

First, behavioral additionality has been insufficiently tested in empirical studies, as there is a narrow focus on a small range of behavioral dimensions (Clarysse et al., 2009). Particularly, very few studies investigate the effects generated by R&D subsidy on firm-level behavioral additionality in emerging market contexts such as China, especially about how R&D subsidy recipient firms change their S&T knowledge learning behaviors. Current studies of R&D subsidy in China usually focus on ascertaining the existence of the additionality effect or crowding-out effect from public intervention on firms' R&D input and output (Boeing, 2016; Guan & Yam, 2015; Guo et al., 2016; Liu et al., 2016); investigating the relationship between firm-level factors and winning R&D subsidy

(Wang et al., 2017); and discussing how rent-seeking behaviors can be avoided when providing R&D subsidy (Xin et al., 2016).

Second, current studies also separately investigate the effects of R&D subsidy on behavioral and output additionality, even though more technological output can be generated by R&D subsidy through the change of learning behaviors. A more systemic picture showing the interplays between different types of additionality is also needed (Cerulli, Gabriele, & Potì, 2016).

Furthermore, firm heterogeneity may impact the effectiveness of public R&D subsidies on behavioral additionalities, such as previous experience, technological stock, and the development stages of firms from a learning perspective (Clarysse et al., 2009). The context within which subsidized firms are embedded also potentially impacts the correlation between R&D subsidies and behavioral additionality. According to previous research (Amezcua et al., 2013; Lazzarini, 2015), government capabilities and geographic characteristics can moderate the effect of R&D subsidies. However, the issue of whether such a moderating effect exists on the correlation between R&D subsidies and behavioral additionality is still unresolved.

To better understand the effects of R&D subsidy in China, this dissertation attempts to open further the black box of the link between R&D subsidy and the firm-level R&D output by the investigation of R&D behavioral changes from a learning perspective. In my Ph.D. study, the following research questions are formulated:

1) How do R&D subsidies influence firms' collaborations with universities? What are the moderating roles of science parks and human resources?

2) How do public R&D subsidies influence firms' exploratory learning? Are the effects of public R&D subsidy different at different firms' development stages?

3) Can the participation in public R&D subsidy programs promote firms to adopt novel knowledge to change their core technological focus or not? Do R&D subsidies from central and local governments have different effects on firms' novel knowledge exploration and the change of their core technological focus?

More specifically, I first attempt to explore how public R&D subsidy influences collaborations between high-tech small and medium-sized enterprises (SMEs) and universities. The moderating roles of the science parks and firms' high-educational level R&D human resources are also tested. Combining the knowledge-based view (KBV) with a learning perspective, I will then explore the effects of R&D subsidy on the potential changes in firms' learning behaviors, mainly novel knowledge exploration. The heterogeneous effects of different development stages, namely growth, mature, and declining stages, are also explored. For the changes of technological focus via novel knowledge exploration, I will focus mainly on whether firms in receipt of subsidy generate more patents beyond their familiar technological fields or not. Firms may be reluctant to engage in unfamiliar technological fields, even though more innovative knowledge recombination with unfamiliar knowledge may lead to more breakthrough inventions, as such behaviors may exacerbate risky levels at the same time. R&D subsidy programs from central and local governments will be further classified as well.

1.2.2 Potential Contributions

As will be illustrated within this dissertation, the analysis of public R&D subsidy and behavioral additionality in terms of the knowledge learning process in China represents the most important contribution of my research.

From a theoretical perspective, the present dissertation will enrich existing R&D subsidy literature related to behavioral additionality by extending the use of organizational learning perspective in innovation policy studies in China as well as in a more generalized context. The dissertation will also deepen the understanding of the relationship between organizational development stages and innovation novelty under public sponsorship.

At the same time, this study explores the different effects of R&D subsidy programs from central and local governments. In addition, the test on the moderating effects of science parks and human resources may help to better understand how R&D subsidy can underpin high-tech SMEs to overcome system failure. The system failure is related to the creation of knowledge and learning capabilities and the structure and configuration of the system, which subsequently influence the evolutionary process of innovation.

For practical implications, this present dissertation is expected to extend the rationale for public R&D support policy evaluation from an evolutionary theoretical background beyond the standard neoclassical approach. Specifically, public R&D support policy has increasingly emphasized the enhancement of firm-level essential technological capabilities. The analysis of behavioral additionality may shed light on the effect generated by policy on the firm-level learning process, accumulation of capabilities, and subsequently the R&D outputs. Additionally, it provides references based on empirical evidence for firms in the selection of public R&D support according to which stage they are going through in particular organizational development stages. In this sense, the present dissertation may provide an opportunity for the policy learning and lessons in designing future policy schemes about successful or failed determinants of public interventions, which also provide several potential managerial implications for firms' strategic decisions on when and how to participate proactively pin governmental projects for technological upgrading.

1.3 Key Definitions

1.3.1 Public R&D Subsidy

In this dissertation, public R&D subsidy is defined as one of the policy instruments introduced by governments that adopt economic incentives to promote and encourage private firms to undertake and perform research and development (Becker, 2015; David et al., 2000; Dimos & Pugh, 2016). Public R&D subsidy includes both direct and indirect fiscal support from governments, namely direct R&D grants, R&D subsidized loans and tax incentives for R&D.

1.3.2 Innovation Output

In this dissertation, innovation output is defined as the results or achievements of R&D activities, including economic and technological outputs (Guan & Yam, 2015). The former refers to firm-level new products or high-tech product sales, while the latter refers to new applied or granted patents (Furman, Porter, & Stern, 2002; Georghiou, 2002; Griliches, 1990; Guan & Yam, 2015; Guo et al., 2016).

1.3.3 Behavioral Additionality from a learning perspective

In this dissertation, behavioral additionality is defined as the changes in the learning process that have taken place within R&D subsidy recipient firms (Clarysse et al., 2009).

More specifically, the present dissertation mainly discusses two behaviors in the learning process, knowledge acquisition and knowledge adoption. Based on the Chinese context, R&D collaborations with external knowledge institutions and high-level R&D human resources upgrading are two main ways of acquiring novel knowledge.

Knowledge adoption includes two types of learning behaviors in this dissertation. One is to fully develop and strengthen the knowledge that is deeply rooted in firms' mature technology bases embedded in their technological trajectories, which can be defined as familiar knowledge exploitation (Cohen & Levinthal, 1990; Levinthal & March, 1993). The other is to explore and acquire new knowledge that is new to the firms but not necessarily novel for the industry or may even be mature knowledge to other players in the market. This is referred to as novel knowledge exploration (Ahuja & Lampert, 2001; Kim & Park, 2013).

1.4 Dissertation Structure

The dissertation is a monograph combining and integrating three academic papers written during my Ph.D. and is comprised of eight chapters.

After Chapter 1, the Introduction, the following chapter sets out the literature review to elaborate further on the related research status and prevalent adopted theories for theoretical analysis. Based on the literature review in Chapter 2, a research framework for this dissertation will be presented.

In Chapter 3, the methodology will be discussed including the paradigm and the paradigmatic position of the thesis. The rationale of empirical analysis, the specific data collection, and the cleaning process will be introduced in Chapter 3, as well as the empirical techniques developed.

Following the methodological discussions, research problems will be tested and addressed in three chapters (Chapters 4-6). Chapter 4 will address the question of how R&D subsidy influences high-tech SMEs' collaborations with universities and explore the moderating roles of science parks and human resources. Chapter 5 will explore the effects of R&D subsidy on firms' learning behaviors, and discuss the differences in firms' development stages. Subsequently from Chapter 5, the effect of public R&D subsidy on behavioral additionality related to technological focus change will be explored in Chapter 6. The heterogeneous effects of R&D subsidy programs from central and local governments are also investigated.

In Chapter 7, based on empirical results, an integrated discussion of the four research questions will be presented to provide theoretical reflections.

Finally, in Chapter 8, the main findings of the thesis will be reflected upon and the research questions summarized. The policy implication will also be discussed. Moreover, the limitations of this dissertation will be reflected upon and future research directions will be presented. The dissertation structure is shown in Figure 1.4.

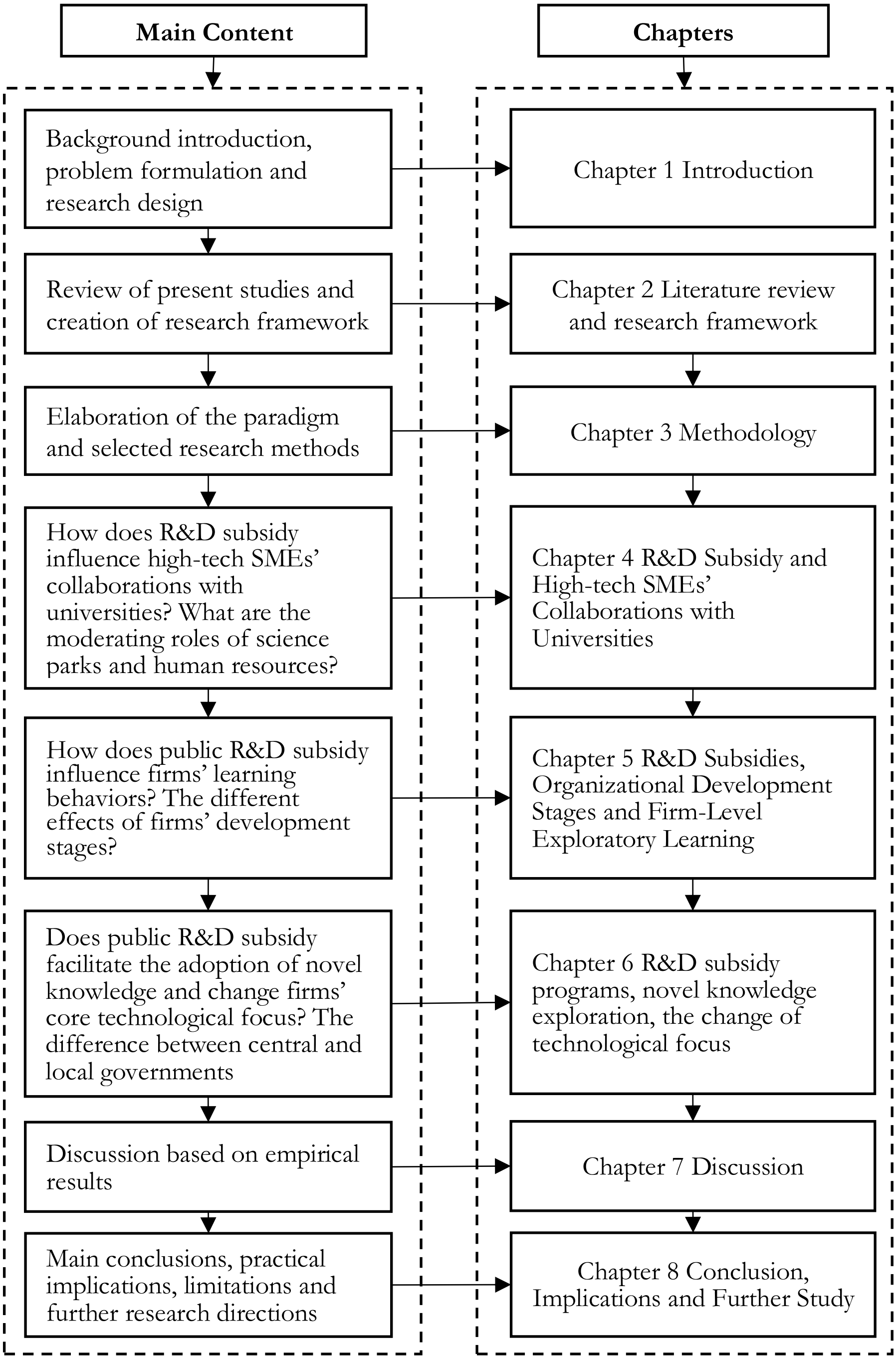

Figure 1.4 Dissertation Structure

2. Literature Review and Research Framework

2.1 Public R&D Subsidy, Input and Output Additionality

2.1.1 Market Failures and the Role of R&D Subsidy

Existing studies have confirmed the key contributions of R&D investment for economic growth at the firm, industry and country level (Aghion et al., 1998; Arrow, 1962; Grossman & Helpman, 1994; Romer, 1986, 1990). However, the presence of market failures of R&D leads to underinvestment in R&D and underproduction of innovation (Arrow, 1962; Griliches, 1994; Nelson, 1959).

First, R&D exhibits typical public goods characteristics. R&D activities have non-competitive and non-exclusive characteristics. The firms' R&D achievements may spill over to their potential competitors, resulting in the private return rate being lower than the social return rate, which hinders firms from appropriating the full benefits associated with R&D investments (Griliches, 1994). This mismatch of investment and return could reduce firm-level initiative to invest in R&D and innovation activities, which results in firm-level R&D investment that does not meet the socially optimal investments on R&D (Arrow, 1962; Bush, 1945; Nelson, 1959).

Second, firms undertaking R&D may fail to attract external financial support because of information asymmetry (Arrow, 1962). The value of R&D cannot be anticipated by external investors as early-stage technologies of firms are usually confidential (Hall, 2002a; Hall & Lerner, 2010). This issue may be exacerbated with the imperfect capital markets as well as weak protection of intellectual property rights (Hall, 2002a; Hsu & Ziedonis, 2013; Klette et al., 2000). As a result, financial support from external capital markets on R&D is insufficient.

In addition, due to the liability of newness, innovation, especially radical innovation, usually suffers a high level of uncertainty and high risk of failure. At the same time, financial returns of R&D investment are usually slow, as R&D investment requires multiple stages and whole investment lifecycles are long (Hall & Lerner, 2010). These factors also reduce the initiative of investment in R&D from private investors. Furthermore, novelties usually lack legitimacy, making it difficult for firms to undertake R&D to establish formal collaboration with external knowledge institutions, or attract external financial support (Amezcua et al., 2013; Zimmerman & Zeitz, 2002).

As a consequence, governments increasingly recognize the importance and benefits of supporting private firm-level R&D investment by public policies. Following the logic of the standard neoclassical approach, the government can use public R&D subsidy, including direct grants and tax incentives, to correct firm-level R&D investments and encourage the private sector to carry out R&D (Arrow, 1962; Dasgupta, 1988; Dasgupta & Stoneman, 2005; Nelson, 1959).

The neoclassical rationale underlying the public R&D subsidy can be analyzed by the interplay between the marginal cost of capital (MCC) and the marginal rate of return (MRR) of R&D under public interventions (David et al., 2000). As shown in Figure 2.1, the upward-sloping curve is the marginal cost of capital, while the downward-sloping curve is the marginal rate of return of R&D. The confluence of the two curves, R*, is the R&D investment. Theoretically, taking a simple example, providing direct R&D grants can potentially raise the marginal return of R&D and enhance R*. Following a similar logic, tax incentives can reduce the marginal cost of R&D, shifting the MCC curve to enhance the R&D investment (David et al., 2000).

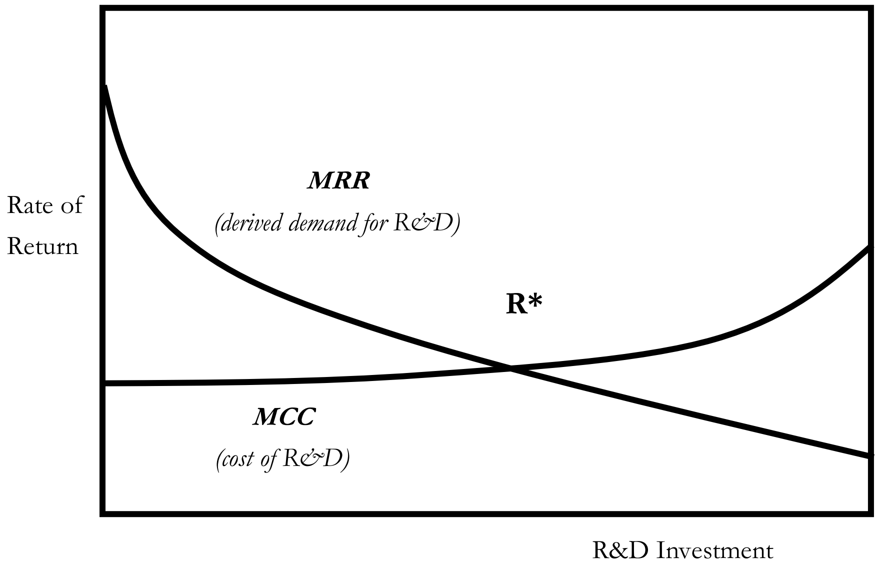

Figure 2.1 Neoclassical analysis of R&D subsidy on firm-level R&D investment

Source: David et al. Research Policy 29 (2000) p. 503

Theoretical rules are set to evaluate the effectiveness of R&D subsidy (Lipsey & Carlaw, 1998). Accordingly, effectual public interventions via R&D subsidy are required to make subsidy recipients undertake R&D with the desired level of R&D investment in the least costly way. The benefits gained by the R&D subsidy should exceed the cost of public intervention. Derived from these criteria, the additionality effect has become a core concept for the evaluation of the effects of public R&D subsidy. Input additionality refers to additional firms' own R&D spending triggered by R&D subsidy, which is clearer due to the straightforward correlation of R&D input with a subsidy from the standard neoclassical perspective (Colander, 2000).

Conversely, R&D subsidy may also crowd out the R&D input of recipients –the crowding-out effect (David et al., 2000; Garcia-Quevedo, 2004). According to the conclusions of Dimos and Pugh (2016), the crowding-out effects on firm-level R&D input generated by R&D subsidy can be further elucidated (see Figure 2.2). Overall, the crowding-out effects on R&D input can be identified as partial crowding out, full crowding out and over-full crowding out (Dimos & Pugh, 2016). More specifically, in the situation of partial crowding out, although the total amount of R&D investments could be more than the amount before receiving R&D subsidy, a part of firm-level R&D investments is replaced with R&D subsidy compared with the counterfactual state of no subsidy, while the situation in which firm-level R&D investments decrease by the full amount of the subsidy and total R&D investments equal the amount of the counterfactual state of no subsidy is full crowding out. If R&D subsidy is used in place of firm-level R&D investments and total R&D investments decrease compared with the counterfactual state of no subsidy, this is the over-full crowding out (Dimos & Pugh, 2016).

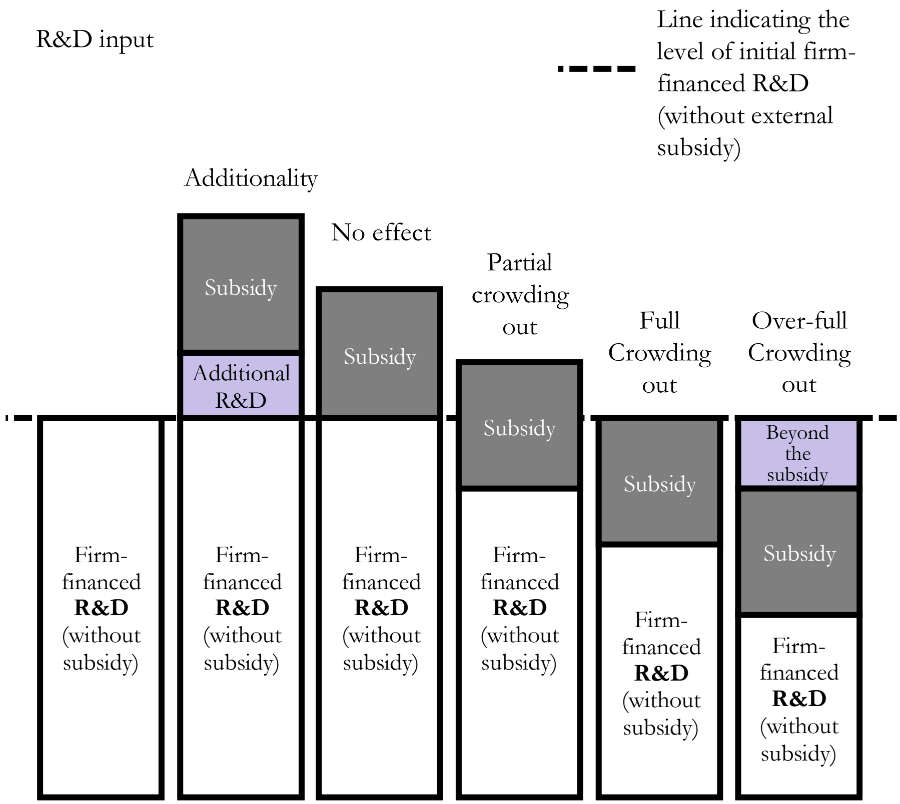

Figure 2.2 Effects of R&D subsidy on firm-level R&D input

Source: Dimos & Pugh Research Policy 45 (2016) p. 799

For R&D output, the paradigm of the additionality effect will be more complex. Although output additionality is key to indicating whether R&D subsidy can correct the underproduction of R&D and innovation generated by market failures or not, the measurement of output, such as patents and new product sales, is not commensurate with the value of subsidies. Specifically, output additionality needs to first satisfy the strict linear assumption between R&D input and output. This oversimplified model implies that additional R&D input would inevitably result in increased firm-level R&D outputs (Falk, 2007; Gök & Edler, 2012). However, the actual process is much more complex and unpredictable (Georghiou & Clarysse, 2006). Furthermore, the results of public intervention on R&D could be different in terms of types, length of time, and stages in the R&D process (Hsu & Hsueh, 2009). It is difficult to estimate the direct causal correlations between R&D subsidies and output without stricter, more focused, and appropriate definitions of R&D outputs (Buisseret et al., 1995; Georghiou, 2002). Thus, at an overall level, the additionality effect remains blurred with partial crowding-out effect in regard to R&D output (Dimos & Pugh, 2016). The full crowding out and over-full crowding out on R&D output can be clearly distinguished (see Figure 2.3). The former refers to the situation that R&D output remains at the same level after receiving R&D subsidy, compared with the counterfactual state of no subsidy. The latter is the situation that subsidy recipient firms generate smaller R&D output than in the counterfactual state.

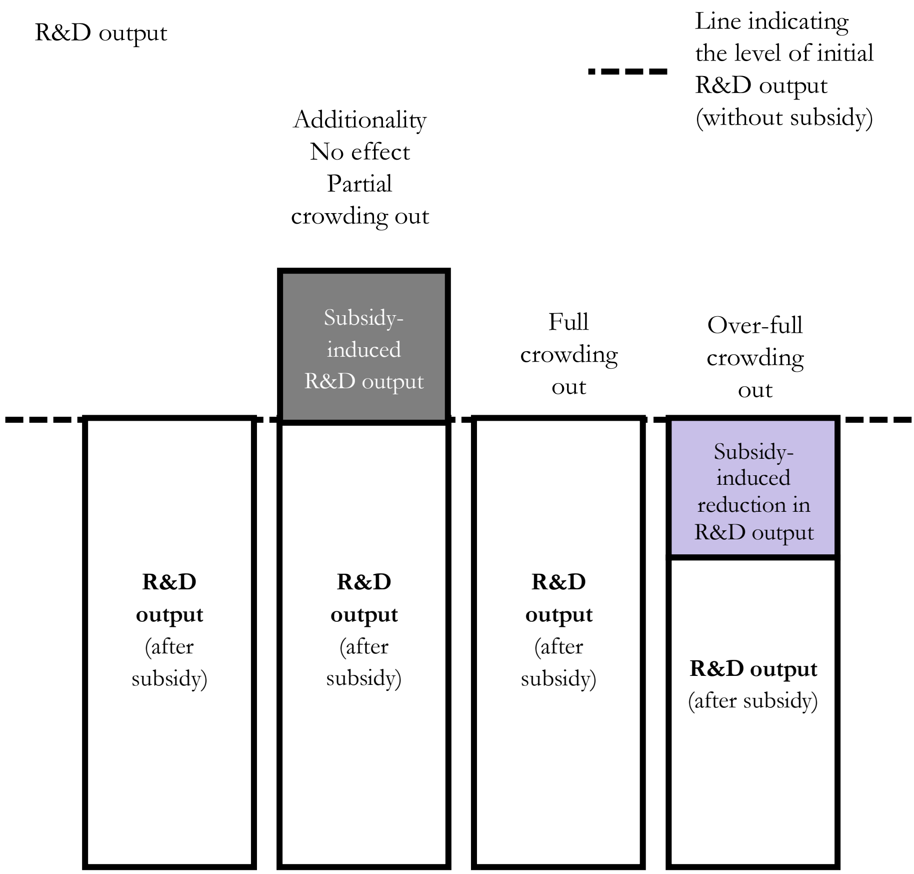

Figure 2.3 Effects of R&D subsidy on firm-level R&D output

Source: Dimos & Pugh Research Policy 45 (2016) p. 799

2.1.2 The Mechanisms of R&D Subsidy

2.1.2.1 Buffering Effect: From Resource-Based View and Resource Dependence Theory

A number of existing studies employ a resource-based view or resource dependence theory to analyze the effects on innovation performance generated by public R&D subsidy. According to the resource-based view, technological capabilities, as well as technology-related resources, are the primary driver for innovation (Verona, 1999). Resources deployed on R&D spur innovation and enhance technological capabilities (Wernerfelt, 1984). Higher technological capabilities can help firms to optimize resource allocation and improve innovation performance (Yam et al., 2004). However, as technological innovation is associated with high risk and uncertainties, and has the inherent public goods characteristics (Dimos & Pugh, 2016; Hyytinen & Toivanen, 2005; Martin & Scott, 2000; Wernerfelt, 1984), firm-level technological innovation activities may be constrained by resources (Guariglia & Liu, 2014; Radas et al., 2015).

According to the resource-based view, the main aim of public R&D subsidy is indirectly increasing the pool of available resources for firms to undertake innovation activities by reducing R&D costs and enhancing returns (David et al., 2000; Radas et al., 2015; Rangan, Samii, & Van Wassenhove, 2006). Based on resource dependence theory, public R&D grants can create a munificent resource environment for firms to undertake R&D independently of other external organizations, which to some degree helps firms to manage overall uncertainty and risk (Amezcua et al., 2013). In other words, public R&D subsidy also buffers a firm's resource constraint on R&D. By using public R&D grants, recipient firms can occupy more favorable competitive positions, compared to rival firms without public resources. To keep a favorable competitive position, firms are more likely to allocate resources on R&D activities and enhance their technology-related capabilities (Jourdan & Kivleniece, 2017). Having been relieved of resource pressure by public R&D subsidies, recipient firms can be protected from potential adverse selection, whereby technological capabilities and resources are enhanced and allocated more effectively (Rangan et al., 2006). Thus, the additionality effect is expected to occur to leverage private resources and enhance firm technological capabilities for innovation with public R&D subsidy provided by the government (Aschhoff & Sofka, 2009; Bloom, Griffith, & Van Reenen, 2002; Wernerfelt, 1984).

2.1.2.2 Signaling Effect and Bridging Effect: From Institutional Theory

Apart from providing the direct resource, public R&D subsidy can also provide a quality signal to potential investors, other innovation actors, and clients to help recipient firms gain external financing and collaborate with external partners (Feldman & Kelley, 2006; Kleer, 2010; Lerner, 1999; Takalo & Tanayama, 2010). Based on the analysis of the Small Business Innovation Research Program (SBIR), Lerner (1999) finds that firms receiving public R&D support can gain endorsements from the government to certify their quality. It is important for firms to gain such certification to leverage external investments, especially in high tech industries or new markets (Lerner, 1999).

As mentioned before, information asymmetry is one of the main reasons to cause the market failure of R&D. Information asymmetry prevents firms from undertaking R&D to attract external financing (Kleer, 2010; Takalo & Tanayama, 2010; Wu, 2017). On the one hand, firms undertaking R&D are reluctant to disclose technological details and secrets for the purpose of self-protection due to the characteristics of the public good of R&D. On the other hand, external investors may also lack relevant professional knowledge of R&D activities (Wu, 2017). These may indicate that it is difficult for external investors to evaluate the quality and risk of innovation and R&D projects, and subsequently, investors will remain cautious about R&D investment (Kleer, 2010). In particular, new technologies exhibit high risk and substantial uncertainty, and asymmetric information will result in difficulties for firms to gain external financing (Ensthaler & Giebe, 2014).

The government needs to play a role as an efficient intermediary to reduce the information asymmetry between firms and investors. As the government is not a direct competitor to firms, firms are more likely to disclose their R&D information to the government. The relevant R&D information disclosures also satisfy the requirements of the screening process of the government for seeking public support (Wu, 2017). The evaluating R&D projects from the government is, therefore, considered more accurate and unprejudiced. With selection based on the evaluation by experts, R&D subsidy recipient firms gain the endorsements from the government. These endorsements yield signals of the quality or commercial potential to market-based financiers and thereby open the door to accessing external financing (Ensthaler & Giebe, 2014; Kleer, 2010; Takalo & Tanayama, 2010).

Apart from the reducing information asymmetry, endorsements from the government via R&D subsidy can also enhance the legitimacy of firms to effectively bridge with outside R&D partners as proposed in institutional theory (Baum & Oliver, 1991; Zeng, Xie, & Tam, 2010; Zimmerman & Zeitz, 2002). Due to newness liability, firms undertaking R&D and innovation may lack legitimacy at the initial stage. Firms' poor reputation and the high uncertainty of innovation may impede the establishment of formal relationships with external partners (Jourdan & Kivleniece, 2017; Kim & Park, 2015; Motohashi, 2013). However, collaboration with external partners is important, as collaboration may reduce the risk level of R&D and provide key complementary assets for firms to achieve a sustainable competitive advantage (Czarnitzki & Delanote, 2017; Flynn, 1993; Rodan & Galunic, 2004). Endorsements from the government, via R&D subsidy, certify the quality of recipient firms, and thereby help them to attract external partners to establish formal collaborative relationships (Amezcua et al., 2013; Jourdan & Kivleniece, 2017). Empirical evidence shows that firms participating in public-sponsored R&D projects are more likely to establish a collaborative relationship with universities and research institutes (Feldman & Kelley, 2006). R&D collaboration also serves as a quality signal for investors to increase their confidence that investment-seeking firms can gain successful R&D achievements (Czarnitzki & Hottenrott, 2012). This bridging mechanism is also expected to contribute to the R&D output enhancement of subsidy recipient firms (Amezcua et al., 2013; Jourdan & Kivleniece, 2017).

2.1.2.3 The Crowding-Out Effect: from public choice theory

As mentioned before, public R&D subsidy may, however, exert negative effects on firm-level R&D investment, which results in government failure (Jourdan & Kivleniece, 2017; Wolff, 2002). The main negative effect is the so-called crowding-out effect which stems from public choice theory (Dimos & Pugh, 2016).

One of the key reasons for the generation of crowding-out effect is the "picking the winner" behavior of government (Dai & Cheng, 2015a; Lach, 2002; Wang et al., 2017). This behavior may result in sponsored firms substituting public funds for private funds. The "picking the winner" behavior stems from governments' avoidance of the loss of state assets due to the misallocation of public funds. R&D subsidy is more likely to be provided to "winner" firms with higher success probabilities and private financial return rates (Lach, 2002). However, these "winner" firms would have been motivated on R&D investment without R&D subsidy ("deadweight effects"). Thus, public R&D subsidy is, *de facto*, superfluous for these "winner" firms (Jourdan & Kivleniece, 2017). At the same time, "winner" firms have no need to invest additional capital to secure the success of R&D activities (Lach, 2002). Firms are more willing to use public funds than their own resources in innovation, as direct financial capital from the public sector is much cheaper than that of firms themselves and the capital market (Carpenter &

Petersen, 2002; Jourdan & Kivleniece, 2017). It is argued that funding such "winner" firms fails to reach social optimum, even though public funding agencies may achieve high-profile successes (Wang et al., 2017). The "picking the winners" behaviors cannot essentially induce the success of R&D by providing R&D subsidy to firms that are financially vulnerable and would fail without public support (Wallsten, 2000).

The characteristics of the public sector, such as unclear property rights, the blurred linkage between managerial actions and performance, weak incentives and different goals from those of the private sector, etc., may also reduce co-investment willingness of the private sector with public financial support (Dixit, 1997; Jourdan & Kivleniece, 2017). Governments are more likely to support R&D activities that satisfy national science and technology strategies and offer high degrees of social return (Stiglitz & Wallsten, 1999). As a consequence, basic research, cutting-edge technologies, and innovation with greater knowledge spillover would be more likely to receive an R&D subsidy (Stiglitz & Wallsten, 1999). However, these potentially sponsored R&D activities may not necessarily match the market-driven targets of profit-seeking firms. This separation of the strategic objectives of governments and the market reduces firms' own R&D input as well as reducing the output in subsidy recipients (Wang et al., 2017).

Furthermore, the mismatch of targets may result in the distortion of managerial behaviors and the removal of market competition (Wang et al., 2017). With public resources, firms can survive by satisfying the requirements of the government without improving the firms' own technological capabilities and resources (Jourdan & Kivleniece, 2017). Firms tend to secure access to public resources and switch the development focus from technological capabilities to political rent-seeking capabilities (Bonardi, 2008; Chen et al., 2011). This resource altering effect results in the stagnation or even an eventual decline in the firms' technological capabilities and resources, and the inhibition of R&D-related performance (Jourdan & Kivleniece, 2017).

In addition, it is also difficult to evaluate and pick firms with technological and market potential to support, if R&D subsidy-bestowing decisions are made by government bureaucrats with limited technological and business expertise (Wang et al., 2017). This may not improve firm-level R&D input and output either. Although public R&D subsidy is professionally administered, it is insufficient to facilitate firm-level R&D and innovation without a developed innovation ecosystem (Gans, Hsu, & Stern, 2008; Martin & Scott, 2000). In the absence of institutions with intellectual property protection, inter-organizational collaboration facilitation, and information exchange promotion, R&D subsidy-providing would fail to improve firm-level R&D performance (Mcdermott & Kruse, 2009; Stuart & Wang, 2016; Wang et al., 2017)

2.1.3 Different types of R&D subsidy

Traditionally, public R&D subsidy is provided through direct grants, which is a type of sponsorship through direct injection of public funds to firms. Direct R&D grants with no interest and repayment, which can directly compensate resource shortage in private sectors, are the most prevalent type of R&D subsidy, especially in transitional economies where the capital markets are less developed (Zheng et al., 2015). Although some of the recent studies demonstrate the existence of an additionality effect on firm-level R&D expenditure of direct R&D grants (Liu et al., 2016), the efficiency of direct R&D grants still remains subject to skepticism in China (Guan & Yam, 2015; Guo et al., 2016). Direct R&D grants, as an *ex-ante* administrative subsidy, are supposed to stimulate crowding-out effects on private R&D investment, poor efficiency of public funds and subsequently productive insufficiency of R&D activities (Hall & Van Reenen, 2000; Perez-Sebastian, 2015). This government failure issue is exacerbated in China due to profound political interference, stronger public intervention and a sophisticated bureaucratic system with Chinese characteristics (Guan & Yam, 2015; Wang et al., 2017). In other words, the Chinese government has greater power, which may result in market distortion and be more likely to crowd out firm-level R&D input and output by public funds allocation.

Other types of public R&D subsidy are designed to remedy the shortages of direct grants. Tax incentives are the most developed instruments (Hall & Van Reenen, 2000). Unlike direct grants, tax incentives minimize the discretionary decisions on the selection of sponsored firms, which is neutral as to industry and the nature of the firm (Busom, Corchuelo, & Martinez-Ros, 2014; Czarnitzki, Hanel, & Rosa, 2011). This means that, regardless of projects or industrial sectors, tax incentives are available to all firms undertaking R&D activities. The basic mechanism of tax incentives is the direct reduction of the marginal cost of R&D, and firms are required to invest in R&D in response to linked tax incentives (David et al., 2000; Radas et al., 2015). Tax incentives for R&D are expected to avoid the crowding-out effect on firm-level R&D expenditure, and at the same time, enable recipient firms to gain the highest rate of private return without any governmental control on the usage of R&D subsidy (Busom et al., 2014; David et al., 2000; Hall & Van Reenen, 2000).

However, tax credits can affect the composition of R&D (Czarnitzki et al., 2011;

David et al., 2000). With tax incentives, firms are more likely to expand their R&D funding and concentrate financial resources on projects that will generate fast returns without governmental control (Czarnitzki et al., 2011). Consequently, long-run exploratory projects with high social welfare may be less favored under the sponsorship of tax incentives. This implies that, although tax incentives are an effective way to minimize "government failure", it does not seem to be the most effective policy instrument to correct the "market failure" of R&D due to the gap between the social and private returns from innovation (Czarnitzki et al., 2011).

Another type of R&D subsidy is also identified – low-interest loans for R&D (Huergo & Trenado, 2010). In China, this type of R&D subsidy is allocated via subsidized loans. For example, R&D subsidized loans are widely adopted to support firm-level R&D in manufacturing sectors in Jiangsu, such as the photovoltaic industry and the LED industry (Grau et al., 2012; Jiang, Wang, & Chen, 2012; Liang, 2014). This distinct type of subsidy plays an important role in the elimination of the distortion of R&D behaviors of firms that are rooted in the public characteristics of direct governmental funds (Xin et al., 2016). Governments expect to rely on banks' more market-driven criteria to select R&D subsidized loan receivers with a stronger willingness to undertake R&D and higher market potential (Xin et al., 2016). R&D risk should not only be borne by the government, but by banks as well. R&D subsidized loans also impose stricter self-discipline on the utilization and the improvement of the efficiency of R&D funds of the recipients (Huergo & Moreno, 2014; Huergo, Trenado, & Ubierna, 2016).

However, subsidized loans may lead to more severe selection bias. Commercial banks by nature choose promising firms with the capability to repay the loan(Huergo & Trenado, 2010). Banks in China are more likely to select loan receivers from amongst those government-certified high-quality firms through their own screening criteria, which are stricter than the government's (Xin et al., 2016). Thus, the effects of R&D subsidized loans for overcoming market failures of R&D are still debated.

2.1.4 Empirical Studies on R&D Subsidy

Initially, the empirical evidence confirms the mismatch between the private rate and social rate of returns without public interventions, which provides supports of the rationale of public R&D subsidy (Griliches, 1998). Focusing on the effectiveness of R&D subsidy, previous studies have provided plenty of empirical evidence.

Most studies focus on providing empirical evidence of the effect of R&D subsidy on firm-level R&D expenditures, namely R&D input, as the more clear definition of

R&D input and its straightforward logical correlation with public funds according to standard neoclassical analysis (Colander, 2000; Dimos & Pugh, 2016). On the other hand, very few empirical studies are provided to investigate the correlation between R&D subsidy and firm-level R&D output (Dimos & Pugh, 2016). For example, according to a recent literature review by Dimos and Pugh (2016), 48 of 52 studies from 2000 to 2013 discuss the effect of R&D subsidy on firm-level R&D input, among which 15 studies discuss the effect on R&D output as well. Only four studies have specifically discussed the correlations between R&D subsidy and firm-level R&D output.

2.1.4.1 Methods on the Empirical Studies of R&D Subsidy

For methodological issues, the major challenges of an empirical study of R&D subsidy are endogeneity and potential selection bias, and the evaluation studies also struggle with establishing fully matched control groups (Almus & Czarnitzki, 2003; Becker, 2015; David et al., 2000; Klette et al., 2000). The endogeneity issue of R&D subsidy stems mainly from the governmental screening processes and criteria on recipient firms (Becker, 2015). More specifically, the success of an application for R&D subsidy depends on the characteristics of the firm, which may result in the issue of mutual causality (Becker, 2015). In addition, unobservable factors may contribute to the success of applying for R&D subsidies, in other words, receiving R&D subsidy or not may be correlated with the error term (Busom, 2000; Guo et al., 2016). The endogeneity issue will result in inconclusive or even conflicting findings in linear regressions (Klette et al., 2000). Instrumental variables (IVs) are usually used to control for endogeneity (Beck et al., 2016; Guo et al., 2016).

For example, by adopting an instrumental variable approach, Oezcelik and Taymaz (2008) indicate that public R&D subsidy has significantly positive effects on firms' own R&D investment in Turkish manufacturing firms. Hewitt-Dundas and Roper (2010) find additionality effects generated by public R&D funds on the firm-level output of Irish firms. They also argue that public R&D grants are effective in both radical and incremental innovations of subsidized firms (Hewitt-Dundas & Roper, 2010).

Selection biases issue is another methodological challenge that stems from the "picking-the-winner" strategy of public sector actors (Dimos & Pugh, 2016). R&D intensive and innovative firms may have a greater propensity to apply for a subsidy (David et al., 2000). At the same time, public agencies are more likely to support those firms which have higher success probabilities on the generation of economic and innovation spillovers (Almus & Czarnitzki, 2003). Therefore, to gain robust results about the essential contributions of public R&D subsidy, the counter-factual situation related to the situation that subsidy recipient firms had not gained public funds should be carefully considered (Almus & Czarnitzki, 2003). However, most of the studies before 2000 neglected this selection bias (David et al., 2000). To cope with the selection bias issue, a matching approach, mainly including nonparametric matching and propensity score matching, has been gradually become one of the prevalent methods to evaluate the effects of R&D subsidy after 2000 (Almus & Czarnitzki, 2003; Becker, 2015).

2.1.4.2 The Effects of R&D Subsidy on Inputs and Outputs

By using matching approaches, for example, the effects of public R&D subsidy on private R&D investment of Spanish, Italian, Finnish, Flemish and German firms are investigated (Aerts & Schmidt, 2008; Almus & Czarnitzki, 2003; Cerulli & Poti, 2012; Czarnitzki & Lopes-Bento, 2013; Czarnitzki, Ebersberger, & Fier, 2007; Gonzalez & Pazo, 2008). Overall, these empirical results reject the crowding-out effect of R&D subsidy on firm-level R&D input. Apart from the research on EU countries, Koga (2005) finds that public R&D subsidy is a complement to private-financed R&D based on panel data of 223 Japanese high-technology start-ups. This additionality effect on R&D input is also supported in developing countries such as Turkey (Oezcelik & Taymaz, 2008). In addition, several other empirical studies have analyzed the signaling or certification effects of R&D subsidy for accessing external financing to enhance R&D input indirectly (Lerner, 1999; Meuleman & De Maeseneire, 2012). For example, Meuleman and De Maeseneire (2008) find a positive certification effect of R&D grants for a Belgian firm to attract external financing, and this certification effect is stronger for infant firms.

Several scholars also investigated the effects of R&D subsidy on firm-level R&D output including technological output measured by patents and commercial output measured by new product sales. In the research of Czarnitzki and Hussinger (2004), they reject the crowding-out effect from R&D subsidy on firms' patent applications. At the same time, it was found that the R&D subsidy generates positive productivity on patents (Czarnitzki & Hussinger, 2004). Czarnitzki et al. (2007) further support Czarnitzki and Hussinger's research findings that the crowding-out effect is rejected on R&D output in Germany. They also find that the R&D subsidy significantly improves the patenting activities of Finnish firms. Hussinger (2008) finds that public R&D subsidy positively influences both R&D intensity and new product sales of firms through applying parametric and semiparametric two-step selection models based on manufacturing firms in Germany. Hottenrott and Lopes-Bento (2014) indicate that greater sales are generated for firms from innovation by receiving R&D subsidies. Bronzini and Piselli (2016) find that R&D subsidy significantly improves the number of patent applications of firms by using regression discontinuity design based on Italian data. However, in recent research, Czarnitzki and Delanote do not find a significant additionality effect of R&D subsidy on firms' new product sales, even though they largely confirm the additionality effect on R&D input (Czarnitzki & Delanote, 2017).

2.1.4.3 The Non-Linear Effects of R&D Subsidy

Dual effects also exist according to several empirical results. In other words, the correlation between R&D subsidy and private R&D input may potentially be non-linear. An inverted U-shape correlation between R&D subsidy and private R&D spending is found by Guellec and Van Pottelsberghe de la Potterie (2003) in a sample of OECD countries. Public R&D subsidy promotes private R&D up to a certain threshold where R&D subsidy accounts for 10% of firm-level R&D, and then R&D subsidy begins to substitute for private R&D (Guellec & Van Pottelsberghe De La Potterie, 2003). Görg and Strobl (2007) also find similar empirical evidence by using the conditional difference-in-differences technique to analyze Irish manufacturing firms. They argue that small grants can generate additionality effects on private financing of R&D, but too large a grant may crowd out the private R&D. An inverted U-shaped correlation also exists between public R&D sponsorship and firms' output over time due to the accumulation of repeated public resources, even though the public sponsorship exerts positive effects at the beginning (Jourdan & Kivleniece, 2017).

2.1.4.4 Heterogeneity in the Effects of R&D Subsidy

Studies related to R&D subsidy have increasingly considered the heterogeneity at different levels as key factors to impact on the effectiveness of R&D subsidy (Becker, 2015; Liu et al., 2016). At the firm level, firm size, as a typical example, remains related to the effectiveness of R&D subsidy (Busom, 2000). Lach (2002) finds that R&D subsidy can greatly enhance small firms' own R&D expenditures, but has a negative effect on large firms in Israel. R&D subsidy also increases innovation output, and the effects differ depending on firm size (Herrera & Sanchez-Gonzalez, 2013). It is shown that the additionality effect of R&D subsidy on patent applications is more significant for smaller firms (Bronzini & Piselli, 2016). Additionally, the development stages of firms also influence the effects of R&D subsidy (Koga, 2005).

At the industry-level, the effect of R&D subsidy differs based on the technological level of sector firms operate in (Becker & Hall, 2013; Gonzalez & Pazo, 2008; Hall, Lotti, & Mairesse, 2009). Gonzalez and Pazo (2008) report that rejection of the crowding-out effect between public subsidy and private investment mainly occurs in Spanish manufacturing firms operating in low technology sectors. Becker and Hall (2013), based on data from the UK, have presented similar findings that public funds only significantly improve low-tech firms' R&D spending. However, Hall et al. (2009) report different empirical results for Italian firms. They find that the boost generated by subsidies on private R&D efforts is more significant in high-tech industries.

At a macrolevel, different embedded economies or periods may result in different effects of R&D subsidy. For example, Czarnitzki and Licht (2006) find the empirical evidence that the additionality effect of R&D subsidy on firm-level R&D input in Eastern Germany during the transition period is larger than in Western Germany. Output additionality is more pronounced in Western Germany, in which the innovation system is more developed (Czarnitzki & Licht, 2006). Hud and Hussinger, (2015) find differential effects of R&D subsidy on firms' inputs before and after the economic crisis in 2008. More specifically, significant additionality effects are found before 2008, while a crowding-out effect is found in 2009 (Hud & Hussinger, 2015).

2.1.4.5 The Effects of Different R&D Subsidy Types on Firms' Innovation

Several scholars further classify direct R&D grants based on different uses for empirical studies. For example, it is shown empirically that subsidies for research can enhance firms' R&D spending while development subsidies crowd out such spending (Clausen, 2009).

Apart from R&D grants, the effects of other types of R&D subsidies, including tax incentives and low-interest loans, have also been studied empirically. For tax incentives, studies show that tax incentives cause additionality effects on firm-level R&D investment (Baghana & Mohnen, 2009; Guellec & Van Pottelsberghe De La Potterie, 2003; Kobayashi, 2014). It is also shown empirically that tax incentives appear to stimulate private R&D financing more effectively than direct grants in Italy (Carboni, 2011). Furthermore, several other studies on tax incentives indicate that additional firm-level R&D outputs, such as producing new products, and patent applications, can be generated by tax incentives (Berube & Mohnen, 2009; Cappelen, Raknerud, & Rybalka, 2012; Czarnitzki et al., 2011; Radas et al., 2015).

For low-interest loans, several studies analyze empirically the determinants of firms that are more likely to apply for low-interest loans to finance their R&D activities. It is found that young firms involved in high or medium-tech industries with previous public-sponsored experience have a higher probability of filing loan applications (Heijs, 2005; Huergo & Trenado, 2010). The recent study of Huergo et al. (2016) also shows empirically that low-interest loans can stimulate firms' own R&D investment in Spanish firms. In addition, the additionality effects of low-interest loans are larger for smaller firms and manufacturing firms (Huergo et al., 2016).

2.1.4.6 Effects of R&D Subsidy in the Context of China

The number of empirical studies related to the effects of public R&D subsidy in the context of China has increased in recent years.

Most studies of Chinese R&D subsidy usually focus on testifying to the existence of additionality effect or crowding-out effect from public intervention on firms' R&D inputs, mainly measured by firm-level R&D expenditure or R&D intensity (Boeing, 2016; Cheng & Chen, 2006; Dai & Cheng, 2015b; Liu et al., 2016; Xin et al., 2016; Yu et al., 2016).

Cheng and Chen (2006) show empirically that R&D subsidy has an insignificant effect on private firms' R&D expenditures in Zhejiang province by using a PSM (propensity score matching) method. While also using a PSM method, Liu et al. (2016) demonstrate the existence of a significant additionality effect generated by R&D subsidy on firm-level R&D expenditure in Jiangsu province. They further find that the additionality effect is stronger for smaller firms, more financially constrained firms, and privately-owned firms. Boeing (2016), based on the data of Chinese listed firms between 2001 and 2006, finds that R&D subsidy instantaneously crowds out firms' R&D investment but is neutral in later periods.

Dai and Cheng (2015b) explore an inverted-U correlation between firms' private R&D investment and the R&D subsidy for Chinese manufacturing firms. The firms' own R&D spending can be stimulated above a threshold value of R&D subsidy; a further increase in public subsidy would crowd out firm-level R&D investment. Similarly to Dai and Cheng's empirical findings (2015b), Yu et al. (2016) find the threshold effect of R&D subsidy on the own R&D expenditure of firms involving Chinese renewable energy sectors. Their results show that public R&D subsidy can only stimulate firm-level R&D inputs by increasing subsidies within a certain range, otherwise, the R&D subsidy exerts negative effects on firms' R&D investment behaviors.

Xin et al. (2016) discuss and compare the effectiveness of different R&D subsidy types, including loan interest subsidies and direct grants. The results indicate that more competitive based loan interest subsidies are more effective in enhancing firm-level R&D inputs, rather than direct grants. Furthermore, this additionality effect is mainly driven by private-owned firms.

Other mainstream research is related to the effects generated by R&D subsidy on firm-level R&D outputs, which are usually measured by patent applications and new product producing or sales (Guan & Yam, 2015; Guo et al., 2016; Hong et al., 2016; Jia, Huang, & Zhang, 2019; Xiong & Yang, 2016; Xu, Huang, & Xu, 2014; Zhou et al., 2018).

At the industry-level, Hong et al. (2016) explore a negative influence exerted by public R&D subsidy on patenting activities of high-tech industries in China by using a stochastic frontier analysis (SFA). At the firm level, Guan and Yam (2015) empirically test the effects of Chinese R&D subsidy in the 1990s. The results show that direct R&D grants from the Chinese government exert a negative effect on firms' patent applications and new product sales. Furthermore, more market-driven subsidy tools, such as special loans and tax incentives, can positively influence the new product sales of firms. Thus they argue that the centrally planned funding system is ineffective for enhancing the technological capabilities of Chinese firms.

By combining PSM with two-stage estimation approaches, Guo et al. (2016) investigated the effects of *Innofund*, one of the largest public R&D sponsorship programs for small and medium-sized enterprises in China, on firms' outputs including the number of patents, new products sales, and exports. They found that subsidy recipient firms generate significantly higher outputs than non-recipient counterparts. Xu et al. (2014) also found a significantly positive correlation between R&D subsidy and firms' new product development based on an empirical investigation of 270 Chinese firms.

Xiong and Yang (2016) found a positive effect of R&D subsidy on firms' outputs at the early exploratory stage in the photovoltaic industry, but little effect at the intermediate stage and mature stage. Based on these results, they also suggest the best entry occasion and a suitable exit occasion of public intervention by using R&D subsidies.

Zhou et al. (2018) distinguish the effects of local and central governments' R&D subsidy on firms' radical and incremental innovation based on new product sales in Chinese cultural and creative industries. They further discuss the moderating effects of firm-level knowledge stocks. Similarly, Jia et al. (2019) also investigate the effects of R&D subsidy on firm-level innovation novelty in Chinese state-owned enterprises.

Several other scholars investigate the issue of subsidy allocation and the determinants for winning R&D subsidy in China (Boeing, 2016; Wang et al., 2017).

Wang et al. (2017), using a regression discontinuity (RD) design, found that firms with observable advantages and political ties are more likely to receive *Innofund* grants. They also empirically test the causal effects between R&D subsidy and firms' survival rates, patenting, or attracting venture capital. Boeing (2016) found that the Chinese government prefers to provide R&D subsidies to firms which have prior grants, high-quality inventions and state-owned background.

A few studies also test empirically the signal or certification effect of R&D subsidy in China (Wei & Zuo, 2018; Wu, 2017). Wu (2017) found that firms can attract more external finance by receiving R&D subsidy, based on data of Chinese listed corporations from 2009 to 2013. This signal effect generated by R&D subsidy is stronger for private firms, rather than state-owned firms in China. Wei and Zuo (2018) investigated the different signaling effects generated by receiving R&D subsidy from local and central governments.

2.2 Public Subsidy and Behavioral Additionality

2.2.1 The Conception of Behavioral Additionality

2.2.1.1 The Definition and Classifications of Behavioral Additionality

Behavioral additionality, as the third type of additionality generated by policy intervention on firms' R&D and innovation activities, has been conceptualized in the academic literature (Buisseret et al., 1995; Falk, 2007; Georghiou, 2002; Georghiou & Clarysse, 2006). Buisseret et al. (1995) first show an explicit conception of behavioral additionality as the persistent changes that occur in firms' R&D and innovation-related behaviors as well as strategies. These changes are attributable to the policy intervention, for example, firms may undertake R&D activities with higher risk and acquire more knowledge via R&D collaborations by receiving public R&D subsidy. Thus, Falk (2007) refines the concept of behavioral additionality as desirable changes in the process of R&D and innovation by using policy intervention.

The main advantage of the efficiency evaluation of public intervention by using behavioral additionality is to assess the essential changes in the recipient firms' innovation process, and subsequently the improvements of related technological capabilities. These profound effects generated by the public intervention may not be captured by the input and output additionality assessments (Antonioli & Marzucchi, 2012). The conception of behavioral additionality helps to understand better how public intervention can essentially change the process of R&D and how innovation can be done in a more consistent way (Georghiou & Laredo, 2006). More specifically, for the research on public R&D subsidy, the conception of behavioral additionality can interpret the effects of public R&D subsidy in a more comprehensive way (Georghiou & Clarysse, 2006). Thus, the conception of behavioral additionality has gained considerable attention in academic literature (Antonioli & Marzucchi, 2012; Falk, 2007; Gök & Edler, 2012). Subsequently, the evidence on the existence and nature of behavioral additionality is increasingly sought in evaluation practice for designing innovation policy (Georghiou & Clarysse, 2006).

Based on the basic definition, the conception of behavioral additionality has been extended to be more specific and further classified (Chapman & Hewitt-Dundas, 2015; Falk, 2007; Gök & Edler, 2012). Current classifications on behavioral additionality can be found in several perspectives, mainly including R&D project implementation and firm-level cognitive capacity enhancement (Falk, 2007; Georghiou, 2002; Knockaert et al., 2014).

From the R&D project implementation perspective, behavioral additionality can be further classified into scope additionality, acceleration additionality and scale additionality (Falk, 2007; Georghiou, 2002). Scope additionality occurs in situations where R&D projects undertaken by firms have been extended to "*a wider range of markets, applications or players*" (Falk, 2007, p. 668) on receiving the R&D subsidy. By extending the scope into new research areas, firms may encounter a greater level of both technological and commercial risks stemming from unfamiliar areas in which firms lack related technological competencies and business experience (Ahuja & Lampert, 2001). Scope extending could also be reflected in the establishment of new partnerships with external actors which can potentially enlarge firm-level knowledge scope (Clarysse et al., 2009). However, the cost arises for firms due to the coordination and maintaining of the new relationships with external partners (Dyer & Singh, 1998). By receiving R&D subsidy, firms can, to some extent, reduce the risk as well as cost related to the scope extending. Thus, the R&D subsidy is expected to generate scope additionality (Falk, 2007).

Acceleration additionality is defined as the effects generated by R&D subsidy on the timing of the R&D projects, usually the speeding up of projects to meet a market window (Georghiou, 2002). Acceleration additionality could be, for example, "*an earlier starting date, a shorter implementation phase, or the earlier completion of the project*" (Falk, 2007, pp 668) without resource constraints under public support. Firms can also shorten the time to market by acceleration additionality. To generate acceleration additionality, firms usually prefer to engage in short-term projects rather than long-term projects. However, if long-term projects are required to be undertaken by sponsored firms to satisfy public strategical targets, firms may decide to get involved in research areas beyond their short-term business needs. In this situation, acceleration additionality would appear with scope additionality at the same time (Falk, 2007).

Scale additionality refers to the situation where a specific R&D project is conducted on a larger scale than previously intended by the firm as a result of government support (Georghiou, 2002; Wanzenboeck et al., 2013). In other words, scale additionality occurs when firms adopt a larger scale of their R&D projects or investments after receiving R&D subsidies (Falk, 2007). Falk (2007) also argues that scale additionality can capture and depict the gradual change in R&D project implementation.

Another key perspective of behavioral additionality is cognitive capacity additionality, which refers to the enhancements generated by R&D subsidies on aspects such as firm-level managerial capabilities, technological know-how and networking skills (Bach & Matt, 2002, 2005; Falk, 2007; Knockaert et al., 2014). The core issue of the cognitive capacity additionality related to R&D subsidy is concerned with whether public support changes the cognitive capacity of the sponsored firms (Bach & Matt, 2002, 2005). Bach and Matt (2002) argue that the changes to firm-level cognitive capacity can result in permanent or persistent changes in firm behaviors at the strategic level or at the level of acquired competences. It is also argued that these aforementioned changes could have stronger significant effects on firms' R&D activities in the long run (Bach & Matt, 2002, 2005). Thus, it is argued that the concept of cognitive capacity additionality reflects an evolutionary-structuralist perspective (Georghiou, 2002).

It is proposed that cognitive capacity additionality can be further classified into network additionality and competence additionality (Antonioli et al., 2014; Knockaert et al., 2014). The network additionality refers to firms' external collaboration and network building with public support (Alexander & Martin, 2013; Falk, 2007). The R&D-related collaborative network can be established not only with knowledge institutes, such as universities and research institutes, but also with industrial actors, including suppliers, users, complementors, even rivals as well (Afcha Chavez, 2011; Antonioli et al., 2014; Guisado-Gonzalez, Ferro-Soto, & Guisado-Tato, 2016; Marzucchi, Antonioli, & Montresor, 2015; Wanzenboeck et al., 2013). Network additionality implies the extending of collaboration networks within or between sectors, therefore, network additionality can also be regarded as a type of scope additionality (Falk, 2007).

Competence additionality refers to the upgrading of firms' internal competence with receiving public R&D funds (Chapman & Hewitt-Dundas, 2015; Knockaert et al., 2014). Currently, the upgrading of human resources, such as the recruitment of high-quality R&D employees and training of staff members, is used to capture competence additionality, as human resources play a key role in the innovation process and enhancement of internal capabilities (Antonioli et al., 2014; Chapman & Hewitt-Dundas, 2015; Knockaert et al., 2014). It is argued that the two types of cognitive capacity additionality are not wholly separable (Georghiou, 2002). The generation of network additionality, for example, usually requires firms to overcome the issue of lack of the necessary competences to manage a partnership, which can be regarded as competence additionality (Afcha & Garcia-Quevedo, 2016).

For cognitive capacity additionality, several scholars have sought to examine the persistency and legacy effects of R&D subsidy on it (Chapman & Hewitt-Dundas, 2015; Clarysse et al., 2009; Gök & Edler, 2012). The legacy effect is defined as the further effects or benefits emerging from additional short-term effects, usually in the subsidy period (Roper & Hewitt-Dundas, 2014). Persistency effects refer to the longer-term additional effects being sustained beyond the subsidy period (Chapman & Hewitt-Dundas, 2015). As mentioned before, the firm-level cognitive capacity additionality can result in permanent or persistent changes in firm behaviors at the strategic level or at the level of acquired competences. Thus, persistency and legacy effects are key aspects to better understand cognitive capacity additionality (Gök & Edler, 2012). The omission of these effects may result in inaccurate evaluations of the additionality effects generated by public support on cognitive capacity (Chapman & Hewitt-Dundas, 2015). Although it is acknowledged that the persistent and legacy effects are crucial, such effects have not been fully explored (Chapman & Hewitt-Dundas, 2015).

In addition, one of the latest studies investigates the behavioral additionality generated by R&D subsidy from the perspective of innovation-orientated attitudes among senior managers, with three sub-categories, which are comprised of support for innovation, risk tolerance, and openness to external knowledge (Chapman & Hewitt-Dundas, 2018). More specifically, support for innovation from senior managers is related to the assistance for innovative behaviors such as the development of new ideas and the provision of adequate resources for innovation activities. Risk tolerance is related to senior managers' ability and willingness to undertake innovation activities under conditions of uncertainty. Openness to external knowledge reflects senior managers' tendency to regularly utilize external knowledge to drive innovation activities (Chapman

& Hewitt-Dundas, 2018).

2.2.1.2 Behavioral Additionality: Beyond the Market Failures to the System Failures

The original intention of public R&D subsidy is to tackle R&D-related market failures, such as under-investment in R&D for innovation (Arrow, 1962; David et al., 2000; Dimos & Pugh, 2016). However, the conception of behavioral additionality goes beyond the market failure rationale (Gök & Edler, 2012). The behavioral additionality is based on an evolutionary perspective to overcome a broader range of failures including system and knowledge processing failures (Hall, 2002b; Metcalfe & Georghiou, 1997; Smith, 2000). Evolutionary theory provides several key tools to interpret and better understand the system failures rationale for introducing the basic intervention logic of innovation policy (Antonioli & Marzucchi, 2012).

According to evolutionary theory, firms' innovation behaviors are heterogeneous, which can be attributed to firm-level specific rules, competencies, cognitive capabilities and particular strategies (Metcalfe, 1995; Nelson & Winter, 1982). These factors constitute firms' routines that determine firms' innovation behaviors (Metcalfe, 1995). At the same time, from the perspective of neo-Schumpeterian evolutionary theory, the firm-level routines are dynamic and selectable (Dosi & Nelson, 1994). Firm-level factors that constitute routines for innovation are influenced by complementary and interconnected factors both internal and external to the firms (Kline & Rosenberg, 1986). Based on this argument, the innovation system perspective further emphasizes that firms do not undertake innovation activities in isolation (Lundvall, 1992; Nelson, 1993). Firms carry out innovation by interacting and collaborating with other actors, such as other R&D-performing firms and universities (Lundvall, 1992; Nelson, 1993). All relevant actors and their interactions constitute the innovation system (Edquist, 2005). Thus, according to the evolutionary theory, the institutional setting and the framework conditions are also important to support firms' innovation activities (Lundvall, 1992; Nelson, 1993).

Unlike neoclassical theory, which emphasizes the supplement and promotion generated by public support on firms' innovation-related resource allocations, evolutionary theory, and the innovation system perspective emphasize the enhancement of firm-level innovation capabilities and promotion of an embedded innovation system (Metcalfe, 2005). The role of the innovation policy should be rethought from a more comprehensive perspective. Thus, innovation policy is not simply designed and implemented to overcome the market failures due to under-investment in R&D and underproduction of innovation. Innovation policy should also be designed to tackle system failures (Smith, 2000).

According to existing literature, two main system failures can be identified (Antonioli & Marzucchi, 2012). The first is the failure in regard to the creation of knowledge and learning capabilities, and subsequently the evolutionary process of innovation (Malerba, 2009). The other is the failure related to the structure and the configuration of the system (Smith, 2000).

The system failures related to the creation of knowledge and learning capabilities usually stem from insufficient human resources and firm-level internal technological knowledge for absorbing external new knowledge (Cohen & Levinthal, 1989). Furthermore, this type of system failure can also be the result of unbalanced evolutionary trade-offs between exploration and exploitation (Antonioli & Marzucchi, 2012). For example, where the innovation activities of firms are characterized by low-level exploration but high-level exploitation, firms are more likely to concentrate their resources on familiar technological fields with sufficient knowledge stock, disregarding novelties (Ahuja & Lampert, 2001). The existing core capabilities which can be regarded as rigidities result in path dependence (Leonard Barton, 1992).

For the system failures related to the structure and the configuration of the system, Antonioli and Marzucchi (2012) conclude two main reasons that result in such failures. The first reason is the weak functioning of both formal and informal institutions, including regulations, standards, common norms, trust, and culture, etc. (Smith, 2000). These institutions shape the external environment, which has significant impacts on firms' innovation behaviors and performances.

Second, the inappropriate or missing components and the interactions between these components may result in system failures (Edquist, 2005; Malerba, 2009; Metcalfe, 2005). A number of key components and their interactions have profound effects on firms' innovation from the innovation system perspective (Edquist, 2005). On the one hand, missing appropriate components may trap firms in limited interactive learning, inhibiting the acquirement of essential resources (e.g., external knowledge) and development of key capabilities via learning for innovation (Malerba, 2009; Metcalfe, 2005). Weak interactions also reduce the possibility for the creation of a common vision for the development of new technologies and exert negative effects on the coordination between actors in the innovation systems, resulting in system failures on innovation

(Carlsson & Jacobsson, 1997). On the other hand, inappropriate components and interactions may result in networks that are too strong. In such networks, the inertia can enhance firms' risk of locking in existing trajectories (Woolthuis, Lankhuizen, & Gilsing, 2005).

In order to tackle the system failures, it should be taken into consideration that policy intervention on R&D and innovation via R&D subsidy needs to be designed and implemented to essentially enlarge firms' knowledge stock and enhance firm-level internal competencies, such as technological capabilities and absorptive capacities. R&D subsidy is also required to provide more opportunities for firms to interact with external actors, especially learning with other innovation-related actors. To briefly conclude, R&D subsidy is expected to generate firm-level behavioral additionality.

2.2.1.3 Behavioral Additionality from Learning Perspective

Organizational learning perspective has been drawn on to examine firm-level behavioral changes stemming from public support (Clarysse et al., 2009; Knockaert et al., 2014). From a learning perspective, R&D subsidy may change firms' routines or behaviors on acquiring, absorbing, creating and exploiting new knowledge (Clarysse et al., 2009). More specifically, R&D subsidy may potentially improve the formation of firms' external networks for acquiring knowledge, the accumulation of firms' internal knowledge stock, the development of firms' technological capabilities and subsequently enhance R&D productivity and commercial benefits from R&D (Roper & Hewitt-Dundas, 2014).

Three sub-categories of behavioral additionality from the learning perspective are identified, including congenital additionality, inter-organizational additionality and experiential additionality (Roper & Hewitt-Dundas, 2014). These three behavioral additionalities stem from the examination of Clarysse et al. (2009) on the effect of R&D subsidy on organizational learning, namely congenital learning, inter-organizational learning, and experiential learning. This classification of behavioral additionality based on the learning perspective also closely mirrors the cognitive capacity additionality adopted by Knockaert et al. (2013).

Congenital learning refers to the firms' internal knowledge stock built up in the past which is closely related to the "absorptive capacity" (Cohen & Levinthal, 1990; Huber, 1991). Absorptive capacity is important in R&D subsidy research, as the policy evaluation based on input and output additionality is complicated by the fact that firms do R&D for other purposes, such as technological upgrading through exploratory innovation, rather than purely getting new products to market or applying for new patents. Congenital learning can be also defined as the stock of human capital at the firm level, which is captured by the education and experience of firms' employees (Roper & Hewitt-Dundas, 2014). Thus, congenital additionality refers to the improvements in the quality of skills of firms' human resources generated by receiving public R&D subsidy (Roper & Hewitt-Dundas, 2014). At the same time, congenital additionality is also closely related to competence additionality (Knockaert et al., 2014).

Inter-organizational learning refers to firms' R&D collaborations for transfer and sharing of both codified skills and tacit knowledge outside firms (Autio, Kanninen, & Gustafsson, 2008; Levitt & March, 1988). Inter-organizational additionality is defined as the enhancement led by public support on the development of new inter-organizational collaborations for potential external knowledge transfer (Roper & Hewitt-Dundas, 2014). R&D subsidy encourages firms to broaden or deepen their external linkages related to R&D behaviors. Inter-organizational additionality is similar to network additionality and is closely linked with congenital additionality (Falk, 2007; Knockaert et al., 2014; Roper & Hewitt-Dundas, 2014). On the one hand, inter-organizational additionality provides more opportunities for both individual and organizational learning with external actors, and increasing firm-level competencies and absorptive capacity (Falk, 2007), and enhancing network competences as well (Ritter & Gemünden, 2003). On the other hand, inter-organizational additionality may be path-dependent according to previously acquired knowledge, in other words, inter-organizational additionality may be constrained by congenital additionality (Roper & Hewitt-Dundas, 2014).

Experiential learning refers to learning-by-doing which is related to knowledge embedding to firms through specific routines and resource configuration (Clarysse et al., 2009; Cyert & March, 1963). Experiential additionality is defined as the potential reconfiguration of existing R&D processes and routines or the introduction of new ones through exploration by receiving R&D subsidy (Roper & Hewitt-Dundas, 2014).

2.2.2 Empirical Studies on Behavioral Additionality

2.2.2.1 The Measurements of Behavioral Additionality

After clarifying the definition of behavioral additionality, several scholars began to verify the effect of public R&D subsidy on firm-level behavioral additionality by employing empirical analysis. In the empirical studies related to behavioral additionality, the first core problem to be addressed is to clarify the measurements of behavioral additionality (Antonioli & Marzucchi, 2012; Falk, 2007; Gök & Edler, 2012).

From the perspective of cognitive additionality, the growth of internal knowledge stocks and the expansion of external inter-organizational learning networks measure the firm-level competence additionality and network additionality, respectively (Knockaert et al., 2014; Roper & Hewitt-Dundas, 2014). More specifically, based on organizational learning theory, human resources are the carriers of complex tacit knowledge and are closely related to the firms' use of knowledge to enhance their R&D capabilities (Roper & Hewitt-Dundas, 2014). In this way, the internal knowledge stocks can be captured by the upgrade of R&D related human resources, that is, the educational level, the growth of R&D experience and capabilities of the R&D staff members of firms. For example, firms can acquire R&D-related capabilities by hiring high-quality researchers (Chapman & Hewitt-Dundas, 2015; Georghiou & Clarysse, 2006). The current studies use counting or continuous variables to directly measure the enhancement of both quantity and quality of employees for capturing the firm-level competence additionality, such as "the ratio of the number of employees with a doctoral degree to the total number of employees" (Kang & Park, 2012), "the differences between the values of natural logarithm of the actual and predicted employment" (Link & Scott, 2013), "the number of tertiary-educated workers divided by the total number of workers" (Gustafsson et al., 2016), and "the recruitment of Ph.D. holders" (Afcha & Garcia-Quevedo, 2016). Antonioli et al. (2014) measure the firm-level competence additionality via a questionnaire survey by setting up three dummy variables related to human resource upgrading. These three variables indicate "*whether the workers' competencies have been widened as a result of the firm's organizational practices*"; "*whether undifferentiated training programs have been implemented*"; and "*whether the firm has organized training programs to improve specific specialized competencies*".

The external inter-organizational learning network is usually measured by the firms' external R&D collaborations in existing research to depict the expansion of the firms' external channels for accessing R&D-related knowledge (Knockaert et al., 2014; Roper & Hewitt-Dundas, 2014). The firm-level external R&D cooperation can be further divided into cooperation with knowledge institutions and industrial partners. Knowledge institutions include universities and research institutes. Cooperation with industrial partners includes vertical cooperation and horizontal cooperation. Vertical cooperation refers to cooperation between firms and their upstream suppliers and downstream users; horizontal cooperation refers to the participation in strategic alliances, cooperation with firms affiliated with the same group, even industrial competitors (Afcha Chavez, 2011; Franco & Gussoni, 2014).

The measurements of firm-level network additionality are diversified, mainly including dummy variables, counting variables, scoring variables based on questionnaires, and continuous variables. Specifically, the dummy variables directly depict whether a firm has R&D cooperation with external organizations (Afcha Chavez, 2011; Antonioli et al., 2014; Busom & Fernández-Ribas, 2008; Guisado-Gonzalez et al., 2016; Marzucchi et al., 2015; Segarra-Blasco & Arauzo-Carod, 2008). For example, Guisado-González et al. (2016) set up 40 dummy variables of R&D cooperation by identifying 40 cooperation sources classified by regions and partners based on the data of the Spanish Community Innovation Survey (CIS). The counting variables usually measure the firms' cooperative behaviors by taking the number of partners of firms (Kang & Park, 2012). The scoring variables are usually defined based on the specific content of the questionnaire (Cerulli et al., 2016; Knockaert et al., 2014). For example, Cerulli et al. (2016) scored 0-6 for the firm-level cooperation based on the Italian Community Innovation Survey (CIS) by considering the factors including the types and geographic locations of the partners for firms. A score of 0 means that a firm has no cooperation at all, and a score of 6 means that the firm has all types of partners. Knockaert et al. (2014) rated the firm-level network additionality by using the seven-point Likert Scale, which included questions about "*The project allowed us to network with universities or public research centers*" (p.382). However, Carboni (2012) argues that the measurements of network additionality by the use of discontinuous variables may lose a large amount of specific information in R&D cooperation, while the continuous variables can compensate for these losses. Thus, he used the ratio of collaborative R&D expenditure to the number of employees as a variable to measure the network additionality (Carboni, 2012).

In addition, there are few empirical studies related to the behavioral additionality from the perspective of implementation on R&D projects. Existing studies usually adopt dummy variables to measure the additionality on the scale, scope and speed of R&D projects (Wanzenboeck et al., 2013). In a recent study, firm-level behavioral additionality from an innovation-oriented perspective was measured by the five-point Likert Scale (Chapman & Hewitt-Dundas, 2018).

2.2.2.2 Public R&D Subsidy and Firm-Level Behavioral Additionality

The empirical studies of the additional effects generated by public R&D subsidy on firm-level R&D behaviors also encounter the issues of selection bias and endogeneity related to research on policies. At the same time, due to the characteristics of measurements of behavioral additionality, the existing prevalent empirical research methods are mainly matching models (Antonioli & Marzucchi, 2012).

Similarly to the research on the effects of R&D subsidy on the firms' input and output additionality, most studies adopt propensity score matching (PSM) for controlling selection bias and endogeneity issues (Afcha Chavez, 2011; Antonioli et al., 2014; Busom & Fernández-Ribas, 2008; Chapman & Hewitt-Dundas, 2018; Marzucchi et al., 2015). Apart from the PSM algorithm, two related studies used coarsened exact matching (CEM) (Afcha & Garcia-Quevedo, 2016; Gustafsson et al., 2016). Compared with the PSM algorithm, CEM does not need to estimate firms' propensity probabilities for obtaining the R&D subsidy at first, that is, it does not need to estimate the propensity score via the logit or probit regression (Afcha & Garcia-Quevedo, 2016; Gustafsson et al., 2016). The CEM algorithm layers and weights related variables that affect firms' acquirements of R&D subsidy in accordance with the distance between the treated and control groups. Thus, the CEM algorithm is suited to situations in which the factors influencing the R&D subsidy allocation are continuous variables (Gustafsson et al., 2016).

Busom and Fernández-Ribas (2008) investigate the effect of R&D subsidies on firms' collaborations with public research organizations as well as other firms including customers and suppliers. Based on the data from 716 Spanish manufacturing firms in 1998, Busom and Fernández-Ribas (2008) adopted a parametric structural model and a score matching method as their empirical technique. The results show that public R&D subsidies significantly enhance the likelihood of firms' external R&D collaboration. Specifically, on the one hand, the probability of R&D collaboration between recipient firms and public research institutions has increased by 28%. On the other hand, although public R&D subsidies promote collaborations between firms and customers and suppliers, such additionality effects are not as significant as that between firms and public research institutions. In addition, these additionality effects of R&D subsidy on collaborations between firms and the private industrial partners are significant only when recipient firms have certain intangible knowledge assets.

Afcha Chávez (2011) analyzed the additionality effects of public R&D subsidies from central and local governments on the manufacturing firms' technological cooperation. The study further differentiates the firms' cooperation with universities or technology centers, as well as with customers and suppliers. Based on a set of panel data from a group of Spanish manufacturing firms from 1998 to 2005, the study adopts the PSM algorithm. The empirical results show that R&D subsidies from central and local governments can significantly promote cooperation between firms and universities or technology centers. However, such additionality effects are insignificant on the promotion of cooperation between firms with customers and suppliers. Furthermore, the study also finds that local R&D subsidies exert higher additionality effects on firms without antecedent experience in R&D cooperation, whereas subsidies from the central government are more effective in fostering cooperation in those firms already engaged in R&D cooperation.

Antonioli et al. (2014) explore the effects of R&D subsidies on both firm-level competence and network additionalities at the same time. By adopting PSM based on a set of regional firm-level data from Italy in 2006-2008, the study finds that firms sponsored by R&D subsidy are more likely to upgrade their internal capabilities. However, the R&D cooperation of these firms is not significantly affected by receiving such R&D subsidies.

Based on a business dataset for the Italian region of Emilia-Romagna, Marzucchi et al. (2015) first verified the significant contribution of R&D subsidy to cooperation between firms and universities or research institutes by adopting PSM. They further indicate that the R&D subsidy to regional firms affects their intra-regional more than their extra-regional cooperation. A generalized propensity score matching technique is then employed to explore the effect of the amount of subsidy. It is found that R&D subsidy can promote firms' cooperation with extra-regional universities only when the amount of provided subsidy reaches a minimum threshold. The potential reason is that extra-regional cooperation has a higher cost.

Gustafsson et al. (2016) tested the question about whether R&D subsidy has a positive effect on firms' performance. They adopted CEM and diff-in-diff approaches combined with a qualitative case study of the Swedish public innovation subsidy program. The firms' human resource upgrading is an important indicator to measure firms' performance. The empirical results show that the R&D subsidies exert a significantly positive but short-run effect on the firms' human capital investment. However, no significant effects of R&D subsidy can be found on the long-term performance of firms.

Afcha and Garcia-Quevedo (2016) examine the effects of R&D subsidies from national and regional governments on firms' R&D personnel recruitment. First, this study evaluated the efficiency of R&D subsidies on firm-level R&D expenditures and the number of R&D staff members. Second, this study further focuses on the effect of public R&D subsidies on the recruitment of R&D personnel with a high educational level. Based on a dataset from the Spanish Technological Innovation Panel from 2006 to

2011, the research adopts a combination of CEM and PSM to control selection bias and endogeneity issues. The empirical results indicate that R&D subsidies significantly increase the number of R&D employees. It is also shown that regardless of the firm size, R&D subsidies would significantly increase firms' recruitment of employees with a Ph.D. degree in the first year after receiving public funds. From the perspective of the sources of subsidies, the additionality effects of R&D subsidy on the recruitment of Ph.D. holders are insignificant when firms only receive subsidies from the regional government.

In a recent study in 2018, Chapman and Hewitt-Dundas (2018) adopted PSM to explore the effects of R&D subsidies on innovation-orientated attitudes of firms' senior managers. Their empirical results show that public support induces the most significant positive change in openness to external knowledge, followed by the risk tolerance of senior managers. The positive effect of R&D subsidy on senior manager attitudes for supporting innovation is the smallest.

Apart from the matching algorithm, several other empirical techniques have been employed in existing related research. To cope with the endogeneity issue, most studies choose to set the instrumental variables. The endogenous nature of the effects of R&D subsidy on firm-level behavioral additionality in empirical research mainly comes from unobservable factors that may have effects on firms' R&D behaviors (Antonioli & Marzucchi, 2012). On the other hand, to enhance the probability of successful acquirement of R&D subsidy, firms will deliberately change their R&D behaviors based on the application requirements to cater to public agencies (Georghiou, Clarysse, & Steurs, 2004). This may result in reverse causality issues to generate endogeneity.

The selection of instrumental variables in existing research is mainly comprised of firm-level and industry-level variables. The firm-level instrumental variables are closely correlated to the possibilities of firms' acquirement of R&D subsidy, but not directly related to the behavioral additionality. For example, Link and Scott (2013) use "*whether a firm acquires other public support before receiving public R&D subsidy*" and Guisado-Gonzalez et al. (2016) use "*firms' export share*" as instrumental variables. The industry-level instrumental variables depict the degree of innovation as well as the priority of obtaining an R&D subsidy of the industry in which the firm engages. The industry-level instrumental variables do not directly affect firm-level behavioral additionality as well. For example, Carboni (2012) uses "*the amount of industry grant per worker*"; Franco and Gussoni (2014) use "*the innovation costs, incoming spillovers, appropriability and permanent R&D at industrial level*"; Guisado- Gonzalez et al. (2016) used "*mean of R&D subsidy at the industry* *level*' as instrumental variables (see Table 2.2 for a summary of instrumental variables). Based on the instrumental variables, the existing studies adopt the Structural Equation Model (SEM), Two-Stage Least Squares (2SLS) regression as the main empirical techniques (Franco & Gussoni, 2014; Guisado-Gonzalez et al., 2016; Link & Scott, 2013).

Link and Scott (2013) investigate conditions in which R&D subsidies promote the employment growth of SMEs sponsored by the Small Business Innovation Research program (SBIR). By using linear regression with instrumental variables, the study finds that R&D subsidy has more significant stimulating effects on employment growth under two conditions. First, the recipient firms acquire additional funding from external investors for the R&D at the same time. Second, the firms create an exceptional amount of intellectual property with publicly subsidized R&D. In addition, the signing of commercial agreements between subsidized firms and other firms has played an important role in employment growth. This also promotes the success of the commercialization of technological achievements which are developed under R&D subsidy.

Franco and Gussoni (2014) explore the effect of R&D subsidy on firms' R&D cooperation. This study adopted SEM with instrumental variables based on a dataset of innovative firms in seven European countries. The results show that R&D subsidy has a significantly positive effect on firms' participation in various types of R&D cooperation in all countries. At the same time, R&D subsidy has a higher effect on firm-level network additionality in the service sector.

Guisado-Gonzalez et al. (2016) verified that public R&D subsidy has significant additionality effects on firms' R&D cooperation. The study uses a two-stage least squares method with instrumental variables based on a set of cross-sectional data from a group of 4,311 Spanish manufacturing companies in 2010. The study also finds that the implementation of differentiation strategies will have a significant adverse effect on R&D cooperation. Firms with differentiated strategies may have different knowledge and therefore are not keen to gain competitive advantage by the R&D spillovers generated by other firms. Consequently, these firms may not have much interest in the establishment of R&D cooperation. Thus, the government should grant more support for firms' R&D to firms positioned in a differentiation strategy, rather than encourage firms to establish more R&D cooperation via such subsidies.

Carboni (2012) explores whether public R&D subsidy is a determinant in promoting firm-level R&D cooperation. Continuous variables are used to measure behavioral additionality, which is the ratio of cooperative R&D expenditure to the number of employees. Due to the censoring bias, the Tobit model with instrumental variables is adopted after the preprocessing of the dependent variable by using the Inverse Hyperbolic Sine (IHS) transformation. The empirical results show that public R&D subsidy has a significantly positive effect on R&D cooperation. Besides, the absorption capacity measured by the R&D personnel intensity is also significantly positively correlated with the level of cooperative R&D expenditure.

At the same time, several studies do not set instrumental variables. For example, Segarra-Blasco and Arauzo-Carod (2008) adopt a logit model to explore the determinants of R&D cooperation establishment between firms and five types of partners (i.e., firms under the same groups, customers and suppliers, competitors, universities and public research institutes). R&D subsidy is found to significantly promote firms' R&D cooperation with all these five types of partners, resulting in additionality effects. The study further distinguishes the sources of R&D subsidy into region-level, state-level, and EU-level. The empirical results show that regional subsidy only significantly promotes cooperation between firms and universities and research institutes, while national and EU subsidies significantly promote all types of cooperation. In addition, R&D subsidy at the state-level significantly promotes firms' cooperation with domestic universities, while EU subsidy has significant additionality effects on firms' cooperation with foreign universities.

Kang and Park (2012) adopt the SEM to explore the effects of R&D subsidy on firm-level internal R&D activities and external collaborations with universities, research institutes and other firms based on the survey data of Korean biotechnology SMEs from 2005 to 2007. The empirical results indicate that R&D subsidy has significantly enhanced the internal R&D investment and the recruitment of highly educated employees of Korean firms. At the same time, the R&D subsidy also plays an essential role in promoting firms' domestic and international R&D cooperation.

Based on the Italian Community Innovation Survey data, Cerulli et al. (2016) employ the treatment random coefficient model to verify the effects of public R&D subsidy on firms' R&D cooperation. The research results show that the R&D subsidy has a significant additionality effect on firm-level R&D cooperation with external partners.

In addition, several empirical studies also explore the correlations between firm-level heterogeneity and behavioral additionality. For example, Clarysse et al. (2009) investigated the additionality effects of three firm-level learning behaviors on firms' R&D behaviors, including "*change way the research path is managed in the firm*" (p.1521), "*formalize the innovation management process within the firm*", and "*increase the innovation management capabilities*" (p.1521). They found that congenital learning and inter-organizational learning can significantly generate the firms' behavioral additionality, but this additionality effect will be eroded if firms have participated in public R&D programs before.

The research of Wanzenboeck et al. (2013) indicates that the firm size, age, and degree of technological specialization will affect behavioral additionality. They find that the smaller, younger and more specialized firms are more likely to generate behavioral additionality with public R&D subsidy.

Knockaert et al. (2014) investigate the effects of technology intermediaries and firm-level absorptive capacity on firms' competence and network additionality. The empirical results show that these two factors cannot directly promote behavioral additionality. However, the higher the absorptive capacity of the firm, the more the firm can fully use the services provided by the technology intermediaries, resulting in higher behavioral additionality.

To sum up, current empirical studies on the effects of public R&D subsidy on firms' R&D behaviors mainly adopt matching algorithms and regressions with instrumental variables. Discontinuous variables including dummy and counting variables are mainly used to measure R&D subsidy. Dummy variables are also used for the measurement of behavioral additionality in almost all the existing related studies, and very a few studies adopt continuous variables, such as the research of Carboni (2012). The existing studies have also differentiated the effects of R&D subsidy on firm-level R&D behaviors by considering the heterogeneity factors. In terms of the sources of R&D subsidy, the effects of subsidies from local, central governments and the European Union were tested. The types of behavioral additionality were further classified, such as cooperation with different partners, and short-run and long-run growth of firm-level competences. Different factors of firms were also considered including firm size, industries the firms were engaged in, and firm-level strategies, which may potentially affect the correlations between R&D subsidy and firm-level behavioral additionality (see Table 2.1 for the summary of relevant empirical studies). In addition, the firm-level absorptive capacity is also an essential factor which influences the behavioral additionality in existing studies.

Table 2.1 Conclusion of Empirical Studies of the Impact of R&D Subsidies on firms' Behavioral additionality

Studies	Empirical techniques	Measurement of R&D subsidy	Measurement of behavioral additionality	Heterogeneity factors	Results
Busom & Fernández-Ribas (2008)	SEM; PSM	Dummy variables	Three dummy variables in collaborations with public research institutes, customers and suppliers, and other firms		Positive on collaborations; More positive on collaborations with public research institutes
Segarra-Blasco & Arauzo-Carod (2008)	Logit model	Dummy variables	Five dummy variables in collaborations with different partners	Sources of R&D subsidies	Positive on collaborations
Afcha Chávez (2011)	PSM	Dummy variables	Two dummy variables in collaborations with universities; customers and suppliers	Sources of R&D subsidies	positive on collaborations with universities; insignificant on collaborations with customers and suppliers
Kan & Park (2012)	SEM	Dummy variables	1) Counting variables of partners of R&D collaborations; 2) ratio of employees with Ph.D. degrees	Domestic or foreign collaboration	Positive on both collaborations and employee recruitment

Table 2.2 Cont.

Studies	**Empirical techniques**	**Measurement of R&D subsidy**	**Measurement of behavioral additionality**	**Heterogeneity factors**	**Results**
Carboni (2012)	Tobit model with IVs	Dummy variables	Firm's external R&D expenditure divided by the number of employees	Firms size	Positive on collaborations
Link & Scott (2013)	OLS with Ivs	Counting variables of R&D subsidy projects	The natural logarithm of the ratio of the actual number to the expected number of employees		Positive on employee recruitment
Franco & Gussoni (2014)	SEM; Ivs	Dummy variables	Four dummy variables in collaborations with different partners	Service and manufacturing sectors; different countries	Positive on collaborations; More positive in service sectors
Antonioli et al. (2014)	PSM	Dummy variables	1) 3 dummy variables in human resource upgrading; 2) 8 dummy variables in collaborations with different partners	Intra-regional and inter-regional collaborations	Positive on human resource upgrading; insignificant on collaborations
Marzucchi et al. (2015)	PSM	Dummy variables	4 dummy variables in collaborations with different partners	Intra-regional and inter-regional collaborations	Positive on collaborations; More positive in Intra-regional collaborations

Table 2.3 Cont.

Studies	**Empirical techniques**	**Measurement of R&D subsidy**	**Measurement of behavioral additionality**	**Heterogeneity factors**	**Results**
Gustafsson et al. (2016)	CEM; DID Fixed-effect model	Dummy variables	the ratio of educated tertiary workers	Long-term and short-term performance	Positive in short-term human resource upgrading, but insignificant in the long term
Afcha & Garcia-Quevedo (2016)	CEM; PSM	Dummy variables	Recruitment number of employees with Ph.D. degrees	Central and local governments	Positive on employee recruitment; but insignificant when receiving local funds
Guisado-Gonzalez et al. (2016)	IVs; 2SLS	Dummy variables	40 dummy variables in collaborations	differentiation strategy	Positive on collaborations
Cerulli et al. (2016)	treatment random coefficient model	Dummy variables	Counting variables of the score on collaborations		Positive on collaborations
Chapman & Hewitt-Dundas (2018)	PSM	Dummy variables	Counting variables of the score on three dimensions of Innovation orientation		Positive on the attitude of senior managers towards innovation

Table 2.4 Instrumental variables in R&D subsidy research

Studies	Instrumental variables
Carboni (2012)	the amount of industry grant per worker
Link & Scott (2013)	prior funding (i.e., funding for the research that was obtained before the Phase II SBIR award)
Franco & Gussoni (2014)	The industry level of 1) innovation costs; 2) incoming spillovers; 3) appropriability; 4) permanent R&D.
Guisado-Gonzalez et al. (2016)	export intensity, basicness of R&D, and Industry level of incoming spillovers (at the 2-digit NACE level)
Oezcelik & Taymaz (2008)	1) sectoral share of supported firms; 2) regional share of supported firms; 3) capital intensity; 4) relative labor productivity; 5) share of skilled employees
Guo et al. (2016)	1) the total number of firms in high-tech zones of the city where the firm is located in each given year 2) the ratio of total investment in fixed assets made by local governments over the total GDP at the county level each year
Liu et al. (2016)	the natural logarithm of the amount of public funding per technology at the 4-digit industry level

2.3 Public R&D Subsidy, Behavioral Additionality, and Output Additionality： A Comprehensive Perspective

According to the argument of Antonioli and Marzucchi (2012), under evolutionary theory and the perspective of the innovation system, close connection and interaction exist between firm-level R&D input, output, and behavioral additivity.

Several scholars have initially explored the relevance of firms' R&D behavioral additionality, R&D input, and output (Baum, Calabrese, & Silverman, 2000; Clarysse et al., 2009; George, Zahra, & Wood, 2002; Madsen, Clausen, & Ljunggren, 2008). For example, Madsen et al. (2008) analyzed the large-scale survey data of Norwegian firms and found that the additional behaviors of the firm, such as launching additional new R&D projects, is a prerequisite for generating more R&D investment. Clarysse et al. (2009) indicated that firms are more willing to invest in R&D activities and hire R&D personnel as they improve their R&D management processes. The research findings of Baum et al. (2000) and George et al. (2002) show that firms can increase their knowledge stocks through more interactions with external R&D partners. Increased knowledge stocks help firms to overcome the deficiency of information and scientific knowledge and to enhance related R&D resources and capabilities, thus gaining more R&D output.

Since R&D subsidy has a specific effect on the change of firms' R&D behaviors, in recent years, several scholars have begun to pay more attention to the interaction between firm-level R&D input, output and behavioral additionality under the sponsorship of R&D subsidy. The relevant studies focus primarily on the research question about how R&D subsidy promotes firms' R&D input or output through the changes in firms' R&D behaviors (Cerulli et al., 2016; Kang & Park, 2012).

Kang and Park (2012) test the effect of public R&D subsidy on R&D output through the internal competence and external network additionality. They find a significant positive correlation between firm-level R&D output (measured by the number of patent applications) and the upgrading of firms' human capital. A similar significant positive correlation can be also found exerted by the establishment of R&D collaborations on firms' patent applications. Furthermore, a significantly stronger effect is generated by international collaborations, than by domestic collaborations. The study argues that South Korea is weaker in the knowledge base and market compared with Western developed countries, thus acquiring advanced knowledge through international collaborations can promote more R&D output of biotechnology firms in South Korea. In addition, the empirical results show that, as an essential way to improve absorptive capacity, the upgrading of firms' own human capital will play a significant role in promoting R&D output.

Cerulli et al. (2016) explore the mediating role of R&D input and collaborations in the effect of R&D subsidy on firms' R&D output. The empirical results show that the input additionality, as well as the interaction of input and investment on collaborations, play a significant mediating role in the effect of R&D subsidy on firms' R&D output. The effect of investment in R&D collaborations alone on the firm-level R&D output is shown as an inverted U-shaped curve. When the investment of R&D collaborations exceeds a certain threshold, it will have a negative effect on firm-level R&D output. Cerulli et al. (2016) argued that excess R&D collaborations will increase the coordination cost which affects firms' resource allocation and thus inhibit the generation of R&D output.

2.4 Review of Existing Literature and Research Framework

According to the literature review, from the logic of neoclassical economics, the effect of public R&D subsidy on firms' R&D input has been extensively and thoroughly studied and discussed by academia. In recent years, Chinese scholars have also paid increasing attention to this research topic. Compared to the discussion around R&D input, fewer studies have explored and tested the effect of the public subsidy on firms' R&D output, and the conclusions are also inconsistent. The complicated "black box" exists between R&D input and output. More factors make up this black box, which will potentially affect the efficiency of R&D subsidy on firm-level R&D output. Thus, scholars and policymakers are increasingly aware of the importance of the effect generated by R&D subsidy on firms' changes in R&D behaviors. Research on behavioral additionality brought by public funds is gaining more and more attention.

Specific to the existing research on R&D subsidy in the Chinese context, according to the literature review, several research gaps still remain. First, few studies focus on the effect of public R&D subsidy on firm-level behavioral additionality in the Chinese context. At present, the studies related to R&D behavioral additionality provide support for our understanding and analysis of the correlations between R&D subsidy and firms' changes in R&D behaviors. However, the definition of behavioral additionality still requires to be more focused and specific, which can be easily captured and measured for empirical analysis. At the same time, the research of behavioral additionality should echo evolutionary theory and the perspective of the innovation system. As an essential resource for R&D and innovation activities, knowledge acquisition and utilization will profoundly affect firms' R&D input and output. Organizational learning theory is closely related to knowledge acquisition and utilization, which can reflect the R&D and innovation process from a dynamic evolutionary and systemic perspective. At the same time, the related research on knowledge-based view and organizational learning theory is relatively complete with a systematic theoretical framework and measurements of variables. Therefore, based on the current literature review, it is appropriate to study the effect of public R&D subsidy on firm-level behavioral additionality from the learning perspective.

Second, most studies examine the correlations between public R&D subsidy and firms' R&D output, or the correlations between the changes in firms' R&D behaviors and output. Very few studies consider the interactions between these three factors in a more comprehensive framework. However, based on the literature review, in order to open the "black box" of the effect on firm-level R&D output generated by public R&D subsidy, the deeper mechanisms need to be explored. Thus, behavioral additionality should be discussed in conjunction with R&D subsidy and firms' output from a more comprehensive perspective. For example, firms' absorptive capacities are essential for organizational learning, and the external network building is also crucial for these learning behaviors. The question about whether synergistic effects exist between firms' absorptive capacities enhancement or network building and R&D subsidy on firm-level learning behaviors is still under-explored. Third, the firms-level heterogeneity, especially the characteristics related to organizational learning, may have an impact on the way and effect of using R&D subsidy and thus moderate the effect of R&D subsidy on firms' R&D behaviors. However, the research of this moderation effect is scant and this effect needs to be studied.

In addition, the existing literature has formed systematic empirical methods to evaluate the effects of public R&D subsidy. More specifically, the existing literature adopts propensity score matching to overcome selection bias, instrumental variables to tackle the endogeneity issue, and Tobit regression to cope with censoring bias. These methods will also be applied and combined in this dissertation to obtain robust empirical results. At the same time, according to the specific issues and data structures, this dissertation will also use Cox regression, which is the first instance of adopting such an empirical model in R&D subsidy related studies. In the selection of variables for R&D subsidy, most of the existing studies employ dummy variables or counting variables, which loses information contained in the subsidy amount. Thus, this paper will employ continuous variables to measure R&D subsidy.

In summary, this dissertation will focus on firms' learning behaviors in the R&D process. A knowledge-based view and organizational learning theory are selected as the theoretical basis of this study. The resource-based view and institutional theory will also be combined into the theoretical framework. In this dissertation, firm-level learning behaviors are further divided into the acquisition and the utilization of novel knowledge. This study will investigate the effect of public R&D subsidy on firms' novel knowledge acquisition and the adoption behaviors in the context of China, and then the impact on the R&D output of firms. The research framework of the work is shown in Figure 2.4.

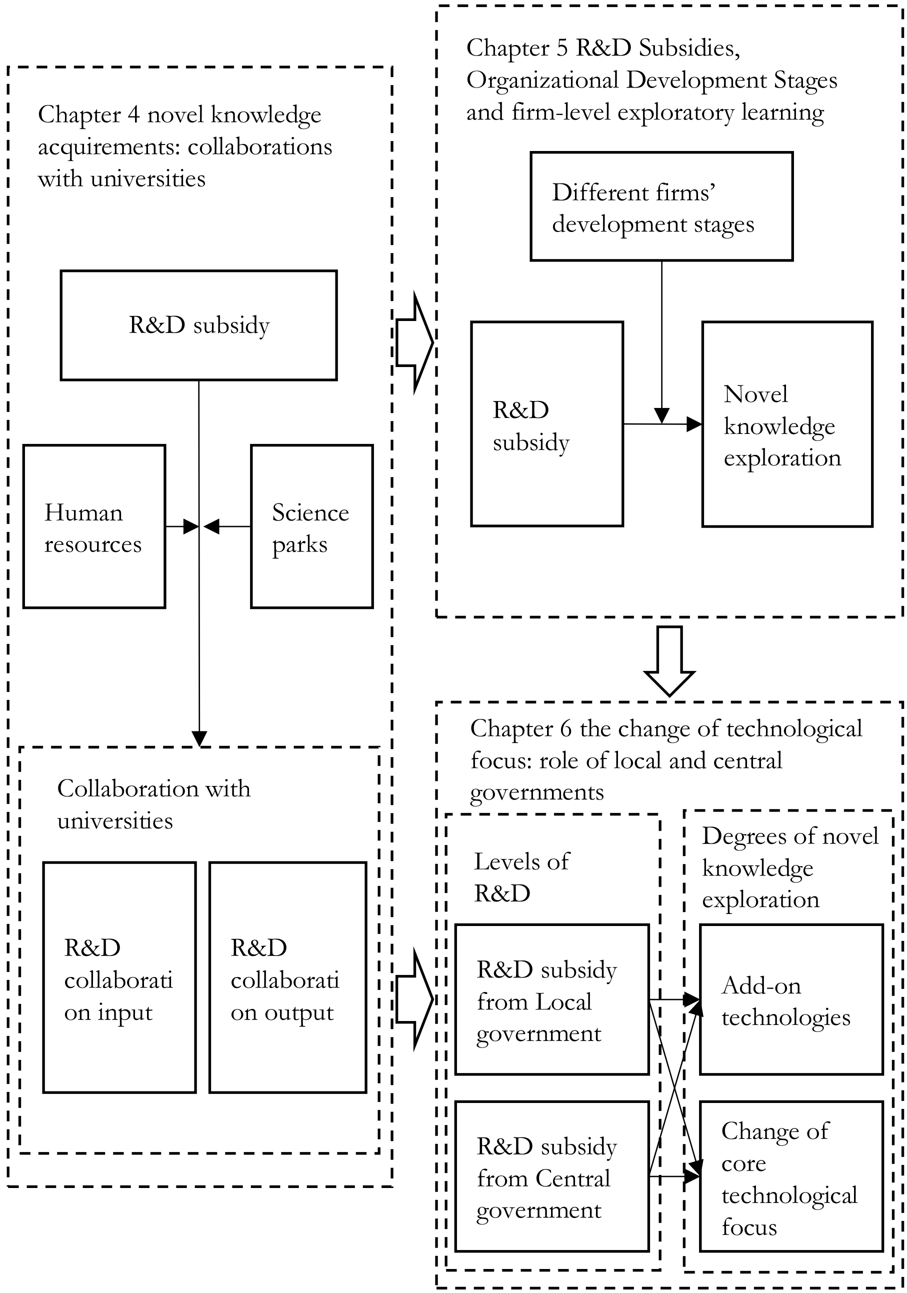

Figure 2.1 The research framework

3. Methodology

The purpose of this chapter is to discuss the paradigmatic position of this dissertation, including essential assumptions and underlying logic. It commences by defining a paradigm and its content, based on which the main components underpinning this study are explained. Then the research design will be presented, where the reasons for the choice of the methods and techniques of data collection for this study will be put forward. Finally, the research process will be elaborated as well.

3.1 Paradigm

It is generally agreed that the paradigmatic foundation of research has a substantial impact on the overall strategy of the research methods (Kuada, 2012). Therefore several philosophical discussions are necessary and the paradigmatic position of this dissertation is required to be explicitly presented.

The modern use of the term paradigm is derived from Kuhn (1970), who uses the term to describe the structure of scientific revolution and waves of research in a given scientific field. Overall, a paradigm is defined as a set of beliefs with common understandings, including what should be studied, how research should be done, and how results should be interpreted (Kuada, 2012; Kuhn, 1970). Thus, in essence, a paradigm is a priori framework for understanding and investigating a phenomenon. First of all, ontology and epistemology are two critical components of understanding the research philosophy, as a paradigm consists of a common belief and understanding of the study which guides disciplined inquiry (Kuada, 2012).

3.1.1 Ontology and Epistemology

Ontology refers to "assumptions which concern the very essence of the phenomena under investigation" (Burrell & Morgan, 1979, p.1). In other words, ontology is used to describe the nature of the reality related to what the researcher seeks to know something about (Blaikie, 2009). The question about whether social entities need to be perceived as objective or subjective is at the central position of ontology. Accordingly, ontology can be further specified as objectivism and subjectivism (see Table 3.1).

More specifically, objectivism asserts that social phenomena and their meanings are pre-given. Social phenomena and their meanings are also independent of human and social actors. Based on this ontological position, an organization is viewed as a tangible object with a particular set of principles, rules, and rules that are learned and applied by the individuals involved in it (Bryman & Bell, 2015). In contrast to objectivism, subjectivism views reality as purely subjective. Social phenomena and their meanings are socially generated and modified by human beings and social actors through continuous interaction. Thus, rather than regarding them as pre-existing, organizations and their rules are evolving through the stages of construction and reconstruction (Bryman & Bell, 2015).

Associated with the ontological issues, the epistemological assumption is about "the ground of knowledge, about how one might begin to understand the world and communicate this as knowledge to fellow human beings" (Burrell & Morgan, 1979, p.1). In simple terms, epistemology deals with the sources of knowledge. More specifically, possibilities, nature, sources, and limitations of knowledge in a given field of study can be the central problem of epistemology (Hallebone & Priest, 2008). Thus, epistemology describes the nature of knowledge and the means of actually knowing.

Table 3.1 Classification of Ontology

Ontology	Descriptions
Objectivism	Objectivism is "an ontological position that claims that social phenomena and their meanings are independent of social actors" (Bryman & Bell, 2015).
Subjectivism	Subjectivism is "an ontological position which asserts that social phenomena and their meanings are continually being accomplished by social actors" (Bryman & Bell, 2015).

Ontology and epistemology have direct implications of a methodological nature which refers to "the way in which one attempts to investigate and obtain knowledge about the social world" (Burrell & Morgan, 1979, p.2). Therefore, the methodology is the strategy or plan of action-guiding the entire research, which describes reasons underlying the choice of scientific methods in the research process. Different ontologies and epistemologies are likely to result in researchers choosing diversified research philosophies that adopt different methodologies.

3.1.2 Positivism, Interpretivism, and Pragmatism

Based on different ontological and epistemological assumptions on reality, diversified research philosophies exist. In this dissertation, three basic research philosophies will be introduced, which are positivism, interpretivism, and Pragmatism (Saunders, Lewis, & Thornhill, 2009).

Positivism research philosophy adheres to the view that it is trustworthy to gain "factual" knowledge through observation and measurement (Saunders et al., 2009). In positivist studies, researchers are limited to data collection, meaning that they should maintain an objective stance and be independent of the collected data (Wilson, 2014). Researchers should also imitate and apply the methods of natural sciences to the study of social reality, therefore, adopted methods under positivism research philosophy are usually quantitative and highly structured. The research procedure is to generate a hypothesis based on the deduction of theories, and the hypothesis must be verifiable (Crowther & Lancaster, 2008). The research findings are usually observable and quantifiable.

In contrast to positivism, interpretivism asserts that social sciences are subjective (Saunders et al., 2009). The purpose of research in the interpretivism research philosophy is to understand the roles of social actors and the subjective meaning of the social phenomena. According to interpretivism research philosophy, it is argued that researchers are involved to interpret elements of studies, in other words, human interest is integrated into a study. In simple terms, researchers in terms of interpretivism research philosophy, are part of what is being researched. It implies that researchers can never be objective about the interpretation made by others since our understanding of others is heavily impacted by personal viewpoints and values (Hatch & Cunliffe, 2006).

From the epistemology perspective, the researcher's view in terms of what adequate knowledge can be constituted is different in positivism and interpretivism (Saunders et al., 2009). Positivism focuses on causality and law-like generalizations. Thus, the source of knowledge of positivism relies on empirical findings gained via valid and reliable measures of constructs (Saunders et al., 2009). Interpretivism, on the other hand, focuses on the reality behind the details of the situation, related to subjective meanings which can motivate actions. Interpretivism accepts personal experiences associated with observation, feelings, and senses as a valid source of knowledge. Thus, qualitative data from interviews, observations, documentaries, etc. is the primary data source of studies in interpretivism research philosophy (Saunders et al., 2009).

Positivism and interpretivism are two extreme, mutually exclusive paradigms regarding the nature of research and sources of knowledge. However, some research topics may shift the philosophical assumptions over time, and move to a new position of paradigms (Collis & Hussey, 2013). Pragmatism research philosophy accepts the concept that researchers do not have to adopt one single philosophical position. According to pragmatism research philosophy, one study can be investigated via many different ways, and one single point of view may fail to give the entire picture to show the multiple realities of the social research (Saunders et al., 2009). Within pragmatism research philosophy, research questions are the essential determinant for the selection of the research philosophies. Researchers can integrate research techniques of both positivist and interpretivist positions within a single study based on the research question. The differences between these three research philosophies are shown below (see Table 3.2).

Table 3.2 The differences between Positivism, Interpretivism, and Pragmatism

	Ontology	Research approach	Research strategy
Positivism	Objective	Deductive	Quantitative
Interpretivism	Subjective	Inductive	Qualitative
Pragmatism	Objective or subjective	Deductive/Inductive	Qualitative and/or quantitative

Source: Wilson (2014)

3.2 The Paradigmatic Position of the Dissertation

In order to determine the paradigmatic position of this research, conceptions from the objectivist-subjectivist dispositions in social science need to be compared and the specific assumptions, which will be used in this research, need to be chosen.

First, the aim of this dissertation is to investigate the correlations between three main elements, R&D subsidy, firm-level R&D behaviors, and technological output in China. This social phenomenon is explained by observing causal relationships between three main elements. Furthermore, by studying the regularities and causal relationships between these three key elements, this research is expected to understand and predict the social phenomenon related to the effectiveness of R&D subsidy in China. Thus, the ontology of this study has characteristics of objectivism or positivism in nature (Kuada, 2012).

Second, the epistemological assumption of this dissertation also satisfies objectivist or positivist criteria. More specifically, the number of relevant existing studies focusing on R&D subsidy has provided plenty of codified knowledge in terms of appropriate theories and models for analysis. Furthermore, existing studies also provide mature measurement ways to refine the social phenomenon to the simplest constructs and evaluate these primary constructs for research (Saunders et al., 2009). Based on the source of knowledge, prior explanations of the studied social phenomenon of this dissertation can be provided by hypotheses formed by existing theories related to R&D subsidy logically (Babbie, 1989). These hypotheses can then be tested to verify and/or falsify according to the empirical evidence generated by the analysis of objective data (Snieder & Larner, 2009; Wilson, 2014).

Therefore, based on ontological and epistemological assumptions, the methodology of this dissertation can adopt a *hypothetic-deductive* methodology (Kuada, 2012). In management and business studies with a *hypothetic-deductive* methodology, a set of hypotheses deduced from theories are formulated initially. Each hypothesis needs to be formulated in operational terms and proposes relationships between two specific variables and tested with the application of appropriate econometric methods. The empirical results need to be examined in order to confirm or reject the hypothesis. The *hypothetic-deductive* method is linked with the positivist paradigm (Crowther & Lancaster, 2008). By employing a positivist approach, the research procedure of this dissertation needs to be purely objective, and the researcher needs to maintain minimal interaction with the research participants (Wilson, 2014). Therefore, in this dissertation, a large set of objective data from Jiangsu manufacturing firms is employed for the analysis to gain empirical evidence.

3.3 Research Design

Following the logic of *hypothetic-deductive* methodology, appropriate theories need to be selected for the theories' deductions for hypotheses building initially. Appropriate econometric methods will be then chosen to gain the empirical evidence for testing the hypotheses, thus, in the following section, the rationales of selected theories and econometric methods in this dissertation will be elaborated, and samples and data resources will also be depicted as well.

3.3.1 Theories Selection for Hypotheses Building

3.3.1.1 Organizational Learning Theory

Organizational learning theory argues that an organization can adapt to the changes of both its internal and external environments through organizational learning (Fiol & Lyles, 1985). Organizational learning is related to the effective processing, interpretation of, and response to changes both inside and outside the organization by exploration and the exploitation of knowledge, technology, and capabilities.

Clarysse et al. (2009) argued that organizational learning theory explains how the behaviors of a company change through its learning processes. This learning perspective can complement the previous literature in regard to additionality effects generated by R&D subsidy by using economic arguments, as existing studies largely neglect the organizational theories that might explain different additionality results (Clarysse et al., 2009).

Three forms of learning have been identified with regard to R&D subsidy and behavioral additionality, namely: experiential learning, congenital learning and inter-organizational learning (Clarysse et al., 2009). Experiential learning refers to learning-by-doing (Cyert & March, 1963). Congenital learning refers to the knowledge stock built up in the past (Huber, 1991). The knowledge stock may determine firm-level behaviors and is closely related to the "absorptive capacity" (Cohen & Levinthal, 1990). Inter-organizational learning is related to the R&D collaborations of firms by knowledge transfer and sharing (Autio et al., 2008; Levitt & March, 1988).

In terms of the potential changes of firms' behaviors generated by receiving R&D

subsidy, experiential learning implies the accumulation of experience related to sponsored projects application and operation (Clarysse et al., 2009; Levitt & March, 1988). With the increasing experiences on sponsored projects application and operation, especially when firms know how they can satisfy the public agencies providing R&D subsidy, the efficiency of experiential learning may decline or even disappear in firms' R&D behavioral changes (Clarysse et al., 2009). In the context of R&D subsidy, on the one hand, congenital learning can contribute to firm-level capabilities for understanding new knowledge to undertake R&D activities sponsored by R&D subsidy (Cohen & Levinthal, 1989; Zahra & George, 2002). On the other hand, congenital learning may result in learning inertia with knowledge stock (Ahuja & Lampert, 2001). Firms may undertake R&D in their familiar technological fields to avoid risk and uncertainty, even though they would have received R&D subsidies. For inter-organizational learning, R&D subsidy may encourage firms to establish formal R&D collaborations for exchanging both codified skills and tacit knowledge. R&D subsidy can also support firms to maintain such relationships for inter-organizational learning as well (Autio et al., 2008; Kale, Singh, & Perlmutter, 2000).

3.3.1.2 Knowledge-Based View

A knowledge-based view considers knowledge as the most strategically significant resource of a firm. It is argued that knowledge-based resources are usually difficult to imitate and socially complex. Heterogeneous and unique knowledge determines firm-level performance and the creation of sustained competitive advantages accordingly (Grant, 1996). Thus, one of the main tasks of an organization is to create knowledge through knowledge development, integration, and exploitation (Conner & Prahalad, 1996; Grant, 1996; Macher & Boerner, 2012).

To create unique knowledge, firms can access and transfer external knowledge across organizations (Grant, 1996). At the same time, firms need to enhance capabilities to better absorb and exploit knowledge for the integration with internal resources to develop new knowledge, as knowledge development within firms from learning is facilitated by technological resources and capabilities (Cohen & Levinthal, 1990). Technological resources can be allocated for the acquisition of new technologies, equipment, or even human capital, to improve firm-level technological capabilities (Hitt et al., 2001). In turn, firms can optimize technological resource allocation with a higher level of technological capabilities to improve innovation performance (Baker & Sinkula, 2007).

However, assimilation and exploitation of technology-related knowledge are complex and costly in nature, and firms may also lack sufficient resources for the development of technological capabilities as well as the deployment of technology-related resources (Conner & Prahalad, 1996; Grant, 1996). Public R&D subsidy can be provided to enhance technology-related resources and to help firms to facilitate technological capabilities (Xu et al., 2014). Thus, public R&D subsidy is expected to be helpful for recipient firms to acquire, assimilate, transform, integrate and exploit knowledge.

3.3.1.3 Resource-Based View

The resource-based view (RBV) argues that the competitive advantages of a firm stem from valuable resources at the firm's disposal (Barney, 1991; Newbert, 2008). The firm-level valuable resources, including physical capital, human capital and organizational capital are rare, inimitable, and non-substitutable (Galbreath, 2005; Newbert, 2008). Controlled by a firm, these valuable resources enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness for obtaining excess returns (Peteraf & Barney, 2003; Priem & Butler, 2001).

However, the cost of R&D is comparatively high, R&D activities are usually associated with high risk and uncertainties with inherent public goods characteristics (Dimos & Pugh, 2016). The resources deployed on R&D activities are usually scarce, and R&D activities may be constrained by resources. According to the resource-based view, public R&D subsidy can directly increase the pool of available resources for firms to undertake innovation activities. At the same time, public R&D subsidy reduces R&D costs and enhances returns as well (David et al., 2000; Radas et al., 2015; Rangan et al., 2006). Thus, governments also play a key role in resource allocation in firms' resource management via providing R&D subsidies based on RBV (Lazzarini, 2015).

3.3.1.4 Resource Dependence Theory

Resource dependence theory (RDT) focuses on the issue of how external resources of an organization affect its behavior (Hillman & Dalziel, 2003; Hillman, Withers, & Collins, 2009). The theory assumes that organizations are constrained by a network in which they have interdependencies with other organizations (Hillman & Dalziel, 2003; Hillman et al., 2009). RDT proposes that organizations will be dependent upon others in order to gain necessary resources when they lack essential resources on their own. At the same time, organizations attempt to minimize their own dependence or increase the dependence of other organizations on them for altering their dependence relationships with others (Pfeffer & Salancik, 1978).

Based on resource dependence theory, public R&D subsidy mainly influences firms' R&D activities via the resource-buffering effect (Amezcua et al., 2013). The R&D subsidy creates a resource munificent environment for firms to undertake R&D independent of other external organizations, which to some degree helps firms to manage overall uncertainty and risk (Amezcua et al., 2013; Jourdan & Kivleniece, 2017). By using public R&D subsidy, recipient firms can occupy more favorable competitive positions, compared to rival firms without public resources. To keep a favorable competitive position, firms are more likely to allocate resources on R&D activities and enhance their technology-related capabilities (Jourdan & Kivleniece, 2017). Having been released from resource pressure by public R&D subsidies, recipient firms can be protected from potential adverse selection, whereby technological capabilities and resources are enhanced and allocated more effectively (Rangan et al., 2006).

3.3.1.5 Institutional Theory

An institutional theory emphasizes rational myths, isomorphism, and legitimacy (Scott, 2008). Institutions are governance structures constructed by rules, norms, values, and systems of cultural meaning. According to institutional theory, organizations' behaviors are deeply rooted in institutions, thus, behaviors must be explained on a situational basis. In other words, the institutional theory focuses on the processes by which external institutions become authoritative guidelines for organizations' behaviors (Scott, 2008). Scott (1995) indicates that organizations must conform to the rules and belief systems dominant in the environment. In this way, organizations will earn the organization legitimacy in order to survive (Scott, 1995). The behaviors of an organization for seeking legitimation are the result of seeking resource stability.

According to institutional theory, receiving R&D subsidies shows an endorsement from the government and enhances firms' legitimacy (Armanios et al., 2017; Jourdan & Kivleniece, 2017). With the enhancement of legitimacy, a quality signal is provided by public R&D subsidy to potential investors, other innovation actors and clients, which is helpful for recipient firms to gain external financing and to establish formal collaborative relationships with external partners (Feldman & Kelley, 2006; Kleer, 2010; Lerner, 1999; Takalo & Tanayama, 2010). Thus, legitimacy enhancement generated by R&D subsidy may potentially result in firm-level learning behaviors' changes.

3.3.2 Empirical Techniques

Empirical studies on public R&D subsidy mainly confront three challenges. The first is the selection bias generated by the picking-the-winner behavior of governments derived from public choice theory (David et al., 2000; Dimos & Pugh, 2016). Another is the endogeneity issue stemming from omitted variables bias, reverse causality and measurement error (Guo et al., 2016). The selection bias and endogeneity issue may further result in an overestimation of the actual effect of R&D subsidy (Boeing, 2016; Liu et al., 2016). The evaluation of the effects of R&D subsidy is also disturbed by unobservable heterogeneity (Boeing, 2016). This means not all firm characteristics that determine the reception of R&D subsidy and influence the effect of firm-level R&D activities can be observed. In addition, the dependent variables in R&D subsidy studies are usually non-negative continuous variables but contain amounts of observations with value 0, which suggests left-censored data. This may result in censoring bias by sampling adopting a linear regression model (Carboni, 2012; Li, Xia, & Zajac, 2018).

Following the suggestions of previous studies, propensity score matching (PSM), fixed-effect regression with instrumental variables (IVs) and Tobit regression are adopted as the core empirical techniques of this dissertation to cope with the aforementioned challenges.

3.3.2.1 Propensity Score Matching (PSM)

PSM is a non-parametric estimation which matches the treated to the control observations with a set of similar observable characteristics for eliminating potential selection bias (Rosenbaum & Rubin, 1983).

More specifically, PSM methods estimate the counterfactual outcomes of individuals by using the outcomes from a subsample of "similar" individuals from the other group, i.e., estimate the treatment effect based on outcome differences between comparable individuals. This means that control groups present the same likelihood as if being treated compared with the treated groups, even though they are not treated in reality. The selection into treatment is not random but is systematically correlated with some variables that may influence the outcome. Based on PSM, the difference between the outcomes in the treated and the control groups can be attributed to the treatment. PSM is now prevalent in the research on R&D subsidy (Dimos & Pugh, 2016). For this dissertation, R&D subsidy recipient firms are denoted as the treated group while the potential effectiveness of R&D subsidy is the estimated average treatment effect. Control groups are built by using a PSM algorithm, which is comprised of non-recipient firms.

PSM relies on two main assumptions, namely the conditional independence assumption (CIA) and the common support condition (CSC) during the matching procedure. The conditional independence assumption (CIA) allows the untreated units to be used to construct an unbiased counterfactual for the treatment group. Under the CIA, a set of observable variables, i.e., covariates, exists. After controlling for covariates, the potential outcomes are independent of treatment status which is identified by groups. CIA implies that after controlling for covariates, the assignment of units to treatment is "as good as random." This assumption requires that all variables relevant to the probability of receiving treatment should be observable and included in covariates.

The common support condition (CSC) ensures that there is sufficient overlap in the characteristics of treated and untreated units to find adequate matches. That is, for each possible value of covariates, there must be a positive probability of finding both a treated and an untreated unit.

PSM usually has three basic steps for calculating the treatment effects (Caliendo & Kopeinig, 2008). The first step is the estimation of propensity scores. The propensity score is defined as the probability of receiving treatment conditional on the covariates.

By comparing propensity scores alone, it is unnecessary to attempt to match on all covariates (Rosenbaum & Rubin, 1983). To estimate the propensity score, a logit or probit model is usually used with a set of covariates. Covariates should contain variables that influence the treatment status and the outcome variable simultaneously. Furthermore, variables that are unaffected by treatment should also be included as covariates in the model. To ensure this, variables selected as covariates should either be fixed over time or measured before participation. In the context of this dissertation, obviously explicit criteria that satisfy the requirements of governments in regard to public sponsored R&D project or program eligibility should be included as these factors are thought to influence self-selection and administrative selection.

The second step is the selection of a matching algorithm to match untreated units to treated units according to the estimated propensity scores. Four matching algorithms, including nearest neighbor matching, radius matching, caliper matching, kernel (local-linear) matching, are in common use based on estimated propensity scores. More specifically, nearest-neighbor matching chooses a fixed number of nearest neighbors. The nearest neighbors could be one or multiple in the match based on the absolute difference in the propensity score between treated and untreated units. Radius matching specifies a "caliper" or maximum propensity score difference. Larger differences will not result in matches, and all units whose differences lie within the caliper's radius will be chosen. This permits variation in the number of matched observations as a function of the quality of the match. Caliper matching is a combination of nearest neighbor matching and radius matching. Within the caliper's radius, a "caliper" will be set for matching nearest neighbors to avoid "bad matching" (Boeing, 2016). Kernel (local-linear) matching is a nonparametric method that compares each treated unit to a weighted average of the outcomes of all untreated units. In addition, instead of using propensity scores to measure the difference between the treated and the untreated, the matching algorithm measuring the distance between covariates of the treated and those of the untreated can also be used.

The third step is the estimation of the impact of the intervention with the matched sample. T-test for significance on the mean value of matched treatment and control groups can be used to measure the validity of average treatment effects.

3.3.2.2 Endogeneity Issue and Instrumental Variables

Generally, the PSM method can control for the selection bias caused by the counterfactual outcomes, which cannot eliminate endogeneity bias from an independent variable which is correlated with the unobserved error term. An endogeneity issue occurs when an independent variable is correlated with the error term (Greene, 2003; Wooldridge, 2015). Endogeneity causes estimators of ordinary least squares regression to be biased and inconsistent. Endogeneity can arise as a result of omitted variables bias, simultaneous causality (or simultaneity), and measurement error (Antonakis et al., 2010; Kennedy, 2003).

Omitted variables bias occurs when a model is created incorrectly by leaving out one or more important factors (Greene, 2003; Wooldridge, 2015). In other words, a model which omits one or more independent variable that both affect the independent variable and separately affects the dependent variable will have an endogeneity issue. The model compensates for the missing factor by overestimating or underestimating the effect of one of the other factors, resulting in estimation bias (Greene, 2003; Wooldridge, 2015). Simultaneous causality supposes that two variables are codetermined (Greene, 2003; Gujarati, 2004; Wooldridge, 2015). It means that at least one of the independent variables is determined simultaneously along with the dependent variable in a system of equations. Measurement error occurs as an inherent part of the results of measurements and of the measurement process in which proxies are used to measure unobservable variables or variables which are hard to quantify. The measurement error is the difference existing between a measured value of a quantity and its true value (Dodge, 2006).

More specific in the studies of the R&D subsidy, an endogeneity issue may exist as R&D capabilities or management capabilities of firms are unobserved and unmeasured (Guo et al., 2016; Liu et al., 2016). However, these capabilities are key for firms to win and to allocate R&D subsidy (Guo et al., 2016; Liu et al., 2016). Thus, omitted variables bias usually occurs in the research of R&D subsidy. Furthermore, firm-level innovation behaviors and performances, such as R&D collaborations and patent applications, can influence the decisions of deployment of R&D subsidy from public agencies to firms. Thus, simultaneous causality may potentially exist in the studies on the correlations between R&D subsidy and firm-level innovation behaviors and performances (Cerulli, 2010; Gonzalez, Jaumandreu, & Pazo, 2005).

To cope with the endogeneity issue, the method of instrumental variables (IVs) is prevalently adopted. An instrumental variable is a variable that must be strongly correlated to the endogenous variable but does not itself belong in the explanatory equation, meaning that the selected instrumental variable is unrelated with unobserved variables that may affect dependent variables (Wooldridge, 2015). The main challenge of this technique used for the studies on R&D subsidy is to find proper instrumental variables (David et al., 2000). Following the suggestions of previous studies, IVs which are related to the probability of a firm winning public R&D subsidies and have significant effect on the R&D grants distribution, but unrelated with unobserved variables that affect firm-level innovation inputs and outputs, can be employed (Guo et al., 2016; Jaffe, 2002; Liu et al., 2016).

Two-Stage least squares regression analysis (2SLS) is usually used with the IVs method. In the first stage regression, IVs are used to estimate the endogenous variables.

At the subsequent second regression, the endogenous variables are replaced by their estimated value calculated by IVs at first stage regression for the explanatory equations.

3.3.2.3 Tobit Regression

Tobit regression can be used for reducing the potential censoring bias (Tobin, 1958). The Tobit model takes into account the fact that the underlying distribution of the model's error term is truncated. The model is estimated by adopting maximum likelihood estimation procedures to combine the probit and regression components of the log-likelihood function. The two parts represent the traditional regression for the non-limit observations and the relevant probabilities for the limit observations. It generates consistent estimators for the model parameters. Normally, random effects are used with Tobit models.

3.3.2.4 Cox Regression

Cox regression is also adopted as the main empirical technique, as the timeline that each firm employs novel knowledge or change the technological focus may not coincide during the observation period. Cox regression does not require any restrictions on the baseline risk function, and it does not require additional assumptions about the baseline risk over time (Cox, 1975). Therefore, Cox regression could be appropriate. Since the point in time of novel knowledge usage of different firms overlap, meaning that multiple individuals have the same failure time, the Efron algorithm which can gain more accurate results will be employed (Cleves, Gould, & Gutierrez, 2008).

3.3.3 Samples and Data

The present dissertation will focus the samples on officially identified high-tech firms in the manufacturing sectors in Jiangsu province.

The effect of public R&D subsidies is influenced by the embedded S&T and economics environment (David et al., 2000), differences in subsidy effect also exist across manufacturing and other industries (i.e., service sectors). Thus, a province-level study of the manufacturing industry alone can reduce potential unobservable influences regardless of any regional disparity in terms of economic, policy and culture heterogeneity of widely dispersed Chinese provinces (Dimos & Pugh, 2016).

Jiangsu Province is one of the earliest areas (from 2004) which set aside various funds and developed policy tools to support innovation of local firms. Jiangsu province is also one of the coastal regions and leading innovative areas in China. In 2016, the total R&D expenditure in Jiangsu was 202.68 billion RMB with an R&D intensity of 2.66%, and firms' R&D expenditure was 174.64 billion RMB. The total product value of the high-tech industry in the year 2016 was 6712.4 billion RMB[3]. Jiangsu has more than

3 2016 Statistical Communiqué on High-tech Industry in Jiangsu Province
http://www.jssts.com/Item/608.aspx (in Chinese)

100,000 active high-tech SMEs. According to the *Handbook of Policies towards Firm's Technological Innovation*[4], seven national-level and thirteen provincial-level innovation incentive programs can be accessed by Jiangsu firms, among which six programs provide public R&D subsidies for SMEs[5]. 15.3 billion RMB R&D grants were allocated to firms in 2016. There are also 167 universities and colleges[6] at Jiangsu to provide collaboration opportunities and R&D talents. Furthermore, by the end of 2016, Jiangsu had 15 national-level science parks with 1696 incubating high-tech firms.

Reasons, why firms in Jiangsu Province are selected, are 1) strong innovation capabilities in the private sector, strong government support with diversified support tools; and 2) easy-to-match samples on a provincial level. Thus, Jiangsu is an ideal region for a provincial-level study.

One of my data sources is the database of the official high-tech firms identified by Jiangsu Provincial Science and Technology Bureau. All the data is collected by the Jiangsu Provincial Science and Technology Bureau through annual surveys. The time series of this data is from 2010 to 2014. Up to 2014, this official database has 7928 firms in the manufacturing sector. During the observation period, 1029 manufacture firms have received R&D subsidies, accounting for 12.98% of the total number. Another data source is the official patent database of the State Intellectual Property Office of the People's Republic of China. Patent information of 2024 firms in the manufacturing sector is included in this database. Two databases are matched and combined for this dissertation.

4 Handbook of Policies towards Firm's Technological Innovation http://www.jstd.gov.cn/zwgk/fggw/ck348/2009/04/11162315687.html (in Chinese)

5 Four national level R&D subsidies and two provincial level R&D subsidies for SMEs, according to *Handbook of Policies towards Firm's Technological Innovation* http://www.jstd.gov.cn/zwgk/fggw/ck348/2009/04/11162315687.html (in Chinese)

6 List of universities and colleges in Jiangsu (2017) http://www.moe.gov.cn/srcsite/A03/moe_634/201706/t20170614_306900.html (in Chinese)

3.3.4 Technical Roadmap of Dissertation

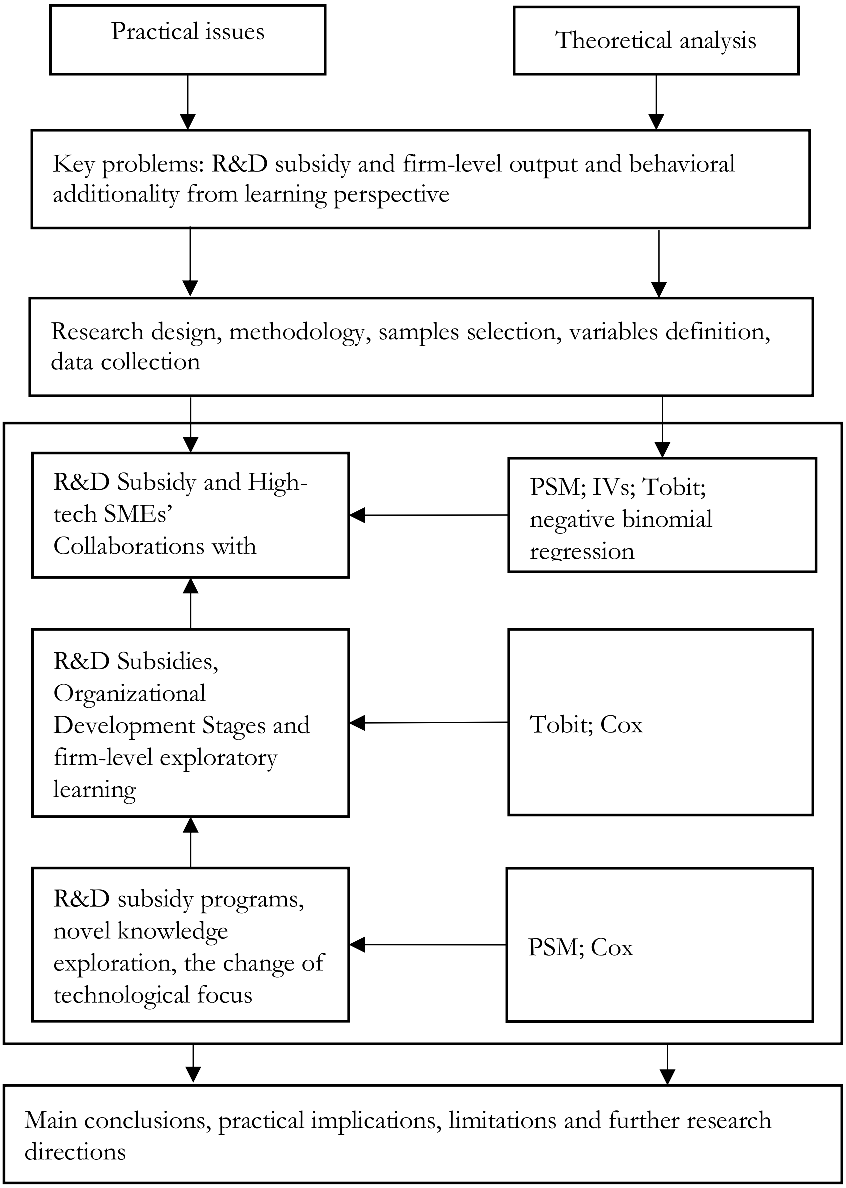

Figure 3. 1 Technical Roadmap of Dissertation

4. R&D Subsidy and High-tech SMEs' Collaborations with Universities

4.1 Introduction

The primary purpose of the study of this chapter is to explore how public research and development (R&D) subsidies influence collaborations between high-tech small and medium-sized enterprises (SMEs) and universities from a knowledge-based view with a learning perspective. This study also tests the moderating roles of science parks and firms' highly educated level R&D human resources on the effects of R&D subsidy on high-tech SMEs' collaborations with universities.

High-tech SMEs have become an essential driver of economic growth in the era of the knowledge-based economy via new technological knowledge creation in R&D activities, as the importance of the scale of economies in many fields have been eroded by new technologies (Cin, Kim, & Vonortas, 2017; Doh & Kim, 2014). However, high-tech SMEs still encounter several bottlenecks when undertaking R&D, such as financial resource constraints, low technological capabilities and lack of legitimacy (Arora & Cohen, 2015; Caloffi, Rossi, & Russo, 2015; Oughton, Landabaso, & Morgan, 2002). Thus, a critical policy concern around the world is the promotion of technological capabilities and knowledge intensity of high-tech SMEs (Cin et al., 2017).

In this public support, high-tech SMEs are especially encouraged to collaborate with universities (Okamuro & Nishimura, 2015). For example, the innovation coupon of the Netherlands is one of the typical policy instruments for encouraging high-tech SMEs to collaborate with universities. By establishing such R&D collaborations, high-tech SMEs are encouraged to acquire and apply frontier scientific and technological (S&T) knowledge from universities when undertaking R&D activities. By such facilitations on firms' learning behaviors, high-tech SMEs are expected to expand the scope and depth of knowledge searching and learning (Courseault Trumbach, Payne, & Kongthon, 2006; Xu et al., 2014). As a result, high-tech SMEs can substantially enhance technological know-how, innovative capabilities, and thereby long-term growth (Courseault Trumbach et al., 2006; Jones & Corral De Zubielqui, 2017).

As a transition economy, China has the legacy of a socialist planned economy and weak capability at the firm level. The government used to play an essential role in improving business activities through direct and indirect ways, even after entering the WTO. Since 2012, having launched the innovation-driven development strategy, the Chinese government increasingly emphasizes the importance of the enhancement of firm-level technological capabilities (Liu et al., 2017). High-tech SMEs in China has become a vital force of innovation and national economic growth (Liu et al., 2017). To motivate the SMEs to learn from universities, the Chinese government designed and adopted a series of R&D subsidy programs. In our pre-research interview in 2017, a key official from the provincial science and technology bureau stated that the main target of R&D subsidy now is to guide and motivate high-tech firms to acquire the frontier S&T knowledge across organizations, especially from universities. At the same time, the Chinese government has also launched several support programs for SMEs' recruitment of highly educated personnel to strengthen firms' internal absorptive capacities and established more than one hundred science parks to provide learning opportunities for SMEs with universities. Both internal absorptive capacities and external intermediaries are regarded as the key to high-tech SMEs for tacit knowledge transfer from universities (Kodama, 2008).

However, little research on Chinese R&D subsidy focuses on the effect of R&D subsidy on high-tech SMEs in the changing of S&T knowledge learning behaviors in China, which may neglect to consider the black-box of R&D subsidy. More specifically, very few studies investigate the effect of public funds on SMEs' R&D collaborations with universities, even though universities are the primary source of advanced S&T knowledge in China. Furthermore, the potential moderating effects of firm-level internal and external factors on the learning behavior changes of sponsored SMEs are also under-explored.

On the one hand, highly educated R&D human resources are one typical internal factor influencing firms' absorptive capacities on learning frontier knowledge generated from universities (Afcha & Garcia-Quevedo, 2016; Knockaert et al., 2014). However, few studies investigate whether synergistic effects exist between such human resources and R&D subsidy on firms' learning from universities. On the other hand, science parks are key intermediaries in China to link high-tech SMEs to universities (Armanios et al., 2017; Gao & Hu, 2017; Xie et al., 2018), which serves as an important external factor for firms to improve knowledge learning. However, science parks in China are usually sponsored by public funds, which are also a channel for the government to provide public support. Thus, both science parks and R&D subsidy are public resources. Which effects, synergistic or antagonistic, can be exerted by the different types of public resources on industry-university R&D collaborations? The empirical evidence is scant.

This chapter attempts to answer two main questions: 1) how does public R&D subsidy influence high-tech SMEs' collaborations with universities? 2) What is the effect of R&D subsidy on high-tech SMEs' collaborating with universities moderated by firms' highly educated R&D human resource and science parks? The input and output of high-tech SMEs' R&D collaboration with universities are measured by SMEs' investment in firm-university R&D collaboration and the citation of knowledge (i.e., patents or scientific papers) from universities in SMEs' patent applications, respectively. Panel data Tobit models and negative binomial regression with fixed-effect based on PSM sampling are adopted as the main empirical techniques.

4.2 Theoretical Development and Hypotheses

4.2.1 The effect of R&D subsidy on high-tech SMEs' collaborations with universities

According to a knowledge-based view and the learning perspective, one primary mechanism for firms to obtain long-term and sustainable competitive advantage is to create unique knowledge by new knowledge development, integration and exploitation (Conner & Prahalad, 1996; Grant, 1996; Macher & Boerner, 2012). New technologies usually stem from the recombination of technology-related knowledge (Ahuja & Lampert, 2001; Schoenmakers & Duysters, 2010a). A core path for firms to obtain such new knowledge is to access and transfer external knowledge across organizations (Grant, 1996). Especially for tacit knowledge with the characteristic of imperfect mobility, the transfer of such knowledge is more likely to require inter-organizational arrangements (Das & Teng, 2000).

More specifically in this study, high-tech SMEs in China are expected to gain frontier S&T knowledge and enhance their innovation capabilities by establishing R&D collaborations with universities. R&D collaborations with universities can facilitate the focal firm to expand and improve its scope and depth of external knowledge searching and learning that results in an increase in the firm-level knowledge base and technological capabilities (Clarysse et al., 2009; Xu et al., 2014). Although collaborating with universities can potentially benefit firms' acquirement of S&T knowledge, enhancement of technological capabilities, and even generation of radical innovation, high-tech SMEs may still be reluctant to do so (Arora & Cohen, 2015; Caloffi et al., 2015; Oughton et al., 2002).

This is directly due to the complex and costly nature of new technology-related knowledge, especially tacit knowledge (Grant, 1996). The SMEs often lack resources for such external knowledge transfer and exploitation (Afcha & Garcia-Quevedo, 2016). The high risk and uncertainties of new but unfamiliar knowledge absorption and exploitation also imply massive resource deployment to it (Ahuja & Lampert, 2001). This exacerbates the SMEs' unwillingness to form R&D collaboration with universities (Radas et al., 2015). Coordination and maintenance costs incurred during the collaboration with external partners can sometimes be significant for SMEs constrained by financial resources (Cerulli et al., 2016). Further, collaborating with universities may lead to technological breakthroughs, but are usually slow in terms of commercialization (Gao & Hu, 2017; Motohashi, 2013). Thus, financially vulnerable SMEs may prefer agile development and commercialization of new products, rather than being involved in long-term and uncertain collaborations with universities and research institutes on applying frontier

S&T knowledge (Motohashi, 2013). This issue may be exacerbated due to the imperfect capital market in China (Wang et al., 2017). In addition, lack of legitimacy due to low reputation and information asymmetry, is another main reason for SMEs to have little connection with universities (Jourdan & Kivleniece, 2017; Kim & Park, 2015).

Public R&D subsidy can directly increase the pool of available resources and create a resource-munificent environment for high-tech SMEs, and thus buffer the financial constraints of them for external new knowledge transfer (Amezcua et al., 2013; Xu et al., 2014). Receiving an R&D subsidy also shows an endorsement from the government and enhances SMEs' legitimacy (Armanios et al., 2017; Jourdan & Kivleniece, 2017; Zeng et al., 2010). Most top universities in China are public, thus the endorsement from the government is of high relevance for firms to connect with universities, not only for knowledge creation but also for social welfare improvement (Xu et al., 2014; Zeng et al., 2010). Consequently, R&D subsidy recipients are more likely to establish R&D collaborations with universities or say SMEs and universities are linked by the government (Okamuro & Nishimura, 2015; Zheng et al., 2015).

At the same time, by using public R&D subsidy to reduce the resource constraints, recipient SMEs are more likely to deploy more resources on R&D activities to stimulate innovation and enhance technological capabilities (Dimos & Pugh, 2016). Furthermore, firms receiving R&D subsidies occupy a favorable competitive position, compared to rival firms without public support. To keep a favorable competitive position, firms are more likely to allocate resources on R&D activities and enhance their technology-related capabilities, in order to differentiate from rivals and sustain their competitive positions (Jourdan & Kivleniece, 2017). Higher technological capabilities can in turn help firms (Yam et al., 2004) to better absorb frontier knowledge generated by universities, and hence, optimize SMEs' resource allocation and improve innovation performance.

Thus, public R&D subsidy is expected to improve high-tech SMEs' collaboration with universities in China, from both input and output perspectives of the industry-university collaborations. We hypothesize:

Hypothesis 1: Public R&D subsidy generates a positive effect on high-tech SMEs' initial input on R&D collaboration with universities.

Hypothesis 2: Public R&D subsidy generates a positive effect on high-tech SMEs' final output from R&D collaboration with universities.

4.2.2 The moderating effect of high-educational level R&D human resources

Human resources, especially the recruitment of highly educated R&D staff, is regarded as a critical internal component for firms' learning process of the new, especially tacit knowledge (Georghiou & Clarysse, 2006; Lundvall, 2008). First, high-educational-level staff can foster firms' internal capacities for knowledge generation (D'Este, Rentocchini, & Vega-Jurado, 2014; Leiponen, 2005; Muscio, 2007). R&D staff with higher education also improves firm-level absorptive capacity for acquiring and absorbing external knowledge (Herrera & Nieto, 2015; Muscio, 2007). More specifically, R&D personnel, as tacit knowledge carriers, directly expand firms' knowledge stocks (Huber, 1991). Such knowledge stocks can help firms deepen their exploitation of existing knowledge and experience (Katila & Ahuja, 2002). On the one hand, firms can identify innovation directions with more potential, and thereby choose to learn new knowledge that can recombine with existing knowledge more efficiently (Cohen & Levinthal, 1990; Zahra & George, 2002). On the other hand, the expansion of knowledge stock enhances firms' absorption capacity, which helps firms better understand and integrate external new knowledge with firms' internal knowledge (Clarysse et al., 2009). Therefore, firms with higher absorptive capacity have less difficulty in adopting and using new knowledge and implementing innovation than firms with lower absorptive capacity (Clarysse et al., 2009; Cohen & Levinthal, 1990).

Second, R&D staff may utilize their social networks helping build SMEs and maintaining R&D collaborations with universities (Garcia-Quevedo, Mas-Verdú, & Polo-Otero, 2012; Herrera & Nieto, 2015). More specifically, in the research careers of highly educated individuals, social capital is accumulated through the interactions between them and different professional R&D institutes (Dietz & Bozeman, 2005). Herrera and Nieto (2015) argued that such social capital helps firms that recruit more highly educated individuals to be closer to scientific knowledge networks. At the same time, highly educated individuals more easily maintain informal and formal relationships via alumni networks (Gao & Hu, 2017; Motohashi, 2013). Thus, the recruitment of highly educated individuals may help firms to have a better tie with universities or research institutes for the improvement of R&D collaborations (Hess & Rothaermel, 2011), and thereby to better absorb frontier external knowledge during the process of collaborating with universities (Afcha & Garcia-Quevedo, 2016). We have the following moderating hypotheses:

Hypothesis 3：The higher the ratio of higher education graduate R&D employees of an SME, the more input the SME has on the R&D collaboration with universities, and the positive effect of R&D subsidy on firm-level input on R&D collaborations with universities is stronger.

Hypothesis 4：The higher the ratio of highly educated R&D employees of an SME, the more output the SME generates from the R&D collaboration with universities, and the positive effect of R&D subsidy on firm-level output from R&D collaborations with universities is stronger.

4.2.3 The moderating effect of location in science parks

Science parks, as a core component of the Chinese national innovation system, play a significant role in facilitating technological collaborations between Chinese universities and high-tech SMEs (Hu & Mathews, 2008; Liu & White, 2001). More specifically, science parks facilitate industry-university collaborations by three main mechanisms. First, spatial proximity allows SMEs in science parks to have more opportunities for the establishment of links with universities (Albahari et al., 2017; Chen & Lin, 2017). Through these links, SMEs can facilitate knowledge learning and absorbing from universities. In particular, the related tacit knowledge, which is usually spatially diffusion, requires face-to-face communication (Chen & Lin, 2017; Motohashi, 2013; X. Li, 2009).

Second, located in science parks, SMEs can benefit from the endorsements provided by the science parks (Armanios & Eesley, 2018; Lecluyse, Knockaert, & Spithoven, 2019). On the one hand, science parks play the role of intermediaries to link universities and SMEs for knowledge transfer (Amezcua et al., 2013; Armanios et al., 2017). On the other hand, science parks also facilitate the attraction of external venture capital for firms (Ng et al., 2019; Xie et al., 2018) to enhance SMEs' willingness to invest in R&D collaborations with universities and underpin the success of knowledge transfer. This is important especially in emerging economies where capital markets and legal systems are usually imperfect (Eesley, 2016).

Third, the professional services provided by science parks also facilitate the industry-university collaborations of SMEs (Wang et al., 2017; Xie et al., 2018). The professional services containing specialized technical and managerial consulting services can strengthen SMEs' R&D capabilities (Lyu et al., 2017). These services can, therefore, promote the flow of knowledge and mitigate risks during the collaborations between SMEs with universities, enhancing the success of firms' knowledge absorption (Lecluyse et al., 2019; Xie et al., 2018). Thus, we have the following hypotheses on moderating effects:

Hypothesis 5： Located in science parks, the SME has more input on the R&D collaboration with universities, and the positive effect of R&D subsidy on firm-level input on R&D collaborations with universities is stronger.

Hypothesis 6： Located in science parks, the SME generates more output from the R&D collaboration with universities, and the positive effect of R&D subsidy on firm-level output from R&D collaborations with universities is stronger.

4.3 Data and Method

4.3.1 Data Description

We focus our research on high-tech SMEs. We employ a set of exclusive panel data from a survey of high-tech firms conducted by the Jiangsu Science and Technology Department, covering the period from 2010 to 2014. This set of data is used to evaluate the effects of R&D subsidy in Jiangsu Province only through to 2014, which happened to be the tenth anniversary since Jiangsu reformed the R&D subsidy policy. We also employ a set of patent data of Jiangsu high-tech SMEs from the National Intellectual Property Administration of China (SIPO), covering the period from 2009-2015. Based on the combination of these two main databases, several other databases, such as China Torch Statistical Yearbook and Municipal Statistical Bulletins of Jiangsu cities, are also used. High-tech SMEs are further identified and selected from this dataset according to the criteria[7] with no more than 10 years' history and 300 employees in 2010. For non-subsidized SMEs, we retain the SMEs without any R&D subsidy from 2010 to 2014.

We choose a province-level study, as the efficiency of the public R&D subsidy is influenced by the embedded S&T and the wider economic environment (David et al., 2000). A province-level study can reduce potential unobservable influences regardless of any regional disparity in terms of economic, policy and culture heterogeneity of dispersed Chinese provinces (Dimos & Pugh, 2016).

4.3.2 The PSM sampling

To create propensity score matching (PSM) samples, we adopt the cross-sectional dataset in 2010 as the baseline data. 325 SMEs received public R&D subsidy in 2010, which is the first year the firms start their subsidized programs. The treated group in our study contains the SMEs receiving public R&D subsidy in 2010. The control group presents the same likelihood as if being treated compared with the treated groups, even though they are not treated in reality. PSM is appropriate for our study, as it eliminates the selection bias of the R&D subsidy stemming from the prevalent picking the winner behavior of the government.

The treatment variable of our PSM is a dummy variable that measures whether firms received public R&D subsidy in 2010 or not (*Treat_Govrd*). We have 325 treated and 769 untreated observations for the PSM. A set of covariates is selected for the first-step probit model of PSM. Basic factors of firms including industry dummies (the industrial distributions are shown in Table 4A.1), firm size (*Firm_Size*) and firm age (*Firm_Age*) are controlled. Indicators showing firms' technological level such as R&D employee ratio (*RD_Emp*) and patent stock (*Pat_Stock*) are also set. The patent stock is calculated by the perpetual inventory method[8]. Capital intensity (*Cap_Int*) measures the financial strength of firms (Boeing, 2016). In addition, export volume (*Export*) is considered as a covariate,

7 Ministry of Industry and Information Technology of People's Republic of China, "the standard of small and medium-sized enterprises"

8 $Pat\_stock_{2010} = (1-\delta)\ Pat\_stock_{2009} + Pat\_Application_{2010}$, rate of depreciation ($\delta$ = 0.15)

as export-oriented firms are assumed to be more innovative if exposed to international competition (Radas et al., 2015).

To establish PSM samples, we first adopt the probit estimation to compute the propensity score for each firm on receiving R&D subsidy. After the estimation of propensity scores, 1-1 nearest neighborhood matching (NNM) with replacement is performed to identify the control group of firms that are eligible to apply for R&D subsidy but did not apply or did not win such subsidy. Based on the PSM sample, we re-estimate the propensity scores by probit estimation.

Table 4.1 Probit Estimation for PSM

	Model 1 Pre-matching	Model 2 Post-matching
Export	-0.034***	-0.010
	(0.011)	(0.014)
Firm_Size	0.124**	0.065
	(0.058)	(0.076)
Cap_Int	0.055	-0.188
	(0.040)	(0.286)
Firm_Age	-0.042	-0.045
	(0.086)	(0.105)
Pat_Stock	0.003*	0.000
	(0.001)	(0.002)
RD_Emp	0.793***	0.342
	(0.195)	(0.236)
_cons	-1.032***	-0.068
	(0.327)	(0.423)
Number of obs	1094	553
Prob > chi2	0.0000	0.5931
Pseudo R2	0.023	0.002

Note: 1) Standard errors in parentheses; 2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.1 presents the results of PSM, and suggest the existence of additionality. As shown in Table 4.1, none of the covariates remains significant and the pseudo-R2 drops sharply from 0.023 to 0.002 after matching. This means that the systematic differences in the distribution of covariates between the treatment and the control groups have been removed from our PSM sample. We also provide a balance test for the means of covariates between the treatment and control groups (see Table 4.2).

Table4.2 Balance Test for PSM

	Mean		t-tests		MSB (%)	
Covariates	Treated	Control	t-Stat	p>t	pre-matching	post-matching
Export	2.686	2.620	0.250	0.799	-20.900	1.700
Cap_Int	0.004	0.030	-0.940	0.348	5.700	-1.600
Pat_Own	19.058	19.235	-0.090	0.931	9.900	-0.700
Firm_Age	1.773	1.758	0.460	0.643	-6.500	3.300
Firm_Size	4.578	4.536	0.800	0.425	-3.900	5.200
RD_Emp	0.398	0.399	-0.040	0.970	25.200	-0.300

According to the t-test statistic and the corresponding p-value on mean differences for covariates, the means of covariates are balanced between the treatment and control groups based on our PSM matching. In addition, the mean standardized bias (MSB) drops sharply after matching which suggests that the matching is a success according to Liu et al. (2016). Based on PSM results, after supplementing data of subsequent years, we get the final dataset including 553 firms with 2707 firm-year observations for the next step analysis.

4.3.3 Methods and Variables

Dependent variables

Following the suggestions of previous studies, this study adopts the natural logarithm of the R&D expenditure which firms spend on collaborations with universities with one year lagged to measure the input of SMEs' R&D collaborations with universities (*Tech_coll*). To measure the output of industrial-university collaborations, this study employs the number of firms' invention patent applications with citation of knowledge (i.e., patents or scientific papers) from universities (*Tech_citation*), also with one year lagged (Lei, Sun, & Wright, 2012; Li, 2012).

For the continuous dependent variable, the input of collaborations, we adopt panel data Tobit regressions with controlling time fixed effects. Tobit regression can be used for reducing the potential censoring bias (Li et al., 2018). As the dependent variable measured by investment on R&D collaborations are usually non-negative continuous variable but containing amounts of observations with value 0, which suggests left censored data.

For the counting dependent variable, the output of collaborations, we adopt panel data negative binomial regression model with controlling fixed effects. The data used in this paper in the case of the number of patent applications shows excessive dispersion, that is, the variance is significantly greater than the mean. Thus, the negative binomial regression model, which assumes that the samples come from a negative binomial distribution, is more appropriate than the Poisson model.

In addition, we also adopt the generalized method of moments (GMM) with an instrumental variable to cope with the potential endogeneity issue of the correlation between R&D subsidy and investment on collaborations with universities to test the robustness of Tobit regression results (Carboni, 2012). The yearly investment on fixed assets at the city level is adopted as the instrumental variable, which follows the suggestion of Guo et al. (2016). Furthermore, Cox regression by using the Efron algorithm is used for the robust check of the effect of R&D subsidy on the citation of universities' knowledge in patent applications.

Independent variables

We employ the natural logarithm of the amount of R&D subsidy, *GovRD*, as the independent variables (Liu et al., 2016). Following the suggestion of Li et al. (2018), we added 1 to all observations with a value of zero before transforming by the natural logarithm.

Moderating variables

High-educational-level R&D human resources (*Human_res*) are measured by the ratio of R&D employees with a bachelor or higher degree (Afcha & Garcia-Quevedo, 2016; Soderblom et al., 2015). Located in science parks is measured by a dummy variable (*Sci_park*) which equals 1 if the SME is located in a science park, otherwise 0 (Ramirez & Dickenson, 2010; Zhang, 2005).

Control variables

We control firm-level technological capabilities by patent stock per person (*Pat_Own*), and whether the firm has a formal R&D department or not (*RD_Dpart*) (Almus & Czarnitzki, 2003; Guan & Yam, 2015; Hussinger, 2008). We also control for the value of exports for each firm (*Export*), as export-oriented firms are assumed to be more innovative to meet international competition (Radas et al., 2015). We control firm-level financial strength by capital intensity (*Cap_Int*) (Boeing, 2016). The ownership is also controlled for (*SOE*), as state-owned enterprises in China are more likely to gain public support and collaborate with public-backed universities (Wu, 2017). Basic factors including the year dummies and industry dummies firm size (*Firm_Size*) and firm age (*Firm_Age*) are also controlled for.

To test the existence of serious multicollinearity problems, we also conduct a multi-collinearity test in this study. The results show that the VIF values of the selected variables are acceptable, and there is no serious multi-collinearity problem. Descriptive statistics and correlation matrix for variables based on PSM samples are presented in Table 4.3.

Table 4.3 Descriptive statistics and correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	Tech_coll	1.0000											
2	Tech_citation	0.0802*	1.0000										
3	GovRD	0.2428*	0.0814*	1.0000									
4	Human_res	-0.0080	0.0330	0.0452*	1.0000								
5	Sci_park	-0.1114*	0.0463*	-0.0206	0.0308	1.0000							
6	RD_Dpart	0.0862*	0.0234	0.0512*	-0.0191	-0.1434*	1.0000						
7	Pat_Own	-0.0265	0.0033	0.0366	0.4965*	0.0603*	-0.0022	1.0000					
8	Export	-0.0376	-0.0296	-0.0170	-0.0043	-0.0005	0.0702*	-0.0383*	1.0000				
9	Cap_Int	0.0016	-0.0041	0.0214	0.6179*	0.0234	-0.0149	0.7087*	-0.0173	1.0000			
10	SOE	-0.0358	0.0178	0.0417*	0.0338	0.1070*	-0.0557*	-0.0386*	-0.1302*	-0.0149	1.0000		
11	Firm_Size	0.0918*	0.0156	0.0350	-0.2902*	-0.1062*	0.1880*	-0.3646*	0.2914*	-0.3566*	0.0175	1.0000	
12	Firm_Age	-0.0389	-0.0246	-0.1012*	-0.0402*	-0.0477*	0.1164*	0.0005	0.0664*	-0.0326	-0.0002	0.1570*	1.0000
	Mean	1.705	0.269	2.204	0.223	0.305	0.853	0.268	3.554	0.122	0.075	4.830	2.091
	Std.Dev.	2.790	1.528	3.077	0.970	0.460	0.355	0.699	3.984	0.643	0.263	0.807	0.421
	N	2150	2706	2706	2706	2706	2706	2706	2706	2706	2706	2706	2706

Note: * $p < 0.05$

4.4 Empirical Results

Table 4.4 reports the results of the main effect of R&D subsidy on SMEs' R&D collaborations with universities. As depicted in Model 4, R&D subsidy has significantly facilitated the SMEs' investment in R&D collaborations with universities ($b=0.350$; $p<0.01$). The economic effect of the R&D subsidy is also calculated. Specifically, we derived the marginal effect of a variable on the expected investment in R&D collaborations with universities, given that a firm has not been censored (i.e., having an investment in R&D collaborations above zero) (Li et al., 2018). It is found that holding all other variables at the mean level, receiving R&D subsidy leads to an increase of firm-level invention patent applications with familiar knowledge per person by 0.011. For every 1% increase in R&D subsidy, SMEs receiving public support increase their investment in R&D collaboration by 0.099%. In Model 5, after adding the instrumental variable, this significant enhancing effect still exists, proving the robustness of the results. To ensure the robustness of the results, the firms receiving specific public funds dedicated to supporting industry-university collaborations are further excluded. One of the key evaluation criteria of such funds on recipient firms is the investment in the industry-university collaborations, which may result in the overestimation of the effect of R&D subsidy. Model 6 reports the results of fixed-effect IV regression with samples excluding firms receiving specialized funds on industry-university collaborations. The result indicates that the R&D subsidy that is not dedicated to facilitating industry-university collaborations still has a significantly positive effect on firms' investment in collaborations with universities.

As depicted in Model 8, public R&D subsidy has also significantly promoted SMEs' absorption of knowledge from universities and increased the probability of citing university patents or scientific papers in their invention patent applications. For every 1% increase in R&D subsidies for publicly-sponsored SMEs, the probability of citing university patents or scientific papers in invention patent applications increased by 5.5%, significantly at the 5% level. In the Cox regression, for every 1% increase in R&D subsidy, the probability of citing university knowledge by publicly-sponsored SMEs increases by 9.4%, significantly at the 1% level. This result is consistent with the result of the negative binomial regression, supporting the robustness of the effect of R&D subsidies on SMEs' citing university knowledge. Thus, Hypotheses 1 and 2 are supported.

Table 4.5 and Table 4.6 report the moderating effects of firms' highly educated

R&D personnel and science parks on R&D subsidy influencing the investment in collaborations and the citations of universities' knowledge, respectively. As shown in Table 4.5, on the one hand, the ratio of highly educated R&D personnel has no significant moderating effect on the R&D subsidy affecting R&D collaboration investment (Model 11). Hypothesis 3 is not supported according to our empirical results. On the other hand, being located in science parks has a significantly negatively moderating effect (significant at the 1% level, Model 13). At the same time, the investment of SMEs located in the science parks on R&D collaborations with universities is 75.4% lower than those outside the science parks. Following the suggestion of Li et al. (2018), we draw Figure 4.1 to illustrate how science parks moderate the effect of R&D subsidy on SMEs' investment on collaborations with universities, based on Tobit regression results. Figure 4.1 indicates that the enhancement effect of R&D subsidy on firm-level investment for collaborations is negatively moderated by the location in science parks. Therefore, Hypothesis 5 is not supported.

As shown in Table 4.6, highly educated R&D personnel significantly positively moderates the promoting effect of the R&D subsidy on firms' citation of knowledge from universities (Model 16). More specifically, the percentage of R&D personnel in an SME increases by 1%, and the R&D subsidy increases by 1%, the probability of citing university knowledge has increased from 0.044% to 0.105%, which is significant at the 10% level. At the same time, the higher the ratio of highly educated R&D employees, the higher the probability that the firm will absorb and cite the knowledge generated by universities in the invention patent applications. Hypothesis 4 achieves support. Located in the science parks, the probability of citing university research achievements by high-tech SMEs can be significantly improved. The probability of firms in the science parks citing university achievements in invention patent applications is 87.76% higher than that of firms outside the science parks, which is significant at 10% (Model 17). However, located in the science parks will negatively moderate the effect of the R&D subsidy on firms' citations of knowledge from universities. For every 1% increase of the R&D subsidy given to high-tech SMEs in the science parks, the probability of citing university achievements is reduced by 3.44%, which is significant at the 10% level. Therefore, Hypothesis 6 only receives partial support.

Table 4.4 the effect of R&D subsidy on SMEs' R&D collaborations with universities

	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	Panel data Tobit	Panel data Tobit	Fixed effect-IV	Fixed effect-IV	Fixed effect-NBR	Fixed effect-NBR	Cox regression
		Tech_coll				Tech_citation	
RD_Dpart	0.149	0.062	-0.361**	-0.337*	0.076	0.093	0.059
	(0.584)	(0.578)	(0.181)	(0.186)	(0.228)	(0.230)	(0.208)
Firm_Size	0.817**	0.799**	0.041	-0.030	-0.154	-0.161	0.141
	(0.386)	(0.374)	(0.159)	(0.169)	(0.146)	(0.146)	(0.101)
Firm_Age	-1.403***	-0.869*	-0.084	-0.124	-0.674***	-0.620***	-0.106
	(0.522)	(0.524)	(0.230)	(0.240)	(0.178)	(0.181)	(0.183)
Export	-0.070	-0.078	0.025	0.004	0.007	0.005	-0.036*
	(0.070)	(0.068)	(0.033)	(0.033)	(0.031)	(0.031)	(0.019)
Cap_Int	1.079***	1.026**	0.185	0.170	0.104	0.121	-0.219**
	(0.413)	(0.407)	(0.131)	(0.131)	(0.230)	(0.230)	(0.106)
Pat_Own	-1.106*	-1.132*	-0.160	-0.163	-0.196	-0.216	0.329***
	(0.639)	(0.628)	(0.125)	(0.125)	(0.159)	(0.161)	(0.094)
SOE	-2.185*	-2.263**	-0.873	-1.522**	0.338	0.330	0.546**
	(1.119)	(1.072)	(0.594)	(0.666)	(0.464)	(0.467)	(0.223)
GovRD		0.350***	0.209***	0.193**		0.054**	0.090***
		(0.067)	(0.073)	(0.079)		(0.024)	(0.024)
_cons	-4.635**	-6.225***	1.493	2.008**	0.887	0.608	
	(1.995)	(1.968)	(0.938)	(0.961)	(0.764)	(0.766)	
N	2150	2150	2150	1850	899	899	2190
Firms	553	553	553	478	180	180	556
Prob > chi2	0.0004	0.0000	0.0000	0.0000	0.0058	0.0015	0.0000
Log likelihood	-2684.741	-2674.108	N/A	N/A	-573.469	-570.844	-1175.974
left-censored	1527	1527	N/A	N/A	N/A	N/A	N/A
uncensored	623	623	N/A	N/A	N/A	N/A	N/A

Note: 1) For models 5, 6 & 9, robust standard errors are in parentheses (clustered by firms), for models 3,4,7 & 8, standard errors are in parentheses; 3) *p < 0.1, **p < 0.05, *** p< 0.01; 4) industry and year dummies for all models (not reported); 5) Underidentification test (Anderson canon. corr. LM statistic): 174.165, Chi-sq (1) P-val = 0.0000; 6) Weak identification test (Cragg-Donald Wald F statistic): 194.504, Stock-Yogo weak ID test critical values: 10% maximal IV size 16.38

Table 4.5 The moderating effect on R&D subsidy influencing SMEs' investment on R&D collaborations with universities (Panel Tobit regression models with fixed effects)

DV: Tech_coll	Model 10	Model 11	Model 12	Model 13	Model 14
RD_Dpart	0.236	0.239	0.082	0.148	0.154
	(0.583)	(0.583)	(0.584)	(0.583)	(0.583)
Firm_Size	0.886**	0.846**	0.778**	0.801**	0.791**
	(0.385)	(0.389)	(0.375)	(0.371)	(0.382)
Firm_Age	-0.222	-0.243	-0.314	-0.366	-0.371
	(0.613)	(0.612)	(0.607)	(0.605)	(0.605)
Export	-0.074	-0.074	-0.071	-0.076	-0.077
	(0.068)	(0.068)	(0.068)	(0.067)	(0.067)
Cap_Int	0.946**	1.151**	0.907**	0.908**	0.963**
	(0.408)	(0.471)	(0.396)	(0.389)	(0.412)
Pat_Own	-0.971	-0.893	-0.912	-0.819	-0.767
	(0.598)	(0.624)	(0.585)	(0.550)	(0.588)
SOE	-2.245**	-2.199**	-1.903*	-1.813*	-1.797*
	(1.071)	(1.071)	(1.072)	(1.066)	(1.066)
GovRD	0.322***	0.327***	0.321***	0.321***	0.323***
	(0.070)	(0.070)	(0.070)	(0.070)	(0.070)
Human_res	0.020	-0.387			-0.089
	(0.293)	(0.574)			(0.350)
GovRD×Human_res		-0.200			-0.071
		(0.207)			(0.114)
Sci_park			-2.468***	-2.338***	-2.331***
			(0.684)	(0.678)	(0.678)
GovRD×Sci_park				-0.376***	-0.368***
				(0.139)	(0.139)
_cons	-7.688***	-6.798***	-6.192***	-6.312***	-6.276***
	(2.110)	(2.105)	(2.087)	(2.033)	(2.074)
N	2150	2150	2150	2150	2150
Firms	553	553	553	553	553
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Log likelihood	-2674.106	-2673.372	-2667.412	-2663.714	-2663.405
left-censored	1527	1527	1527	1527	1527
uncensored	623	623	623	623	623

Note: 1) Standard errors are in parentheses; 2) *p < 0.1, **p < 0.05, *** p< 0.01; 3) industry & year dummies for all Models (not reported)

Table 4.6 The moderating effect on R&D subsidy influencing SMEs' citations of knowledge from universities (Panel negative binomial regression models with fixed effects)

DV: Tech_citation	Model 15	Model 16	Model 17	Model 18	Model 19
RD_Dpart	0.117	0.072	0.114	0.195	0.097
	(0.232)	(0.232)	(0.230)	(0.251)	(0.233)
Firm_Size	-0.115	-0.183	-0.178	-0.083	-0.184
	(0.167)	(0.174)	(0.146)	(0.167)	(0.177)
Firm_Age	-0.649***	-0.665***	-0.646***	-0.622***	-0.690***
	(0.182)	(0.182)	(0.182)	(0.194)	(0.184)
Export	0.004	0.003	0.005	0.017	0.005
	(0.030)	(0.030)	(0.031)	(0.032)	(0.031)
Cap_Int	-1.503	-2.702**	0.143	0.249	-2.529*
	(1.047)	(1.348)	(0.234)	(0.248)	(1.404)
Pat_Own	-0.162	-0.164	-0.242	-0.299	-0.162
	(0.171)	(0.180)	(0.162)	(0.182)	(0.181)
SOE	0.257	0.264	0.198	0.105	0.185
	(0.465)	(0.466)	(0.463)	(0.490)	(0.465)
GovRD	0.052**	0.043*	0.050**	0.051**	0.048**
	(0.023)	(0.024)	(0.024)	(0.025)	(0.024)
Human_res	0.660**	0.746**			0.639*
	(0.314)	(0.345)			(0.360)
GovRD× Human_res		0.057*			0.066*
		(0.033)			(0.037)
Sci_park			0.630*	0.901**	0.518
			(0.367)	(0.410)	(0.379)
GovRD×Sci_park				-0.086*	-0.083*
				(0.050)	(0.048)
_cons	0.395	1.168	0.583	0.242	1.204
	(0.860)	(0.936)	(0.767)	(0.912)	(0.950)
N	899	899	899	833	833
Firms	180	180	180	172	172
Prob > chi2	0.0005	0.0003	0.0010	0.0076	0.0066
Log likelihood	-567.622	-565.890	-569.311	-519.945	-516.511

Note: 1) Standard errors are in parentheses; 2) *p < 0.1, **p < 0.05, *** p< 0.01; 3) industry & year dummies for all models (not reported)

Figure 4.1 The moderating effect of science parks on R&D subsidy influencing SMEs' investment in collaborations with universities.

Table 4.7 The conclusion of the empirical results of Chapter 4

Hypotheses	**Empirical results**
Hypothesis 1: Public R&D subsidy generates a positive effect on high-tech SMEs' input on R&D collaboration with universities.	Support
Hypothesis 2: Public R&D subsidy generates a positive effect on high-tech SMEs' output from R&D collaboration with universities.	Support
Hypothesis 3：The higher the ratio of highly educated R&D employees of an SME, the more input the SME has on the R&D collaboration with universities, and the positive effect of R&D subsidy on firm-level input on R&D collaborations with universities is stronger.	Not supported
Hypothesis 4：The higher the ratio of highly educated R&D employees of an SME, the more output the SME generates from the R&D collaboration with universities, and the positive effect of R&D subsidy on firm-level output from R&D collaborations with universities is stronger.	Support
Hypothesis 5：Located in science parks, the SME has more input on the R&D collaboration with universities, and the positive effect of R&D subsidy on firm-level input on R&D collaborations with universities is stronger.	Not supported
Hypothesis 6：Located in science parks, the SME generates more output from the R&D collaboration with universities, and the positive effect of R&D subsidy on firm-level output from R&D collaborations with universities is stronger.	Partial support

4.5 Discussion

The results of the study in this chapter, as expected, indicate that R&D subsidy promotes high-tech SMEs' input and output of collaborations with universities, i.e., investment in R&D collaborations with universities and citations of knowledge generated by universities in firms' invention patent applications. Firms' internal factor, highly educated R&D human resources, is found to positively moderate R&D subsidy to promote the firms' citations of knowledge from universities in invention patents. At the same time, highly educated R&D personnel also directly facilitates high-tech SMEs' absorption and exploitation of universities' research achievements. However, the presence of highly educated R&D personnel has no significant moderating effects on the correlations between R&D subsidy and investment in R&D collaborations. Surprisingly, located in science parks is found to negatively moderate the promotion effects of R&D subsidy on SMEs' investments on industry-university collaborations, as well as the citation of knowledge generated by universities. Furthermore, the citations of university knowledge are promoted, but the investment in R&D collaborations is inhibited if SMEs are located in science parks. These research findings have important theoretical contributions. First, we find that the R&D subsidy can help to facilitate the learning behaviors of high-tech SMEs for new knowledge acquisition and assimilation from universities. We also test the moderating roles of science parks and firms' highly educated R&D human resources, which are two key factors for firms' learning internally and externally. Our findings support extant studies on the positive effects of R&D subsidy on industry-university collaborations (Greco, Grimaldi, & Cricelli, 2017; Guisado-Gonzalez et al., 2016; Kang & Park, 2012; Shin et al., 2019). We also complement current technology transfer related studies by identifying the effect of R&D subsidy on SMEs' absorption of knowledge from universities. We hence argue that R&D subsidy is also a potential path to solve the question posed by Motohashi (2013) on how financially vulnerable high-tech SMEs can be encouraged to establish formal collaboration with universities in China for technological knowledge acquirement and absorptive capacities enhancement. We deepen our understandings of how public R&D subsidy influences on high-tech SMEs' technological output in emerging economies.

Second, this study further reinforces and supplements the study of Clarysse et al. (2009) by extending the usage of learning perspective on the R&D subsidy studies. The internal absorptive capacities or the congenital learning capabilities are found to play a key role in industry-university collaborations of SMEs under the support of R&D subsidy. This echoes the viewpoints of current R&D subsidy literature related to organizational learning (Broekel, Fornahl, & Morrison, 2015; Crass, Rammer, & Aschhoff, 2017; Karhunen & Huovari, 2015; Smith, Feldman, & Anderson, 2018). The related findings imply that although high-tech SMEs have more chances to gain new knowledge from universities under public intervention in China, SMEs should enhance their own absorptive capacities, through, for instance, increasing their highly educated R&D human resources. In other words, R&D subsidy recipient firms need to strengthen firm-level absorptive capacity to fully grasp and utilize complicated new knowledge gained through collaborations with universities and then contribute to technological outputs (Clarysse et al., 2009; Knockaert et al., 2014).

Third, our study has deepened the understanding of the role of the science parks in the R&D subsidy research in the Chinese context, which contributes to the studies on innovation systems. Our results indicate that antagonistic effects exist between the science parks and R&D subsidy. Initially, in the Chinese context, there may be an overlapping of public resources between R&D subsidy and science parks. Science parks in China, especially national-level university science parks, are often public sponsored (Shi et al., 2016; Xie et al., 2018). In addition to providing infrastructure and innovation services, these science parks may provide financial support for tenant firms as well (Shi et al., 2016; Walcott, 2017; Xie et al., 2018). Therefore, this leads to an oversupply of public resources, resulting in an antagonistic effect. Furthermore, science parks, as an important innovation intermediary, can provide high-tech SMEs with more inter-organizational learning opportunities (Del Giudice et al., 2018; Yan et al., 2018). Although science parks help to promote collaborations between high-tech SMEs and universities, due to geographical proximity, firms in the science parks find it easier to establish an informal partnership with universities for tacit knowledge transfer (Lyu et al., 2017; Motohashi, 2013). This eliminates the need for firms to spend resources on the establishment of formal partnerships with universities to avoid high maintenance and coordinating costs for such collaboration (Motohashi, 2013). Therefore, the science parks will negatively moderate the effectiveness of R&D subsidy and inhibit the investment from firms on collaboration, but at the same time significantly promote the tenant firms' absorption of knowledge from universities and citations of such knowledge in their invention patent applications. Additionally, due to the public sponsored background of science parks, firms in the science parks have more experience of participation in governmental R&D programs and can keep more closely in touch with the government (Albahari et al., 2017; Armanios et al., 2017; Dalmarco, Hulsink, & Blois, 2018). According to the hypothesis of the learning curve's decreasing returns to experience, the experience of undertaking governmental R&D programs has eroded the effect of public funding on firms' learning behavior changes (Clarysse et al., 2009). Specifically, with increasing experience gained from implementing public-sponsored programs, firms will be more aware of government requirements and understand how to satisfy such needs (Li et al., 2018). In order to achieve the goals of government programs, the incentives for firms to seek as well as absorb complicated and expensive knowledge from universities will be reduced (Jiang et al., 2018).

4.6 Appendix

Table A4.1 Industrial distribution

2-digit code	Industrial Description	count
1-5	Agriculture, Forestry, Animal, Husbandry, and Fishery	3
6-12	Mining	2
13	Processing of food from Agric products	2
14	Manufacture of foods	8
17	Manufacture of textiles	6
18	Manufacture of textiles, clothing; apparel industry	2
20	Processing of timber, manufacture of wood, bamboo, rattan, palm, and straw products	1
22	Manufacture of paper and paper products	1
23	Printing and recorded media	2
25	Processing of petroleum, coking, processing of nuclear fuel	2
26	Manufacture of chemical raw materials and chemical products	83
27	Manufacture of medicines	43
28	Manufacture of chemical fibers	9
29	Manufacture of rubber and plastics	7
30	Manuf. of non-metallic mineral products	27
31	Smelting and processing of ferrous metals	24
32	Smelting and processing of non-ferrous metals	12
33	Manufacture of metal products	27
34	Manufacture of general-purpose machinery	32
35	Manufacture of special-purpose machinery	132
36	Manufacture of automobiles	151
37	Manufacture of railway, ships, aerospace and other transportation equipment	53
39	Manufacture of computers, communication, and other electronic equipment	99
40	Manufacture of measuring instruments	146
41	Other manufacturing	55
42	Comprehensive use of waste resources	5
43	Repair of metal products, machinery, and equipment	1
44-46	Production and Distribution of Electric Power, Gas, and Water	4
47-50	Construction	11
53-60	Transport, Storage, and Post	2
61-62	Hotels and Catering Services	108
73-75	Scientific Research and Technical Services	8
76-78	Management of Water Conservancy, Environment, and Public Facilities	14
79-81	Services to Households and other services	12
total		1094

5. R&D Subsidies, Organizational Development Stages, and firm-level exploratory learning

5.1. Introduction

The main purpose of this chapter is to explore how public research and development (R&D) subsidy influences firms' exploratory learning behaviors at different organizational development stages.

Learning lies at the core of firms' R&D and innovation activities (Ahuja & Lampert, 2001; March, 1991). Firms tend to stay in their comfort zone where they "get by" with familiar technology and know-how without having to break with the established trajectories and face uncertainty and costs (Madhavan & Grover, 1998) and it consume vast resources of firms (Oshri, Pan, & Newell, 2005) to innovate. The expanding of the scope of searching in order to add to firms' knowledge-base and the absorbing of complex and expensive tacit knowledge in the process (Dunlap Hinkler, Kotabe, & Mudambi, 2010; Wadhwa & Kotha, 2006) are often costly and seemingly unnecessary. However, the excessive use of familiar knowledge, relying on successful experience, will lead to the exhaustion of knowledge, which is not conducive to the generation of heterogeneous resources and make firms to suffer from the loss of sustained long-term competitive advantage (Ahuja & Katila, 2004; Fleming, 2001; Hargadon & Sutton, 1997). To gain sustainability, firms need to search for and adopt novel knowledge continuously, which is entirely new to the firms, through exploratory learning (Ahuja & Lampert, 2001). Firms can enter new technological fields and create new technological combinations in the generation of breakthrough inventions during such exploratory learning behaviors, which are vital to innovation (Ahuja & Lampert, 2001; Zhao et al., 2016). However, the expanding of the searching scope in order to add to firms' knowledge-base and the absorbing of complicated and expensive novel knowledge in the process are often costly (Dunlap Hinkler et al., 2010; Wadhwa & Kotha, 2006), thus, although exploratory learning may improve long-term innovation performance, firms are still reluctant to engage.

Public R&D subsidy is considered one of the most widely adopted policy instruments to spur firm-level R&D (Arrow, 1962; Nelson, 1959). On the one hand, several studies from the resource-based view have shown that, by directly compensating, R&D subsidy can facilitate R&D activities that are often perceived to bear higher risk and uncertainty (Beck et al., 2016; Chapman & Hewitt-Dundas, 2018), such as technological recombination by adopting novel knowledge. R&D subsidy is especially important in transitional economies where the capital markets are underdeveloped (Zheng et al., 2015). On the other hand, other studies, based on the agency theory and multi-stakeholder theory, indicate that government R&D subsidies can promote the full exploitation of familiar knowledge to strengthen the existing technological trajectory (Jia et al., 2019; Jiang et al., 2018; Jourdan & Kivleniece, 2017). The twofold effect of R&D subsidy calls for a more comprehensive study, especially, when considering the influences of distinct characteristics of firms presented at different organizational development stages on the effectiveness of R&D subsidies. The accumulation of resources, knowledge, and experience of firms at different development stages varies (Barbosa, Faria, & Eiriz, 2014; Dodge, Fullerton, & Robbins, 1994; Hoopes & Madsen, 2008). This leads to divergent attitudes toward the focus of exploratory learning at each development stage (Barbosa et al., 2014; Eiriz, Faria, & Barbosa, 2013), and thus, the influencing mechanism and the outcome of R&D subsidy on firm innovation at different development stages may show imparity, although it is rarely examined.

This chapter proposes a dynamic view on the investigation of the effect of R&D subsidy on firms' exploratory learning incorporating organizational development stages. This section will attempt to answer two main research questions: 1) What are the roles of government subsidy on firms' exploratory learning? 2) What are the divergent effects of public R&D subsidies at different organizational development stages? Through this study, a crucial practical question is expected to be addressed for policymakers in terms of the design of R&D subsidy: At which development stages of firms should governments subsidize R&D activities in regard to the encouragement of firms' learning on novel knowledge?

5.2 Research Context: R&D Subsidy and Renewable Energy Industry Development in China overall and in Jiangsu province specifically

This chapter focuses on the research on the firms in the manufacturing sectors of renewable energy industries in Jiangsu province. First of all, considering the overall industrial background, according to the report of the President's Council of Advisors on Science and Technology of the USA in 2010, China's new energy manufacturing industry is in the adoption stage in 2010. At this stage, the primary role of the firms in the industry is learning by using (Xiong & Yang, 2016) where new technologies are constantly absorbed in the application process to improve the technological level of firms, and products are developed to meet market demand based on forming a new technology combination. At the same time, the industry at this stage has accumulated ample novel knowledge for firms to acquire. Thus, compared with the mature industries which are still in the diffusion stage, and infant industries which are still in the front-end stage of laboratory research and development, the new energy manufacturing industry is more suitable for the research of firms' new knowledge acquisition behavior.

Secondly, from the perspective of the development of the new energy manufacturing industry in Jiangsu Province, the industry includes firms in growth, maturity and declining stages in the observation period, which provides an ideal research sample for this study. Jiangsu's new energy manufacturing industry is mainly composed of solar photovoltaic, wind power generation equipment and biomass energy manufacturing. From 2004 to 2005, with the increasing demand for international new energy markets, a small number of firms began to enter new energy manufacturing. From 2006 to 2008, with the maturity of the market, a growing number of firms entered the industry, and at the same time, some firms matured. In 2008, China's 4 trillion RMB investment plan was implemented. In 2010, the renewable energy industry is listed as one of the most important high-tech industries with the launch of the Renewable Energy Law of the People's Republic of China (Amendment), and a large number of firms began to enter the industry (Zhang & White, 2016). At this time, the industry has a large number of growing firms, and the firms that entered earlier are in their mature stage as the pioneering firms that were there since the very beginning began to decline (He et al., 2018). By the end of 2016, there were 850 high-tech firms engaged in renewable energy industries in Jiangsu[1]. The total product value of the renewable energy industries of Jiangsu in 2016 is 362.6 billion RMB[2].

Third, the government plays a key role in the development process of the renewable energy industry by using R&D subsidy (John A., David C., & Edward, 2003). Among them, Jiangsu Province set up the independent innovation special guiding fund, which is the most representative. According to the Handbook of Policies towards Firm's Technological Innovation of Jiangsu, the special guiding fund for independent innovation aims to support the research, development and application demonstration of

[1] Data source: Industry and Information Technology Department of Jiangsu
[2] 2016 Statistical Communiqué on High-tech Industry in Jiangsu Province (http://www.jssts.com/Item/608.aspx in Chinese)

frontier technology and core common technology in key areas, including the new energy manufacturing industry, concentrate resources on jointly tackling key problems, to make breakthroughs in several key areas and develop a number of technology and strategic products with independent intellectual property rights. At the same time, the special fund aims to promote firms to absorb and utilize novel knowledge, realize technological leapfrogging, enhance core competitiveness, and provide scientific and technological support for the development of high-tech industries, the upgrading of traditional industries and the cyclic economy in Jiangsu Province. Therefore, exploring the effects of this R&D subsidy program will help us understand the impact of government funding on firms' acquisition of new knowledge and the creating of new knowledge combinations.

5.3 Literature Review and Hypotheses

5.3.1 R&D Subsidy and the Firm-level Learning Behaviors

According to prior studies, the R&D activities of firms follow the cyclic interaction of experience and competence (Ahuja & Lampert, 2001). Firms are experienced in using familiar knowledge and readily available technology due to stronger absorptive capacity (Cohen & Levinthal, 1990). It is beneficial to the establishment of the firm's specialized competence and reduces the difficulty of learning and problem-solving in specific technological areas (Cohen & Levinthal, 1990; Levinthal & March, 1993). However, firms may risk being caught in the "familiarity trap" by the exploitation of a familiar knowledge base (Ahuja & Lampert, 2001).

To overcome such learning traps, firms are encouraged to build new knowledge recombination with uniqueness and novelty (Hargadon, 2003; Nerkar, 2003). One main source of creating new knowledge recombination is to search, acquire and adopt novel knowledge (Ahuja & Lampert, 2001; Amabile, 1988; Zhou & Li, 2012). However, there are some difficulties and obstacles for firms to explore novel and unfamiliar knowledge. Firstly, having no prior experience, firms often find new technology to be more expensive due to the complexity of knowledge in essence (Oshri et al., 2005). In order to apply novel knowledge, firms have to invest considerable resources in the process of continuous utilization of the newly acquired knowledge to strengthen firms' absorptive capacity for such novel knowledge (Hitt et al., 1996; Madhavan & Grover, 1998). It is also expensive for firms to engage in networking and interactions with external organizations for novel knowledge search. Secondly, firms may face higher risks when using novel knowledge (Dunlap Hinkler et al., 2010; Wadhwa & Kotha, 2006). Lacking past experience means higher uncertainty, resulting in the failure of technology R&D (Levinthal & March, 1993) and a waste of investment.

The governments can be expected to help and encourage firms' learning behaviors of novel knowledge with public R&D subsidy. R&D subsidy, according to the resource-based view, directly increases the pool of available resources for firms to undertake innovation activities, enhancing the return and reducing the cost of R&D (David et al., 2000). By helping firms to overcome resource constraints, R&D subsidy encourages firms to invest in novel knowledge searching as well as in related technological capabilities enhancement (Jiang et al., 2018; Lazzarini, 2015). Furthermore, R&D subsidy increase firms' risk-taking (Chapman & Hewitt-Dundas, 2018), which promotes firms to conduct more challenging R&D activities, which have higher uncertainty, and require more novel knowledge (Czarnitzki & Delanote, 2015; Hsu & Hsueh, 2009). Therefore, we hypothesize:

Hypothesis 1: Firms receiving R&D subsidy are more likely to undertake exploratory learning

5.3.2 The Heterogeneous Effects throughout Organizational Development Stages

Prior studies argue that knowledge learning behaviors differ in each organizational development stage, which also causes firms' innovation strategies and their outcomes to vary at stages (Barbosa et al., 2014; Eiriz et al., 2013; Koberg, Uhlenbruck, & Sarason, 1996). With the alternation of stages, organizational structure and firm strategy will also adapt (Drazin & Kazanjian, 1990; Milliman, Glinow, & Nathan, 1991). Especially for firms in the high-tech industries, the impact of organizational development stages on the pattern of technological innovation and patent development is even more apparent (Barbosa et al., 2014; Eiriz et al., 2013). Studies show that along with the progression of development stages, innovation capability of firms will change dynamically alongside the accumulation of resources, knowledge, and experience (Chang, Lee, & Wong, 2018; Hoopes & Madsen, 2008; Zahra & Filatotchev, 2004). Meanwhile, organizational innovation practices also transform, thus influencing and shaping the innovation-related capabilities and organizational learning behaviors at different stages (Helfat & Peteraf, 2003; Zollo & Winter, 2002). In this regard, existing research suggests that the novelty of R&D and innovation declines as firms develop (Balasubramanian & Lee, 2008). The main reason is that firms with increasing maturity levels may have higher organizational inertia. It is very difficult and costly to adapt organizational practices, processes and structures in response to the need for innovation and the novelty of R&D activities (Henderson, 1993; Miller & Friesen, 1984).

More specifically, firms in the growth stage are more willing to explore novel knowledge in R&D and innovation activities (Barbosa et al., 2014), because they need to enhance their R&D and innovation capabilities, which is conducive for seizing markets, thereby gaining competitive advantage (Miller & Friesen, 1984). Meanwhile, firms in the growth stage have more flexible organizational structures, with which they can effectively collect, acquire, adapt and accumulate external novel knowledge, and form tacit knowledge rooted in the firm (Barbosa et al., 2014). However, at this stage, firms often lack funds (Chang et al., 2018; Clarysse & Bruneel, 2007). With earning pressure, firms are eager for efficient economic returns by quickly turning out products with learned familiar knowledge (Chang et al., 2018), rather than continuously exploring novel knowledge. By alleviating the resource constraints of firms, R&D subsidies may encourage firms in the growth stage to acquire and adopt more novel knowledge. We hypothesize:

Hypothesis 2 a: Firms in the growth stage are more likely to undertake exploratory learning if receiving R&D subsidy.

Extant studies point out that firms in the mature stage have stronger innovation capabilities, such as capital supply, greater market power and organizational capacity, and more experience (Aghion et al., 2009; Chandy & Tellis, 2000; Dewar & Dutton, 1986). These advantages will enable firms in the mature stage to realize more potential by using novel knowledge in innovation (Barbosa et al., 2014). However, the main aim of firms at the mature stage is to further develop existing technology and familiar knowledge to gain economic benefits by selling related products (Barbosa et al., 2014). Firms in this stage are unwilling to adjust their innovation strategy on a large scale before their existing technology reaches economic optimization (Barbosa et al., 2014). Managers will be more inclined to carry out less risky R&D activities (Habib & Hasan, 2017). Thus, firms in the mature stage may be reluctant to search for and use novel and unfamiliar knowledge in R&D activities (Ahuja & Lampert, 2001). R&D subsidy, as mentioned before, can enhance the risk-bearing level of firms, and encourage them to explore new knowledge and plan for the layout of technology ahead of time to ensure the sustainable competitive advantage of firms. Therefore, we hypothesize:

Hypothesis 2 b: Firms in the mature stage are more likely to undertake exploratory learning if receiving R&D subsidies.

Exploratory learning to break the familiar trap and to innovate is the most important strategy for firms in the decline stage (Sirmon et al., 2010). The original technological maturity of firms is saturated. This means that the efficiency of technological output is declining, coupled with the exhaustion of market potential (Ahuja & Katila, 2004; Sirmon et al., 2010).

Both the profitability and market competitiveness of firms are declining (Miller & Friesen, 1984). At this stage, firms urgently need to break free from the original technological trajectory, by novel knowledge exploration to innovate to reboot market competitiveness, so that firms may begin a new life cycle (Ahuja & Lampert, 2001). As a consequence, the risk-taking of firms in the decline stage is higher (Habib & Hasan, 2017). However, firms in the decline stage suffer from negative growth due to the contraction of the market, and they face resource constraints (Sirmon et al., 2010). It is hard for firms in the decline stage to provide necessary financial support for novel knowledge exploration (Faff et al., 2016). R&D subsidy can provide resource buffering, and thereby facilitate firms in the decline stage to break their technological routines via exploratory learning.

Hypothesis 2 c: Firms in the decline stage are more likely to undertake exploratory learning if receiving R&D subsidies.

5.4 Data and Methods

5.4.1 Data

The panel data employed in this study is an exclusive survey of high-tech firms in Jiangsu Province conducted by the Jiangsu Science and Technology Department, covering the period from 2010 to 2014. We further screened out manufacturing firms engaged in renewable energy technology[3]. At the same time, we have selected 108 new energy and environmental protection manufacturing firms that have received the government's "independent innovation special guidance fund" from 2010 to 2014. In all, 128 firms that have never received any form of R&D subsidy during the observation period were retained. The panel data contains 236 firms and 853 observations. The industrial distributions based on 2-digit industrial codes are shown in Table A5.1 in the appendix of this chapter.

Because the ratio of subsidized to non-subsidized firms is close to 1:1, propensity score matching is not viable. Therefore, we take "whether received R&D subsidy" as the

[3] Firms coded 501/502/601/602/603/604/605/606 in the technical field

dependent variable, using government screening criteria for subsidy recipients as an independent variable and applied Probit regression to test for selective bias. The results show that there is no significant relationship between the affecting factors and "whether received R&D subsidy" except the age of the sample firms (see Table A.2 in the appendix). It can be concluded that there is no obvious selectivity bias in this sample (Boeing, 2016).

Referring to previous studies and considering the actual circumstances of China's renewable energy manufacturing industry, we group the sample firm into three development stage groups: growth, maturity, and decline (Anthony & Ramesh, 1992; Xiong & Yang, 2016). Specifically, we group the development stages of firms according to the average sales growth rate for five years from 2010 to 2014. On the basis of sorting, we divide the development stages into sub-partitions using 7 and 3 quantiles as cutting points. After phasing, 84 firms in our samples appear to be in the growth stage, 81 in maturity and 71 in the decline stage. Detailed division of developmental stages is shown in Table 5.1.

Table 5.1 The classification of development stages

Development stages	Growth	Maturity	Decline
Sales growth rate	>25%	0%~7.1%	Negative
Established Years	<8	8~13	>13
Number of firms	84	81	71

5.4.2 Cox Proportional Hazard Model

To examine the effects of R&D subsidy on firms' exploratory learning behaviors, this study adopts Cox regression. More specifically, in our study, each sample firm is treated as having probabilities of adopting novel knowledge in its own R&D activities once the firm enters the observation period. The timeline in which each firm adopts novel knowledge may not coincide during the observation period. All firms which have yet to adopt novel knowledge in R&D are right-censored when our observation ends (in the year 2014). Since our research interest is about firms' adoption of novel knowledge rather than their degrees of exploratory learning, we do not model repeated novel knowledge adoption by the same firm. In other words, once an individual firm is observed to adopt novel knowledge, an “exploratory learning” event is coded to occur in the year the adoption happened, and the individual firm is removed from the risk set.

Cox Proportional Hazard function (Cox, 1975) given below is employed to estimate a firm’s probabilities to adopt novel knowledge:

$$h(\mathrm{t}) = h_0(t)exp[\beta X(t)]$$

h(t) is the hazard rate of exploratory learning. h0(t) is the unspecified baseline hazard function, as Cox regression does not require any restrictions on the baseline risk function, and it does not require additional assumptions about the baseline risk over time. X is a matrix of time-varying covariates influencing the hazard rate. β are vectors of unknown regression parameters. The model indicates that under the influence of X covariates, the hazard rate for a firm to adopt novel knowledge in its R&D activities are proportionally amplified or decreased by $exp[\beta X(t)]$.

Since the point in time of novel knowledge adoption of different firms overlap, meaning that multiple individuals have the same failure time, the Efron algorithm which can gain more accurate results will be employed.

5.4.3 Variables

The dependent variable in this study is defined as novel knowledge adoptions of firms and we measure it by the appearance of new combinations of IPC codes with new three-digit technological classes in firms’ invention patent applications. More specifically, we refer to the research of Ahuja and Lampert (2001) in defining the "novel knowledge" of firms. According to the patent history of a firm, if the International Patent Classification (IPC) codes that have not appeared in the past four years show up in the technological combination of a patent application of the firm in a specific year, the patent can be defined as an application of novel knowledge (Ahuja & Lampert, 2001; Phelps, 2010). The reason for the four-year interval is that, even if a firm may have used the technology four years ago, technical knowledge tends to depreciate or become obsolete over time, so technology being idle in the long term can significantly reduce the firm's knowledge stock (Ahuja & Lampert, 2001). Therefore, for the dependent variable of exploratory learning (*Novel_Pat*), given that in the technology combination of invention patents application of a firm in a certain year, if an IPC code has not emerged in any patent application in the previous four years, the firm is considered to be adopting novel knowledge in the present year, which is valued as 1, otherwise 0. According to the requirement of the Cox model, a survival time variable is measured by years, which is the period from firms entering into observation to adopting novel knowledge or to the censored year.

For the independent variables (*RD_Subsidy*), we set a dummy variable to record the receiving of R&D subsidy, i.e. special guidance funds for independent innovation. For the control variables, we adopt a dummy variable '*RD_Dpart*' to denote that firms run their own formal R&D institutions, such as testing base, R&D center and laboratories (Hussinger, 2008) and variable '*Pat_Stock*' to measure firms' patent stock at the end of a given year t to control for R&D capabilities (Cappelen et al., 2012; Hud & Hussinger, 2015). We also control for the value of exports (*Export*) as export-oriented firms are assumed to be more innovative so as to better cope with international competition (Radas et al., 2015). Capital intensity (*Cap_int*) is used to measure the financial status of firms (Boeing, 2016). Basic firm-level information including firm size (*Firm_Size*) and firm age (*Firm_Age*) are also controlled for. Moreover, we restrict the time effect by adding in time dummy variables. Several industrial dummy variables are also set according to the industrial distributions. In addition, we add three regional dummies to control for the developmental differences in Jiangsu, namely the north, central and south regions of Jiangsu province (the city distributions are shown in Table A5.3 in the appendix).

To control the potential endogeneity issue for obtaining robust results, an instrumental variable for IV-Probit regression is also set. Referring to the study of Guo, Guo, and Jiang (2016), we adopt the ratio of total investment in fixed assets made by local governments over the total GDP at the city level each year as the IV. This IV is highly relevant to firms' probability to gain R&D subsidy but irrelevant to the exploratory learning behaviors at firm-level.

The variables are listed and summarized in Table 5.2. By running a multi-collinearity test based on the ordinary least squares model in this study, we detect no serious multi-collinearity. Table 5.3 depicts the descriptive statistics and correlations matrix.

Table 5.2 List of Variables

Dependent variable of Cox	
Novel_Pat	Whether firms use novel IPC codes in patent applications
Independent variables	
RD_Subsidy	Whether firms gain public R&D subsidy (i.e., Special guidance funds for independent innovation) or not
Control variables	
RD_Dpart	Whether firms run their own formal R&D institutions, such as testing base, R&D center, and laboratories or not
Pat_Stock	The depreciated sum of firms' own patents until t-1 plus the non-depreciated patent applications in t with depreciation rate 0.15
Export	The natural logarithm of the value of export
Cap_Int	The natural logarithm of net fixed assets divided by the number of employees
Firm_Age	The natural logarithm of the number of years since the establishment
Firm_Size	The natural logarithm of the number of employees
Industry_Dummy	Based on 2-digit industrial code
Year_Dummy	Based on the years (2010-2014)
Region_Dummy	Based on city located in the regions of Jiangsu

Table 5.3 Descriptive Statistics and Correlations for Tobit and Cox Regressions

		1	2	3	4	5	6	7	8
1	Novel_Pat	1.000							
2	RD_Subsidy	-0.119*	1.000						
3	Firm_Age	-0.082*	-0.107*	1.000					
4	Firm_Size	-0.023	0.026	0.153*	1.000				
5	Cap_int	-0.056	0.062	0.027	0.132*	1.000			
6	Export	-0.029	0.068*	0.092*	0.487*	0.141*	1.000		
7	RD_Dpart	-0.045	0.010	0.132*	0.195*	0.089*	0.098*	1.000	
8	Pat_stock	-0.071*	-0.015	0.058	0.357*	0.060	0.265*	0.079*	1.000
	Mean	0.192	0.273	2.374	5.568	5.101	4.530	0.905	46.680
	Std. Dev.	0.394	0.446	0.603	1.143	1.194	4.630	0.293	84.517
	N	853	853	853	853	853	853	853	853

* $p<0.05$

5.5 Empirical Results

5.5.1 The effect of R&D subsidy on firms' exploratory learning

Before Cox regression, we conduct the test based on Schoenfeld Residuals. The results are shown in Table 5A.4 in the chapter appendix. Our data satisfies the basic assumptions of Cox regression.

Table 5.4 shows the effect of R&D subsidy on firms' exploratory learning. At the overall level, firms receiving R&D subsidy are less likely to adopt novel knowledge in their invention patent applications. The probability of exploratory learning of R&D subsidy recipient firms is 51.18% lower than that of firms without public R&D subsidy (Model 2). However, this empirical result may have endogeneity issues as the effect became insignificant after employing the regression with instrumental variables (Model 4).

Taking the development stage of firms into consideration, the probability of novel knowledge adoption in invention patents of firms in the decline stage is 82.25% lower than that of firms without public R&D subsidy during the observation period, and is significant at the level of 10% (Model 11). The result of Probit regression with instrumental variables also underpins the significantly negative effect of R&D subsidy on the exploratory learning behavior of the firm in the decline stage (Model 13). Meanwhile, there is no significant impact on the exploratory learning amongst both growth and maturity stage firms (from Model 5 to Model 10).

Therefore, according to our empirical results as well as the robustness check with considering potential endogeneity issues, we can argue that R&D subsidy significantly reduces the probability of novel knowledge adoptions in invention patents, i.e., exploratory learning, of enterprises in the decline stage.

Table 5.4 The effect of R&D subsidy on firms' exploratory learning

	Control	All			Growth			Maturity			Decline		
	Cox	Cox	Probit	iv-probit	Cox	Probit	iv-probit	Cox	Probit	iv-probit	Cox	Probit	iv-probit
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Enterprise_Age	0.158	0.176	0.017	0.051	0.572**	0.050	0.065	-0.029	-0.013	-0.199	-0.068	-0.051	-0.051
	(0.134)	(0.137)	(0.074)	(0.133)	(0.236)	(0.147)	(0.396)	(0.211)	(0.129)	(0.639)	(0.257)	(0.144)	(0.151)
Enterprise_Size	0.163*	0.195**	0.137**	0.168	0.336*	0.161	0.170	0.199	0.156	0.098	0.296*	0.151	0.271
	(0.096)	(0.097)	(0.058)	(0.125)	(0.181)	(0.112)	(0.282)	(0.200)	(0.110)	(0.289)	(0.163)	(0.101)	(0.167)
Cap_Int	-0.085	-0.080	-0.051	-0.023	-0.091	-0.014	-0.017	-0.270*	-0.179**	-0.202**	0.004	-0.055	0.036
	(0.082)	(0.082)	(0.045)	(0.110)	(0.162)	(0.076)	(0.271)	(0.139)	(0.085)	(0.100)	(0.156)	(0.092)	(0.143)
Export	-0.022	-0.023	-0.020	-0.025	-0.024	-0.010	-0.012	-0.038	-0.033	-0.027	-0.005	0.007	0.010
	(0.023)	(0.022)	(0.013)	(0.020)	(0.038)	(0.026)	(0.073)	(0.049)	(0.024)	(0.059)	(0.040)	(0.024)	(0.025)
RD_Dpart	0.123	0.104	0.090	0.051	0.603	0.198	0.194	-0.835**	-0.163	-0.099	0.718	0.621	0.537
	(0.265)	(0.269)	(0.182)	(0.225)	(0.394)	(0.295)	(0.595)	(0.382)	(0.289)	(0.428)	(0.717)	(0.416)	(0.448)
Pat_stock	-0.002	-0.003	-0.001	-0.002	-0.003	-0.001	-0.001	-0.006	-0.003	-0.002	-0.010*	-0.004	-0.006*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.006)	(0.002)	(0.003)
RD_subsidy		-0.717**	-0.721***	-1.233	-0.601	-0.993***	-1.068	-0.072	-0.432	1.284	-1.787*	-0.961***	-2.100*
		(0.354)	(0.168)	(1.790)	(0.496)	(0.264)	(7.429)	(0.848)	(0.397)	(5.076)	(0.962)	(0.325)	(1.091)
N	463	463	846	830	153	296	289	177	293	289	133	242	237
Enterprises	234	234	236	234	84	83	84	80	79	80	70	69	70
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: (1) Robust Standard errors (clustered by firms) are in parentheses for Cox Model; (2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; (3) All models include a set of industrial, year and regional dummies (not reported)

5.5.2 Robustness Check

According to agency theory, in order to quickly and better satisfy government requirements, and subsequently obtain government resources, firms tend to pursue the number of patent applications, especially utility model and design patents (Jia et al., 2019; Jiang et al., 2018). Utility model and design patents are often considered to be a patent with low technology content with less new technological know-how. Thus, by examining if more utility model and design patents are applied after receiving subsidies, i.e., agency risk, I can supplement and support the conclusions of this paper from other theoretical perspectives.

This study adopts the count number of the utility model and design patent applications with one year lagged of a firm as a dependent variable. Panel data negative binomial regression with fixed effects is employed as the empirical technique. As shown in Table 5.5, R&D subsidies do not significantly promote utility model and design of firms in the growth and maturity stages (Model 14 and Model 16), which means that the agency risk of firms in these two stages is weak. However, for enterprises in the decline stage, R&D subsidies significantly increase their probability of non-invention patent applications (Model 18). We also provide results of panel data fix-effect regression with the instrumental variable as yearly city-level fixed asset investment (Model 15, 17 & 19). The estimated results are nearly identical to the results of the negative binomial regressions. This implies that the negative effect of R&D subsidy on exploratory learning of enterprises in the decline stage may be a result of recipients' agency risk.

Table 5.5 Robustness check for firms' familiar knowledge exploitation

	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19
	Growth		Maturity		Decline	
RD_subsidy	-0.264	1.429	0.112	0.260	0.572**	0.556*
	(0.220)	(0.837)	(0.274)	(0.174)	(0.224)	(0.302)
Enterprise_Age	0.245	0.323	-0.107	-0.999***	-0.010	-0.823**
	(0.207)	(1.239)	(0.198)	(0.315)	(0.118)	(0.373)
Enterprise_Size	0.080	-1.271	0.230*	0.393**	0.262*	-0.056
	(0.136)	(1.032)	(0.133)	(0.198)	(0.141)	(0.584)
Cap_Int	-0.036	-0.280	-0.079	0.183	-0.223**	0.246
	(0.062)	(0.437)	(0.074)	(0.140)	(0.093)	(0.368)
Export	0.008	-0.176	0.006	0.014	-0.011	-0.064
	(0.026)	(0.197)	(0.025)	(0.038)	(0.018)	(0.090)
RD_Dpart	0.587***	-2.298	0.211	0.058	0.632**	-0.441
	(0.221)	(1.834)	(0.230)	(0.278)	(0.309)	(0.697)
Pat_stock	0.002**	0.052***	-0.002***	0.032***	0.009***	0.057***
	(0.001)	(0.012)	(0.001)	(0.003)	(0.002)	(0.007)
N	291	268	295	261	237	221
Enterprises	75	71	75	68	64	62
Prob > F or chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: (1) Bootstrap standard errors are in parentheses; (2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; (3) All models include a set of industrial, year and regional dummies (not reported)

Table 5.6 The conclusion of the empirical results of Chapter 5

Hypotheses	**Empirical results**
Hypothesis 1: Firms receiving R&D subsidy are more likely to undertake exploratory learning.	Not supported (insignificant)
Hypothesis 2 a: Firms in the growth stage are more likely to undertake exploratory learning by receiving R&D subsidy.	Not supported (insignificant)
Hypothesis 2 b: Firms in the mature stage are more likely to undertake exploratory learning by receiving R&D subsidy.	Not supported (insignificant)
Hypothesis 2 c: Firms in the decline stage are more likely to undertake exploratory learning by receiving R&D subsidy.	Not supported (negative)

5.6 Discussion

The empirical results show that public R&D subsidies cannot provoke firms' exploratory learning to overcome the learning traps. This study further suggests that the effects of R&D subsidy on firms' novel knowledge adoptions vary at different development stages. One of the key findings is that R&D subsidies can significantly reduce the likelihood of firms in the decline stage to explore, absorb and adopt novel knowledge, however they will prominently increase the number of utility model and design patent applications. For firms in the growth and mature stages, R&D subsidy has no effect on exploratory learning behaviors nor on utility model and design patent applications.

Previous studies have shown that firms in the decline stage need to adopt novel knowledge to break the original technology lock-in and avoid the "familiar trap" in order to form a new technology portfolio and open up new markets because of the exhaustion of existing ones (Ahuja & Katila, 2004). In the research sample, 50 out of 71 firms in the decline stage engaged in exploratory learning, which also confirms extant findings. However, most firms in the decline stage that have been adopting novel knowledge did not receive R&D subsidies. Meanwhile, the empirical results further reveal that R&D subsidies significantly inhibit firms in the decline stage from exploratory learning. It fails to promote the adoption of novel knowledge in their R&D activities for various potential reasons. First, market competition is distorted due to the intervention of cheap public funds (Bonardi, 2008; Chen et al., 2011). Firms can survive without improving their own technological capabilities and resource bases (Jourdan & Kivleniece, 2017), and the incentives to use novel but perhaps risky know-how may, therefore, be reduced. Second, firms may use cheap resources (R&D subsidies) to extend the original technology track to "the last gasp". On the one hand, firms expect to gain fast economic returns with lower risks; on the other hand, firms want to rapidly expand patent applications, such as utility model and design patents, in order to meet the government's requirements to gain subsequent subsidies. Under the quantitative evaluation criteria of government-subsidized R&D projects, the novelty of R&D and the real growth of R&D and the innovation ability of firms are difficult to measure. Meeting the bar for the subsidy has become the primary goal of firms receiving R&D subsidy (Li et al., 2018). Firms will simply pursue the required quantity of R&D and innovation achievements rather than pursuing the novelty of the technology and the improvement of innovation ability and market competitiveness (Jia et al., 2019). In addition, the results of the robustness check also strengthen this argument from the perspective of agency risk.

Moreover, what is unexpected is that R&D subsidies have no significant impact on exploratory learning behaviors of firms in growth and maturity stages. Firms in the growth stage, on the one hand, are less likely to be confronted with path-dependence caused by the accumulation of long-term technology development and experience. On the other hand, growing firms are more active in exploring and absorbing mature but unfamiliar knowledge from the industry to enhance their technological capabilities rapidly and speed up product development. With the accumulation of knowledge and experience, firms in the growth stage will gradually and continuously collect, acquire and utilize novel knowledge to innovate in order to build a cycle of learning and experience to enhance their knowledge stock and strengthen technological competitiveness. In other words, whether firms are supported by the government does not affect their inclinations to seek and adopt novel knowledge.

For firms in the maturity stage, the insignificant effect of R&D subsidy is mainly because firms whose core technology has entered maturity have built up strong technical capabilities and related resources. Specifically, at this stage, with the increasing maturity of technology, firms can maintain and develop suited technological capabilities to obtain sustained profits. Presently, firms in the maturity stage with sufficient financial resources rely less on government resources, and hence, the government's influence on them is weakened. Meanwhile, the internal level of hierarchy in such firms is complicated, and the decision-making process gradually forms a certain path dependence. It is difficult for the government to influence the R&D strategic decision-making of firms in the maturity stage through just R&D subsidy. Therefore, public R&D subsidies have no significant impact on the R&D activities of mature firms. This finding echoes Barbosa et al. (2014).

5.7 Appendix

Table 5A.1 Industrial Distribution based on 2-digit industrial codes

2-digit industrial code	Industrial name	Firm number
26	Manufacture of Raw Chemical Materials and Chemical Products	10
29	Manufacture of Rubber and Plastic Products	2
30	Manufacture of Non-metallic Mineral Products	3
33	Manufacture of Metal Products	4
34	Manufacture of General-Purpose Machinery	25
35	Manufacture of Special Purpose Machinery	76
36	Manufacture of Automobile Equipment	10
37	Manufacture of Transport Equipment	6
38	Manufacture of Electrical Machinery and Equipment	62
39	Manufacture of communications and other electronic equipment	35
40	Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work	3
Total		236

Table 5A.2 Selection Bias Check

DV: receiving R&D subsidy or not	Probit Regression
The age of firms	-0.264***
	(0.101)
The employees of firms	0.009
	(0.068)
Firms' capital intensity	0.059
	(0.057)
Firms' export value	0.022
	(0.016)
Whether the firms run their own formal R&D institutions	0.071
	(0.220)
Firms' knowledge stock	-0.001
	(0.001)
_cons	-0.478
	(0.491)
N	853
Firms	236
Prob > chi2	0.135
Pseudo R^2	0.019

Notes: (1) *** p<0.01, ** p<0.05, * p<0.10; (2) All models include a set of industrial, year and regional dummies (not reported)

According to the *Handbook of Policies towards Firm's Technological Innovation of Jiangsu*, subsidy in Jiangsu Province in support of firms in the renewable energy industry is allocated to firms that meet the following requirements: 1) have good research and development foundation and conditions; and 2) have sound business credit. Based on the screening criteria, we select several factors that may influence the probability of receiving R&D subsidies. The results of probit regression indicate that all the factors except firms' age have no significant effects on the probability of receiving R&D subsidy, thus, it is argued that our samples do not have serious selection bias related to the R&D subsidy received.

Table 5A.3 City distributions in Jiangsu

Regions	Cities
The north region of Jiangsu	Xuzhou, Lianyungang, Huai'an, Yancheng, Suqian
The central region of Jiangsu	Yangzhou, Taizhou, Nantong
The south region of Jiangsu	Nanjing, Suzhou, Wuxi, Changzhou, Zhenjiang

Table 5A.4 Test for Cox regression based on Schoenfeld Residuals

	All firms	Growth	Maturity	Decline
Firm_Age	0.950	0.091	0.857	0.495
Firm_Size	0.130	0.740	0.106	0.853
Fix_Asst	0.419	0.105	0.323	0.761
Export	0.357	0.925	0.345	0.221
RD_Dpart	0.371	0.959	0.712	0.049
Pat_stock	0.708	0.989	0.120	0.403
RD_Subsidy	0.293	0.360	0.116	0.089

The results show that the proportional risk assumptions for Cox regression are supported

6. R&D Subsidy Programs, Novel Knowledge Exploration, the Change of Technological Focus: the Different Roles of the Local and Central Governments

6.1 Introduction

The main purpose of this chapter is to explore how participating in public R&D subsidy programs promotes firms' learning and adoption of novel knowledge and it is, furthermore, the purpose to explore potential heterogeneity effects between central and local governments.

Chinse firms have been catching up quickly through technological innovations since the economic transition. However, it is recognized by researchers that China's rapid development model has two problems (Guan & Yam, 2015; Liu et al., 2017). First, most of the time, Chinese firms emphasize imitating existing products and conducting incremental innovation and secondary innovation, stimulated by cost advantage and enormous domestic market demand (Liu et al., 2017; Wu, Ma, & Xu, 2009). Second, most Chinese manufacturing firms are locked into the low end of the global value chain with a very low technological level (Guan & Yam, 2015). This current innovation model is not sustainable for long-term growth, as China is facing challenges from the labor cost increase, environmental pollution, and shortage of resources. Thus, the Chinese government has launched the National Medium- and Long-Term Plan for Science and Technology Development (2006-2020). The Chinese government has been urging firms to upgrade industrial technology, enter new technological fields and create new markets. At the same time, the Chinese government also emphasizes the indigenous innovation of firms, and finally promotes sustainable economic development (Liu et al., 2017).

To achieve innovation-driven development, the Chinese government encourages firms to carry out exploratory learning of novel knowledge. Novel knowledge is defined as a type of knowledge that is entirely new to the firms but not necessarily novel for the industry or may even be mature knowledge to other players in the market (Ahuja & Lampert, 2001). Exploratory learning of novel knowledge, on the one hand, provides sources for firms' new technological combinations to break the learning traps generated by path dependence on familiar knowledge and problem-solving methods (Ahuja & Katila, 2004; Ahuja & Lampert, 2001). It helps developing country firms to create breakthrough inventions, subsequently breaking the trajectories developed by firms from developed countries. It also helps firms to capture emerging new technological opportunities that are as yet ignored by incumbents. On the other hand, exploratory learning helps firms, especially those engaging in traditional sectors with low and medium technologies, to enter new technological fields and change their core technological focuses to accomplish the industrial upgrading (Liu et al., 2017).

However, there are various obstacles for developing countries firms to explore unfamiliar novel knowledge. First, to search for new technology and knowledge leads to higher costs compared to using existing familiar knowledge (Oshri et al., 2005). Second, firms may face higher risks when using novel but unfamiliar knowledge due to the associated higher uncertainties (Dunlap Hinkler et al., 2010; Wadhwa & Kotha, 2006). Thus, although exploratory learning on novel knowledge may lead to technological upgrading and firms' competitive advantages, incentives to pursue such learning behavior are still weak.

To break the deadlock of learning traps, the government can play an important role in promoting firms' exploratory learning. With public R&D subsidies, the government can reduce firms' research and development costs (Boeing, 2016; Dimos & Pugh, 2016) incurred by exploratory learning. Moreover, the government can also endorse R&D subsidy recipient firms with the legitimacy of novel knowledge seeking (Wang et al., 2017). However, very few studies focus on the effects of R&D subsidy on firms' exploratory learning so as to help firms entering new technological fields and further change their technological focuses.

Thus, the study in this chapter, at first, will focus on the question: "can participating in public R&D subsidy programs promote firms' exploratory learning?" Second, this study will further explore the extent to which firms use novel knowledge after participating in public R&D subsidy programs. More specifically, this study attempts to answer the question: "does public R&D subsidy facilitate firms to use new knowledge to change their core technological focus?" The conception of exploratory learning in this chapter is similar to that in Chapter 5, however, this chapter further considers the degree of exploratory learning. According to previous studies, the results of exploratory learning may remain different (Geels & Schot, 2007; Hall & Andriani, 2003). One possibility is that novel knowledge can be used to strengthen and improve the firms' existing technologies, which are add-on technologies (Geels & Schot, 2007). The other possibility is that novel knowledge may help firms to change the current core technological focus they are engaged in (Hall & Andriani, 2003). This may result in firm-level technological upgrading. In the pilot research for this study, both public agencies and firms claimed that participation in public R&D support programs helps firms to change their technological focus. For example, several sponsored firms have transferred from coating composition to polymeric compound, from medical preparation to microbial and enzyme assays and test methods or from textile to R&D on new materials. Third, the Chinese public R&D subsidy programs can be further divided into central and local levels. The degree of information asymmetry with firms, subsidy targets, and evaluation criteria are different between central and local governments due to the proximity to local firms (Wei

& Zuo, 2018; Zheng et al., 2015; Zhou et al., 2018). Therefore, the effects of R&D subsidies from central and local governments on exploratory learning may differ. Accordingly, "do R&D subsidies from central and local governments have different effects on firms' novel technologies and new knowledge exploitation behaviors?" is another key question of this study.

6.2 Theoretical Development and Hypotheses

6.2.1 Firms' Exploratory Learning behaviors

According to a learning perspective, firms can expand their knowledge base or enter an entirely new technological area by exploring and adopting novel knowledge (Ahuja & Lampert, 2001; Grant, 1996). Novel knowledge exploration also helps firms to enhance their experience of using new and unfamiliar technologies, and strengthens their ability to solve problems in the face of new technological challenges, and thereby helps firms to form new and more efficient technology solutions (Ahuja & Lampert, 2001; Amabile, 1988; Zhou & Li, 2012).

By novel knowledge exploration, firms can also break the cognitive rigidity generated by an existing knowledge base. Firms often fall into "familiarity traps" of technology due to the path dependence derived from the momentum of familiar knowledge exploitation (Ahuja & Lampert, 2001). More specifically, previous experience of familiar knowledge has enhanced firms' absorptive capacity of such knowledge (Ahuja & Lampert, 2001; Cohen & Levinthal, 1990). This promotes the development of such technology and increases its competitive advantage. The competitive advantage afforded by higher technology promotes firms' use of such technology, which in turn increases firms' experience (Cohen & Levinthal, 1990). The cyclical interaction of experience and capabilities benefits a firm's establishment of professional ability and decreases the difficulty of learning and problem-solving in a specific technological area (Cohen & Levinthal, 1990; Henderson & Clark, 1990). However, firms may be locked into well-understood and familiar technologies, which limits the firms' capabilities for radical innovation (Ahuja & Lampert, 2001). Novel knowledge exploration, to a certain extent, provides a new perspective, not only for a better understanding of novel knowledge, but for existing knowledge as well (Lei, Hitt, & Bettis, 1996). This can help firms to create technological combinations of novel knowledge with existing knowledge (Utterback, 1994), or combine existing but less relevant knowledge areas (Keijl et al., 2016; Schoenmakers & Duysters, 2010b). Therefore, learning and using novel knowledge can promote the firms' knowledge recombination, and even change firms' core technological focus, further providing a foundation for firms' technological upgrading (Ahuja & Lampert, 2001).

However, novel knowledge exploration often leads to higher costs to acquire both generic and specialized resources (Jiang et al., 2018; Schilling, 2010; Wang et al., 2014). This is mainly due to the complexity of novel knowledge. On the one hand, firms need to acquire and understand novel knowledge by building and upgrading relevant skills, which require heavy resource investments (Hitt et al., 1996; Madhavan & Grover, 1998). At the same time, heavy investment is also required to strengthen firms' absorptive capacity on novel knowledge and relevant specialized complementary knowledge (March, 1991; Sheng, Zhou, & Li, 2011). Furthermore, firms need to strengthen their absorptive capacities (Zahra & George, 2002), by means such as recruiting new employees to understand and use novel knowledge, which also incurs high costs (Wang et al., 2014). On the other hand, by deepening understanding of firms' existing knowledge and experience, firms can reduce the possibility of making mistakes in learning and using novel knowledge (Katila & Ahuja, 2002; Vrontis et al., 2017; Zahra & George, 2002). However, there remains resource competition between familiar knowledge exploitation and novel knowledge exploration due to different organizational processes and cultures (March, 1991; O Reilly & Tushman, 2008; Raisch & Birkinshaw, 2008). Firms need to invest heavy resources to ensure the balance between these two learning behaviors (Zhao et al., 2016). In addition, due to high risk and high uncertainty, it is also difficult for firms to attract external funding to supplement resource constraints and when to apply novel knowledge in R&D activities (Czarnitzki, Hottenrott, & Thorwarth, 2010). As a consequence, firms tend to use their familiar knowledge to conduct technological R&D to obtain fast returns with lower uncertainty (Cohen & Levinthal, 1990; Levinthal & March, 1993; March, 1991), rather than developing new, efficient technological combinations with novel knowledge (Ahuja & Lampert, 2001; Lei et al., 1996).

6.2.2 Public R&D Subsidy and Firms' Exploratory Learning

By joining the R&D subsidy programs, firms can be buffered by resources from governments (Jourdan & Kivleniece, 2017). Extant research suggests that resources including both generic and specialized resources have a profound impact on firms' novel knowledge exploration (Hitt et al., 2004; Jiang et al., 2018), especially for firms in emerging economies (Li et al., 2013). Generic resources usually refer to finance and infrastructure etc., which do not need to adjust according to technological innovation and can apply to all knowledge acquisition processes (Lazzarini, 2015). Specialized resources are codified and tacit knowledge of specific innovation activity, which depends on specific novel knowledge (Jiang et al., 2018; Teece, 1986). Studies have shown that specialized resources play a more prominent role in novel knowledge exploration to enter new technological fields (Kash & Rycroft, 2002; Mitchell, 1989).

R&D subsidy programs are argued to mainly provide firms with generic financial resources but little specialized resources for novel knowledge exploration (Hitt et al., 2004; Jiang et al., 2018; Sheng et al., 2011). However, this generic financial resource can help firms overcome resource constraints and promote their external exchange of specialized resources (Jiang et al., 2018; Kim & Bettis, 2014; Lazzarini, 2015). For example, governmental resources can promote firms' recruitment of high-quality R&D employees as tacit knowledge carriers, which can enhance firm-level absorptive capacities (Afcha & Garcia-Quevedo, 2016) and promote firms' novel knowledge exploration. The public funds can also help firms to ease resource competition between exploitative and exploratory learning behaviors (Cao, Gedajlovic, & Zhang, 2009; Mathews, 2002). Firms that receive public R&D subsidy can allocate sufficient budget for both learning activities (Sheng et al., 2011). In addition, R&D subsidy increases firms' risk tolerance levels (Chapman & Hewitt-Dundas, 2018). This promotes firms to conduct more challenging research and development activities, which have higher uncertainty, and require more novel knowledge (Czarnitzki & Delanote, 2015; Hsu, Horng, & Hsueh, 2009).

By joining public subsidy programs, firms can also obtain governmental endorsements. From the perspective of institutional theory, the government is the tool to create competitive environments that benefit firms (Hillman & Hitt, 1999). Especially for emerging economies, an unsound institutional environment reduces trust between organizations (Atuahene-Gima & Li, 2002). In this way, information transmitted through the government may be more reliable than information obtained in other ways (Luo, 2003). Therefore, on the one hand, government endorsements release beneficial signals to the market and promote their access to external financing (Kleer, 2010; Wu, 2017; Zhou, Wu, & Li, 2019). On the other hand, government endorsements connect firms with other firms, which help firms learn and obtain key specialized resources and complementary knowledge that can promote firms' exploratory learning (Amezcua et al., 2013; Jiang et al., 2018). Furthermore, since China's top universities and research institutes are often publicly owned, government endorsements also promote formal partnerships between firms and universities and research institutions. This can provide firms with more opportunities to learn from universities and research institutions, and increase firms' capabilities to adopt novel knowledge (Xu et al., 2014).

According to the "experience-capacity" cycle model, firms need to allocate more resources to gain more direct experience and specialized resources for the change of technological focus by adopting novel knowledge (Kash & Rycroft, 2002). This may result in higher costs and greater risk. Public R&D subsidy can make up for the shortage of resources and strengthen the relationship between firms and external partners to support firms in gaining access to resources, especially specialized resources. Thus, this will promote firms to change their technological focus and enter an entirely new technological field, which firms are not familiar with. Therefore, it is proposed that:

Hypothesis 1 a: Participation in public R&D subsidy programs will facilitate firms' novel knowledge exploration behaviors.

Hypothesis 1 b: Participation in public R&D subsidy programs will encourage firms to change core technological focus.

6.2.3 Difference between National R&D Subsidy and Provincial R&D Subsidy

Different effects may exist between R&D subsidy programs of Chinese central and local governments on firms' novel knowledge exploration and further change of the technological focus. The differences stem from the different degrees of central and local governments' administrative, economic and geographic proximity to local firms (Jiao et al., 2016; Qian & Roland, 1998; Zhou et al., 2018). The proximity implies central and local governments' different functions and targets, interaction degree with local firms, speed of response to local business needs, and policies and resource supplies (Nee, 1992; Qian & Weingast, 1997).

The central government is argued to have broader responsibilities as well as strategic targets, and needs to allocate R&D resources nationwide (Pfeffer, 1972). Although the proximity to local firms is less, the central government has more generic financial resources. For example, China's banking industry is mostly under the control of the central government (Shi, Markóczy, & Stan, 2014). Therefore, by participating in the central R&D subsidy programs, firms can often get more generic resources (Arnoldi & Villadsen, 2015; Zhou et al., 2018). The resource munificence helps to reduce firms' dependence on external resources to a greater extent (Zheng et al., 2015) and further strengthen their capabilities of the acquisition on specialized resources related to novel knowledge exploration (Jiang et al., 2018). For example, by joining a central R&D subsidy program, firms' collaborations with higher-level research institutes can be facilitated (Hong & Su, 2013; Zheng et al., 2015) to acquire the necessary complementary knowledge for exploratory learning. In addition, participating in central programs will help to improve firms' legitimacy nationwide and help firms to attract high-quality R&D talent. Extant studies have shown that accepting national R&D subsidies has significantly encouraged firms to attract and recruit R&D personnel with doctoral degrees (Afcha & Garcia-Quevedo, 2016). These can also enhance the capabilities of exploratory learning.

Although the generic resource provision is less than that of the central government, local governments also have the power to allocate scarce and critical resources for the promotion of firms' technological innovations (Li & Zhao, 2015; Zhang et al., 2016). Valuable resources provided by local government can help firms to break resource constraints on novel knowledge exploration (Li & Zhao, 2015). Local governments also promote collaboration of sponsored firms with other local firms and research institutes (Krug & Hendrischke, 2008; Marzucchi et al., 2015), helping firms to acquire specialized resources related to the novel knowledge exploration and learning. Therefore, this study proposes that:

Hypothesis 2 a: Participation in the central R&D subsidy programs can promote firms' novel knowledge exploration behaviors.

Hypothesis 2 b: Participation in the local R&D subsidy programs can promote firms' novel knowledge exploration behaviors.

To change firms' technological focus and make them enter new fields with novel knowledge exploration, the related specialized resources are the most important (Kash & Rycroft, 2002). Local government, due to its greater geographic proximity, has more interactions and information exchange with local firms (Jiao et al., 2016; Qian & Weingast, 1997). This close interaction helps to reduce information asymmetry (Adler & Kwon, 2002), which enables local governments to understand the actual needs of firms on exploratory learning and subsequent change of technological focus. Thus, local governments can better help firms with exploratory learning by providing sophisticated specialized resources with greater specificity and immediacy (Krug & Hendrischke, 2008; Nee, 1992; Prud'Homme, 1995).

Local government also has greater economic proximity to firms (Walder, 1995). Local governments can experience directly the benefits of the development of firms within their jurisdiction (Walder, 1995). Thus, local governments have more incentives to promote and maintain the sustainable development of the local economy. As a result, local governments emphasize firm-level industrial upgrading by changing firms' technological focus (Nahm, 2017; Zhou et al., 2018), in order to serve local economic development. Especially in China, local governments are playing an increasingly important role in industrial upgrading (Boeing, 2016; Springut, Schlaikjer, & Chen, 2011).

At the same time, local governments have greater administrative proximity to local firms. Local firms are directly affected by the regulations and policies of local governments (Trounstine, 2009; Zhou et al., 2018). To explore novel knowledge for the change of technological focus, firms may confront higher uncertainty concerning the need for regulatory approval (Zhang, Tan, & Wong, 2015). For example, the major changes to existing producing processes and products require new permit applications. By participating in local R&D subsidy programs, firms can establish ties with local governments. The institutional flexibility and fast response can facilitate the adjustment of local government regulations and policies for the reduction of uncertainty during firms' radical changes in R&D activities (Zhang et al., 2015), which will underpin changes in firms' technological focus via novel knowledge exploration.

In contrast, policies and regulations from the central government cannot have a direct influence on firms. The central government focuses more on a macro perspective and takes the overall strategic plan view for national innovation and development. Therefore, the central government usually does not interact closely with local firms (Zheng et al., 2015). As a result, the central government fails to meet the specific needs of firms in terms of changing technological focus as quickly and accurately as local governments (Prud'Homme, 1995). At the same time, national R&D subsidy programs often select technology-leading firms to undertake major national R&D projects (Altuzarra, 2010; Blanes & Busom, 2004). These firms tend to have higher technical rigidity and it is difficult to change their main technological focus. Although the firms actively adopt novel knowledge, the purpose of the exploration of novel knowledge maybe just to assist in strengthening the existing technologies.

In addition, firms need to reshape R&D processes and R&D paths and reconfigure resources in order to change technological focus. Excessive generic resources from governments may also strengthen firms' dependence and limit firms' flexibility to adjust the R&D process to adapt to industrial technology changes (Zhao et al., 2016). Existing studies show that the higher the level of government to access resources from, the tighter the restrictions on firms' reconstruction of the R&D process (Li et al., 2018). Therefore, although national R&D subsidies may promote firms' exploratory learning, they cannot further promote firms' technological focus changing by adopting such novel knowledge. This study proposes that:

Hypothesis 3 a: Participation in the central R&D subsidy programs may inhibit the change of firms' technological focus.

Hypothesis 3 b: Participation in the local R&D subsidy programs can encourage the change of firms' technological focus.

6.3 Data, Methods and Measures

6.3.1 Data

This study employs an exclusive panel dataset from a survey of firms in manufacturing sectors conducted by the Jiangsu Science and Technology Department, covering the period from 2010 to 2014. This set of data is used to evaluate the effects of R&D subsidy in Jiangsu Province only through to 2014, which happened to be the tenth anniversary since Jiangsu reformed the R&D subsidy policy. Up to 2014, this dataset is comprised of firms' basic information, main R&D and financial data from 7,928 firms. This study also collects patent data from 2,024 manufacturing firms in Jiangsu with the period from 2006 to 2016 from the State Intellectual Property Office (SIPO) website. This study subsequently illustrates technological development roadmaps of each firm drawn from 4-digit IPC (International Patent Classification) codes, at subclasses level, of the patents. IPC code provides a hierarchical system similar to bibliographic retrieval, which classifies patents according to their technical fields (Park & Yoon, 2017; Verhoeven, Bakker, & Veugelers, 2016). Subclasses further define technologies with the heterogeneity of process, structure, and functionality (Kim et al., 2011). Existing studies use subclasses of IPC codes to illustrate the trends of firms' core technological changes

(Park & Yoon, 2017) and capture the development of core technologies and other relevant capabilities of firms (Ruiz-Navas & Miyazaki, 2017).

The firm and patent databases are combined according to the firm name. This study further retains the firms that have not received any R&D subsidies in 2010-2014 and the firms that only participate in central or local R&D subsidy programs with the sponsored period from 2010 to 2014. *Innofund* provided by the central government is selected as the focus central R&D subsidy program. This study also selected the corresponding local technological innovation fund that has similar screening criteria as the *innofund*. According to the *Handbook of Policies towards Firm's Technological Innovation of Jiangsu*, the aim of both aforementioned central and local funds is to support the development of high-tech industries and upgrading of traditional industries, through promoting firms' innovation capabilities.

The initial database of this study contains 1424 firms with 6171 firm-year observations, among which 395 firms have participated in subsidy programs. 129 firms have only joined the local R&D subsidy programs, while 266 firms have joined the central R&D subsidy programs. To control the potential selective bias, this study employs propensity score matching (PSM) (more details of the PSM process are shown in PSM sampling in the chapter appendix). Based on the matching results of the base period, the corresponding subsequent data in the follow-up period are supplemented, and the final PSM sampling comprises 790 firms with 2960 firm-year observations. The industrial distribution of these firms (based on the 2-digit industrial code[12]) and regional distributions can be found in Table 6A.3 and 6A.4 in the appendix, respectively.

6.3.3 Method

In this study, similar to the study of Chapter 5, Cox regression is adopted as the main empirical technique. Cox regression does not require any restrictions on the baseline risk function, and it does not require additional assumptions about the baseline risk over time (Cox, 1975). The timelines in which each firm employs novel knowledge or changes the technological focus may not coincide during the observation period, therefore, Cox regression could be appropriate. Since the point in time when novel knowledge usage of different firms overlap, meaning that multiple individuals have the same failure time, the Efron algorithm which can gain more accurate results will be employed (Cleves et al., 2008).

6.3.4 Variables Definition

Dependent variables

Following the measurement of "novel technology" in the research of Ahuja and

[12] Industrial Classification for National Economic Activities (GB T4754-2011)

Lampert (2001), this study measures the firms' novel knowledge exploration behaviors and technological focus change. According to each firm's technological roadmaps, if the main IPC codes that have not appeared in the past four years show up in at least one patent applied by the firm in a certain year, it can be defined as firms' novel knowledge exploration (Ahuja & Lampert, 2001). The dependent variable "novel knowledge exploration (*NewTech_App*)" takes a value of 1, otherwise 0. The reason for using a 4-year interval is that even if the firm may have used the same technology 4 years ago, technological knowledge tends to depreciate or become obsolete over time. Therefore, technology being idle for the long term can significantly reduce the firm's knowledge stock (Ahuja & Lampert, 2001). In existing research on technology-intensive industries, a four- to five-year time window has also been used to assess the validity of knowledge stocks for specific technologies (Ahuja, 2000; Stuart & Podolny, 1996). If the number of patent applications with new main IPC codes for two consecutive years, it is regarded that this firm has changed its core technological focus (*NewTech_Turn*) (Li, 2011, 2009). According to event definition, a total of 697 firms adopt novel knowledge during the observation period, and 467 firms changed their core technological focus in the PSM sampling.

Independent Variables

This study set three dummy variables as the independent variables, which are: participation in public R&D subsidy programs (*Public_project*), local programs (*Local_only*) and central programs (*Central_only*). If a firm participates in local or central programs, *Public_project* valued 1, otherwise 0. Considering the governmental levels of R&D programs, if a firm only participates in local programs, *Local_only* valued 1, otherwise 0. Similarly, if a firm only participates in central programs, *Central_only* valued 1, otherwise 0.

Control Variables

The novel knowledge exploration and the change of technological focus can be influenced by firms' own learning behaviors (Clarysse et al., 2009). Thus, this study first controls for the three main learning behaviors of firms, namely congenital learning, inter-organizational learning and experiential learning (Clarysse et al., 2009; Roper & Hewitt-Dundas, 2014).

Extant studies suggest that congenital learning has a close correlation with firm-level knowledge stock (Roper & Hewitt-Dundas, 2014). The knowledge stock is reflected in the technological accumulation of firms (DeCarolis & Deeds, 1999; Park & Park, 2006) and in the reserve of talent as a carrier of tacit knowledge (Bontis, 1998; Roper & Hewitt-Dundas, 2014). With reference to the relevant studies, this study controls for the knowledge stock (*Know_stock*) by adopting firms' patent stock. The patent stock of a firm at t is the depreciated sum of firms' own patents until t-1, plus the non-depreciated patent applications in t with depreciation rate 0.15 (Cappelen et al., 2012). This study also controls for the ratio of employees with a high educational level (*Hi_edu_emp*), which is measured by the proportion of employees with a bachelor's degree or above in the total number of employees (Afcha & Garcia-Quevedo, 2016).

For inter-organizational learning, this study mainly controls for firms' R&D collaborations with universities and public research institutes. The variable "*Tech_coll*" is measured by the natural logarithm of R&D expenditures of firms invested in the collaborations with universities and public research institutes (Carboni, 2012; Gök & Edler, 2012; Roper & Hewitt-Dundas, 2014).

Experiential learning, in the studies of R&D subsidy, may lead to changes in firm R&D behaviors and enable firms to reconfigure R&D-related resources (Clarysse et al., 2009). That is, firms may embed the prior experience of undertaking governmental R&D subsidies programs in the R&D process (Kotabe, Jiang, & Murray, 2011; Luo, 2003). For example, Clarysse et al. (2009) measure experiential learning by the number of R&D subsidy programs that firms have joined before. Therefore, this study set the control variable of experiential learning (*Pre_subsidy*) measured by a dummy of whether the company has experience in the participation in governmental R&D subsidy programs in the three years prior to the observation period.

Besides the above three learning behaviors, basic information of firms is also controlled for in this study. The study controls for firm size (*Firm_Size*) and firm age (*Firm_Age*), capital intensity (*Cap_int*) and the value of export (*Export*). This study also controls for the ratio of employees with a high educational level (*Hi_edu_emp*), which is measured by the proportion of employees with a bachelor's degree or above in the total number of employees (Afcha & Garcia-Quevedo, 2016). This study adopts a dummy variable '*RD_Dpart*' to delegate that firms have their own R&D institutions, such as testing base, R&D center and laboratories to control for R&D capabilities (Hussinger, 2008). Whether the firms are engaged in the high-tech manufacture sectors (*Hi_Tech_ind*) is also controlled. This study also sets 28 industry dummies (*Industry_Dummy*) based on 2-digit industrial codes (Table 6A.3); three regional dummies (*Region_Dummy*) based on south, north and central areas of Jiangsu; five year dummies (*Year_Dummy*) are also set due to the different annual macroeconomic environments. The statistical description and correlation matrix based on PSM sampling are shown in Table 6.1. The correlation between "*Nation_only*" and "*Public_project*" with the value 0.733, means that more R&D subsidy recipient firms in my samples participate in the central government program. This study conducts a multi-collinearity test based on OLS. The results show that the VIF values of the selected variables are acceptable, indicating no serious multi-collinearity problem.

Table 6.1 Descriptive statistics

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	NewTech_Turn	1.000														
2	NewTech_Add	0.118*	1.000													
3	Public_project	0.052*	0.017	1.000												
4	Province_only	0.021	0.011	0.436*	1.000											
5	Nation_only	0.040*	0.009	0.733*	-0.292*	1.000										
6	Know_stock	-0.064*	0.041*	0.036	0.206*	-0.117*	1.000									
7	Hi_edu_emp	-0.011	-0.003	0.001	0.001	0.000	0.005	1.000								
8	Tech_Coll	0.044*	-0.006	0.120*	0.271*	-0.078*	0.086*	-0.002	1.000							
9	Pre_subsidy	-0.087*	-0.160*	-0.116*	0.044*	-0.157*	0.015	-0.009	0.019	1.000						
10	Firm_Age	-0.110*	0.012	-0.002	0.127*	-0.098*	0.087*	-0.020	0.102*	0.053*	1.000					
11	Firm_Size	-0.052*	-0.015	-0.061*	0.386*	-0.357*	0.342*	-0.163*	0.251*	0.007	0.244*	1.000				
12	Hi_Tech_ind	-0.043*	-0.013	-0.009	0.018	-0.022	-0.042*	0.009	0.021	0.031	-0.052*	-0.060*	1.000			
13	Export	-0.020	0.006	-0.041*	0.187*	-0.185*	0.174*	-0.023	0.055*	0.000	0.088*	0.416*	-0.018	1.000		
14	Cap_int	-0.021	-0.029	-0.013	0.201*	-0.166*	0.048*	0.152*	0.097*	-0.027	0.007	0.140*	-0.067*	0.166*	1.000	
15	RD_dpart	-0.043*	-0.001	-0.018	0.073*	-0.075*	0.069*	-0.034	0.113*	0.055*	0.154*	0.175*	-0.128*	0.050*	0.060*	1.000
	N	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960	2,960
	Mean	0.158	0.635	0.477	0.148	0.329	39.949	0.217	2.077	0.077	2.468	5.376	0.284	4.708	4.970	0.905
	Std.Dev	0.365	0.481	0.500	0.355	0.470	77.806	2.005	3.165	0.267	0.524	1.123	0.451	4.371	1.163	0.293

* $p<0.05$

6.4. Empirical Result

6.4.1 Influence of Public R&D Subsidy on Firms' novel knowledge exploration

As shown in Table 6.2, in general, the results illustrate no significant influence of participation in public R&D subsidy programs on firms' novel knowledge exploration behaviors (Model 2). After distinguishing the level of programs, neither local nor central R&D subsidy has significant effects on firms' novel knowledge exploration (Model 3 and Model 4).

As to firms' congenital learning behaviors (Model 1), firms' highly educated human resource has a negative influence on firms' novel knowledge exploration at the 5% significance level. The results show that, when firms' highly educated employee ratio increases by 1%, there is a decrease of 13.5% in firms' novel knowledge exploration (Model 1). As to inter-organizational learning behavior, the variable selected in this study has no significant impact on the firms' novel knowledge exploration. In terms of firms' experiential learning, firms that have participated in public subsidy programs have a 65.29% lower probability of novel knowledge exploration than other firms at 1% significant level (Model 1).

At the same time, firms involved in high-tech manufacturing sectors are less likely to learn and adopt novel knowledge. Larger-scale firms also have lower propensities to explore novel knowledge, while longer-established firms have greater incentives to explore and adopt novel knowledge.

Table 6.2 Cox Regression Model (Event: Novel Knowledge Exploration)

	Model 1	Model 2	Model 3	Model 4	Model 5
Know_stock	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hi_edu_emp	-0.145**	-0.142**	-0.142**	-0.146**	-0.143**
	(0.061)	(0.058)	(0.059)	(0.060)	(0.059)
Tech_Coll	0.019	0.020	0.020	0.019	0.020
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Pre_subsidy	-1.058***	-1.079***	-1.055***	-1.082***	-1.081***
	(0.177)	(0.180)	(0.177)	(0.180)	(0.180)
Firm_Age	0.182**	0.180**	0.182**	0.180**	0.179**
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
Firm_Size	-0.156***	-0.162***	-0.153***	-0.166***	-0.163***
	(0.047)	(0.048)	(0.048)	(0.049)	(0.049)
Hi_Tech_ind	-0.328**	-0.332**	-0.325**	-0.337**	-0.333**
	(0.158)	(0.159)	(0.159)	(0.160)	(0.160)
Export	0.006	0.006	0.006	0.006	0.006
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Cap_int	-0.011	-0.012	-0.009	-0.015	-0.012
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
RD_dpart	-0.114	-0.117	-0.113	-0.118	-0.117
	(0.119)	(0.118)	(0.119)	(0.118)	(0.118)
Public_project		-0.072			
		(0.079)			
Province_only			-0.045		-0.064
			(0.126)		(0.128)
Nation_only				-0.067	-0.075
				(0.090)	(0.091)
N	1239	1239	1239	1239	1239
Firms	765	765	765	765	765
Log pseudolikelihood	-3724.1067	-3723.7306	-3724.0464	-3723.8443	-3723.7277
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000

Note: 1) Robust Standard errors (in parenthesis) are clustered at the firm level; 2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; 3) Efron method for ties; 4) All models include a set of industrial, regional and year dummies (not reported).

6.4.2 Influence of Public R&D Subsidy on Changing of Firms' Core Industrial Technologies

As shown in Table 6.3, in general, the results illustrate that firms participating in public R&D subsidy programs have a higher probability (30.34%) of changing their technological focus than other firms (Model 7) at 1% significance level. After distinguishing the level of programs, this significant positive influence can be observed when firms only participated in local R&D subsidy programs. Firms are 44.05% more likely to change their technological focus than others when participating in local programs (Model 8), at the 1% significance level. No such facilitation effect can be found when firms only receive national R&D subsidies (Model 9).

As to firms' congenital learning behavior (Model 6), firms' knowledge stock has a negative effect on the firms' changing of its technological focus at the 5% significance level. When firms' knowledge stock increases by 1%, there is a decrease of 0.30% in firms' changing of its technological focus. Inter-organizational learning, i.e., collaboration with universities, has no effect on firms' technological focus change. In terms of firms' experiential learning, firms that have participated in public subsidy programs have a 78.97% lower probability of changing their technological focus than other firms at 1% significant level (Model 6).

At the same time, firms involved in high-tech manufacturing sectors are also less likely to change their technological focus. The probability is 31.82% lower than those in low-tech manufacturing sectors.

Table 6.3 Cox Regression Model (Event: Firms' Technological Focus Change)

	Model 6	Model 7	Model 8	Model 9	Model 10
Know_stock	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Hi_edu_emp	-0.085	-0.099	-0.098	-0.088	-0.104
	(0.052)	(0.066)	(0.061)	(0.056)	(0.069)
Tech_Coll	0.021	0.015	0.014	0.020	0.012
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Pre_subsidy	-1.559***	-1.472***	-1.570***	-1.504***	-1.500***
	(0.354)	(0.358)	(0.351)	(0.357)	(0.355)
Firm_Age	-0.008	-0.010	-0.014	-0.007	-0.013
	(0.087)	(0.087)	(0.086)	(0.088)	(0.086)
Firm_Size	-0.091	-0.068	-0.126**	-0.063	-0.095
	(0.058)	(0.059)	(0.060)	(0.062)	(0.062)
Hi_Tech_ind	-0.383**	-0.378**	-0.404**	-0.370**	-0.392**
	(0.184)	(0.184)	(0.187)	(0.184)	(0.187)
Export	0.010	0.010	0.011	0.010	0.011
	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
Cap_int	-0.037	-0.034	-0.055	-0.028	-0.046
	(0.047)	(0.047)	(0.047)	(0.047)	(0.048)
RD_dpart	0.084	0.084	0.085	0.083	0.085
	(0.150)	(0.150)	(0.151)	(0.150)	(0.151)
Public_project		0.265***			
		(0.101)			
Province_only			0.365**		0.414***
			(0.154)		(0.159)
Nation_only				0.155	0.202*
				(0.109)	(0.113)
N	1521	1521	1521	1521	1521
Firms	776	776	776	776	776
Log pseudolikelihood	-2626.8988	-2623.3996	-2624.2759	-2625.9329	-2622.7069
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000

Note: 1) Robust Standard errors (in parenthesis) are clustered at the firm level; 2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; 3) Efron method for ties; 4) All models include a set of industrial, regional and year dummies (not reported).

6.4.3 Robustness Check and alternative explanation

Robustness Check

In the robustness check, this study employs a cross-sectional probit regression with controlling industries and regions in 2011, as time lags exist in the effectiveness of R&D subsidies. At the same time, to control the potential endogeneity issue of R&D subsidy, we also set an instrumental variable for the independent variables and re-run the probit regression. Following the suggestions of Guo et al. (2016), the ratio of total investment in fixed assets made by local governments over the total GDP at the city level is employed as the instrumental variable.

The results from the probit regression (see Table 6.4) are qualitatively similar to the results obtained from the Cox regression. Participating in public subsidy programs has no significant impact on firms' novel knowledge exploration (Model 11, 12, 13). While receiving public R&D subsidy, local R&D subsidy especially has a significant positive impact on firms' technological focus changing (Models 14, 16), but no facilitation effects can be observed by receiving central funds (Model 18). After adding the instrumental variable, the significant positive effects of general and local R&D subsidy programs on firm-level exploratory learning are supported as well (Model 15, 17). The positive effect of national subsidy programs is also rejected by the probit regression with instrumental variables (Model 19). These results provide additional support for our empirical results.

Alternative explanations

One potential alternative explanation is that firms may enjoy much cheaper resources provided by the government on R&D activities. By helping firms to overcome resource constraints and reduce the risk, resource enhancement plays a more critical role in novel knowledge exploration and technological focus change, rather than on organizational learning. If this is the case, regardless of the external learning environment of firms, participating in the R&D subsidy programs will promote firms' novel knowledge exploration and technological focus change. In Jiangsu Province, the regional innovation system is more developed in *Su'nan* (the south region of Jiangsu) area with many more universities and firms. This provides more learning opportunities and a better learning environment for firms in this region, rather than those in *Su'bei* (the north region of Jiangsu) and *Su'zhong* (the central region of Jiangsu) areas. Thus, sub-group Cox regression based on regions has been carried out. The results are shown in Table 6.5. Participating in the local R&D subsidy programs has a significant effect on firms' technological focus change, enhancing the probability with 59.36% (Model 22). However, no similar effect can be found on firms located in *Su'bei* and *Su'zhong* areas. Therefore, the hypotheses from the learning perspective are supported.

Another potential alternative explanation is that firms may seek to satisfy the requirements of the government to explore the novel knowledge and change technological focus for acquiring R&D subsidy. Several Chinese public R&D subsidy programs will require target firms to adopt novel knowledge in order to promote industrial upgrading. If this is the case, the firm may return to the familiar technological track after the technological focus change. To illustrate this hypothesis, we define the event variable of Cox regression as whether the firm returns to the familiar technological track after changing the technological focus. The results are shown in Table 6.6. Participating in local R&D subsidy programs will not increase the probability of the firm returning to the familiar technological track. Therefore, the change of R&D behaviors after receiving the local R&D subsidy can be better explained by the learning perspective, rather than the agency risk perspective.

However, it is also found that firms participating in central R&D subsidy programs were nearly twice as likely to return to the familiar technological tracks as other firms, at the 1% significance level (Model 25). In addition, firms with prior experience in receiving R&D subsidy have nearly three times higher probability of returning to the original technological tracks after changing their technical focus. The results imply that firms participating in central R&D subsidy programs may have higher agency risk.

Table 6.4 Probit estimates for the effect of R&D subsidy in 2011

	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19
Know_stock	0.002	0.002	0.002	0.000	-0.000	0.000	-0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hi_edu_emp	-0.089**	-0.093**	-0.089**	-0.114	-0.060	-0.149	-0.187	-0.101	-0.079
	(0.038)	(0.040)	(0.038)	(0.133)	(0.121)	(0.174)	(0.190)	(0.104)	(0.061)
Tech_Coll	-0.007	-0.008	-0.006	-0.007	-0.069***	-0.010	-0.059**	0.003	0.029*
	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)	(0.022)	(0.027)	(0.022)	(0.016)
Pre_subsidy	-1.301***	-1.302***	-1.308***	-0.169	0.332	-0.206	-0.079	-0.205	-0.464*
	(0.335)	(0.335)	(0.336)	(0.333)	(0.303)	(0.348)	(0.311)	(0.338)	(0.250)
Firm_Age	0.113	0.112	0.113	-0.091	-0.079	-0.095	-0.115	-0.081	-0.009
	(0.115)	(0.115)	(0.115)	(0.117)	(0.098)	(0.117)	(0.105)	(0.117)	(0.093)
Firm_Size	-0.012	-0.022	-0.014	-0.080	0.060	-0.160**	-0.347***	-0.083	-0.366***
	(0.073)	(0.075)	(0.075)	(0.077)	(0.079)	(0.078)	(0.086)	(0.078)	(0.061)
Hi_Tech_ind	-0.144	-0.154	-0.141	-0.075	-0.203	-0.143	-0.509*	-0.047	-0.204
	(0.295)	(0.296)	(0.294)	(0.305)	(0.253)	(0.318)	(0.307)	(0.303)	(0.234)
Export	-0.014	-0.014	-0.014	0.007	0.009	0.004	-0.006	0.007	-0.015
	(0.016)	(0.016)	(0.016)	(0.017)	(0.014)	(0.017)	(0.016)	(0.017)	(0.013)
Cap_int	-0.006	-0.011	-0.008	-0.014	0.059	-0.049	-0.143**	-0.020	-0.193***
	(0.057)	(0.058)	(0.058)	(0.066)	(0.053)	(0.065)	(0.063)	(0.066)	(0.047)
RD_dpart	-0.250	-0.250	-0.252	0.193	0.180	0.191	0.200	0.173	-0.034
	(0.169)	(0.169)	(0.169)	(0.173)	(0.149)	(0.175)	(0.158)	(0.174)	(0.144)
Public_project	0.030			0.279**	1.997***				
	(0.121)			(0.132)	(0.289)				
Province_only		0.079				0.562***	2.707***		
		(0.187)				(0.200)	(0.804)		
Nation_only			-0.003					0.054	-2.342***
			(0.138)					(0.147)	(0.132)
_cons	0.043	0.114	0.069	-0.350	-1.531***	0.390	2.366**	-0.261	3.822***
	(0.732)	(0.733)	(0.751)	(0.697)	(0.564)	(0.714)	(0.974)	(0.732)	(0.568)
N	497	497	497	468	468	468	468	468	468

Note: 1) Standard errors are in parentheses; 2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; 3) All models include a set of industrial and regional dummies (not reported).

Table 6.5 Sub-group Cox regression based on regions

	Model 20	Model 21	Model 22	Model 23
	Su'nan	Su'zhong &Su'bei	Su'nan	Su'zhong &Su'bei
Know_stock	-0.000	-0.000	-0.003*	-0.011***
	(0.001)	(0.001)	(0.001)	(0.004)
Hi_edu_emp	-0.147	-0.151***	-0.037	-0.519
	(0.091)	(0.049)	(0.104)	(0.684)
Tech_Coll	0.019	0.037	0.018	0.046
	(0.016)	(0.027)	(0.020)	(0.030)
Pre_subsidy	-0.784***	-2.116***	-1.353***	-2.213***
	(0.198)	(0.440)	(0.402)	(0.783)
Firm_Age	0.266***	0.036	0.064	-0.287*
	(0.093)	(0.136)	(0.104)	(0.162)
Firm_Size	-0.148**	-0.259***	-0.046	-0.206*
	(0.058)	(0.101)	(0.076)	(0.115)
Hi_Tech_ind	-0.349*	-0.468	-0.449**	-0.195
	(0.184)	(0.358)	(0.208)	(0.474)
Export	0.007	0.012	0.009	0.002
	(0.012)	(0.022)	(0.016)	(0.024)
Cap_int	-0.031	-0.000	-0.046	-0.144
	(0.041)	(0.095)	(0.053)	(0.122)
RD_dpart	-0.167	0.142	0.052	-0.077
	(0.126)	(0.357)	(0.169)	(0.374)
Province_only	-0.041	-0.205	0.466**	0.430
	(0.156)	(0.231)	(0.190)	(0.326)
Nation_only	-0.062	-0.126	0.191	0.284
	(0.107)	(0.177)	(0.137)	(0.199)
N	880	359	1095	426
Firms	544	221	554	222
Log pseudolikelihood	-2501.814	-820.9780	-1742.9326	-595.9633
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Note: 1) Robust Standard errors (in parenthesis) are clustered at the firm level; 2) * p < 0.1, ** p < 0.05, *** p < 0.01; 3) Efron method for ties; 4) All models include a set of industrial, regional and year dummies (not reported).

Table 6.6 Return to the familiar technological track

	Model 24	Model 25	Model 26
Know_stock	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
Hi_edu_emp	-0.556	-0.719	-0.736
	(0.419)	(0.473)	(0.479)
Tech_Coll	0.013	0.008	0.007
	(0.022)	(0.021)	(0.022)
Pre_subsidy	0.829***	1.058***	1.059***
	(0.214)	(0.231)	(0.231)
Firm_Age	-0.045	-0.064	-0.064
	(0.118)	(0.120)	(0.119)
Firm_Size	0.073	0.181**	0.176**
	(0.079)	(0.081)	(0.082)
Hi_Tech_ind	-0.207	-0.173	-0.178
	(0.242)	(0.240)	(0.242)
Export	-0.006	-0.006	-0.006
	(0.016)	(0.016)	(0.016)
Cap_int	-0.103*	-0.068	-0.070
	(0.055)	(0.057)	(0.056)
RD_dpart	-0.095	-0.101	-0.104
	(0.191)	(0.186)	(0.186)
Province_only	-0.114		0.074
	(0.210)		(0.219)
Nation_only		0.732***	0.742***
		(0.149)	(0.154)
N	2080	2080	2080
Firms	785	785	785
Log pseudolikelihood	-1605.3688	-1593.1108	-1593.0541
Prob > chi2	0.0001	0.0000	0.0000

Note: 1) Robust Standard errors (in parenthesis) are clustered at the firm level; 2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; 3) Efron method for ties; 4) All models include a set of industrial, regional and year dummies (not reported).

Table 6.7 The conclusion of the empirical results of Chapter 6

Hypotheses	**Empirical results**
Hypothesis 1 a: Participation in public R&D subsidy programs will facilitate firms' novel knowledge exploration behaviors	Not supported (insignificant)
Hypothesis 1 b: Participation in public R&D subsidy programs will encourage firms to change core technological focus.	Supported
Hypothesis 2 a: Participation in the central R&D subsidy programs can promote firms' novel knowledge exploration behaviors.	Not supported (insignificant)
Hypothesis 2 b: Participation in the local R&D subsidy programs can promote firms' novel knowledge exploration behaviors.	Not supported (insignificant)
Hypothesis 3 a: Participation in the central R&D subsidy programs may inhibit the change of firms' technological focus.	Not supported (insignificant)
Hypothesis 3 b: Participation in the local R&D subsidy programs can promote the change of firms' technological focus.	Supported

6.5 Discussion

By using Cox regression based on propensity score matching (PSM), it is found that firms participating in public R&D subsidy programs have a higher probability of changing their core technological focus with novel knowledge than other firms. Furthermore, R&D subsidies from local governments have significant effects on firms' core technological focus change, while those from the central government have no such effects. The results of this study can contribute to current public R&D subsidy literature by testing the effect of public support on firms' exploratory learning behaviors. This study also expands the application of learning theory in R&D subsidy research by exploring the extent to which firms use novel knowledge. In addition, this study deepens the understanding of R&D subsidies by differentiating the effects of sponsored programs from central and local governments. These findings can provide practical enlightenment for both the governments and firms, especially for those seeking technological upgrading.

In this chapter, we explored the influence of participating in public R&D subsidy programs on firms' exploratory learning behaviors. The empirical results show that public R&D subsidies have no significant effect on firms' general behaviors of novel knowledge exploration, but have a positive facilitation effect on firms' changing their technological focus by adopting novel knowledge. We further distinguish the different effects of R&D subsidy programs of local and central governments. Our results show that participating in local R&D subsidy programs can significantly increase the probability of firms changing their technological focus, but such a facilitation effect cannot be found with participation in the national programs.

Our empirical results contribute to the existing literature in several ways. First, we extend the understanding of public R&D subsidy from the learning perspective, which strengthens the theoretical depth in the related research field. The empirical results show that the firms' existing knowledge stock, such as extant highly educated human resources, has a significant negative effect on their novel knowledge exploration and the change of firm-level technological focus, even though the firms are sponsored by governments. Especially in changing technological focus, firms with higher knowledge stocks have stronger rigidity in their existing technologies, which leads firms to rely more on the existing technological trajectories (March, 1991). Therefore, firms with higher knowledge stocks find it more difficult to change their technological focus. Our results also indicate that prior experience of participating in public subsidy programs has a significant negative impact on firms' novel knowledge exploration and the change of technological focus. With previous experience of working with government, firms may become increasingly dependent on governments and regard the certifications from governments as the most crucial task. Thereby, the motivation for undertaking R&D with novel knowledge and further changing technological focus is reduced (Kotabe et al., 2011). This echoes and reinforces the arguments of Clarysse et al. (2009).

Second, our study differentiates the effects of R&D subsidy from the central and local governments on firms' learning behaviors. From the perspectives of the types of providing resources and the proximity to local firms, it is argued that central government is more likely to subsidize firms with "can be observed" advantages to undertake R&D programs with explicit and concrete targets in order to satisfy national S&T strategy demands (Wang et al., 2017). In other words, participation in programs of central government may restrict the directions of firms' technological development (Grodal, Gotsopoulos, & Suarez, 2015), even though firms sponsored by more generic resources can be better at innovation in frontier technological fields as well as sales of new products (Li et al., 2018; Zhou et al., 2018). Thus, the flexibility is less in reshaping the R&D

process and reconfiguring related resources with participation in programs of central governments (Li et al., 2018). Firms are more likely to innovate on the existing technological directions, than change the technological focus. In contrast, with lower information asymmetry and higher interest alignments with local firms, local governments can create a more stable environment for firms' exploratory learning, technological focus changing and technological upgrading. This supports the argument of Zhang et al. (2015). These arguments provide a new perspective for R&D subsidy studies and expand the strategic research related to the government-industry relationship.

Third, this study further unpacks the "black-box" of R&D subsidy and complements existing relevant studies in the context of China. This study tests the effect of participation in R&D subsidy programs on Chinese firms' learning behaviors. Conventional studies argue that Chinese firms may simply seek economic returns or quick exploitation on familiar knowledge, especially with public funds (Guan & Yam, 2015). However, our results indicate that Chinese firms increasingly emphasize the exploration and adoption of novel knowledge by raising awareness of the importance of innovation-driven development. As a result, Chinese firms have strong motivations in novel knowledge exploration to ensure the success of R&D activities, regardless of whether receiving public subsidies or not. At the same time, the R&D subsidy still facilitates change in firms' technological focus for industrial upgrading, which has higher uncertainty and risk.

6.6 Appendix

6.6.1 PSM sampling

On the basis of this sample, the study takes the firms' first year of receiving R&D subsidy as the baseline period and adopts the propensity score matching (PSM) to constructed PSM sampling to eliminate selective bias. The treatment variable of PSM in this study is a dummy variable that is assigned score 1 if a firm has participated in local or central R&D subsidy programs during the base period, otherwise 0. A set of covariates is selected according to more technology-related screening criteria of R&D subsidy programs.

We adopt a dummy variable '*RD_Dpart*' to denote that firms have their own R&D institutions, such as a testing base, R&D center and laboratories to control for R&D capabilities. We also control for the value of exports (*Export*) as export-oriented firms are assumed to be more innovative so as to cope better with international competition.

Capital intensity (*Cap_int*) is used to measure the financial status of firms. Basic firm-level information including firm size (*Firm_Size*) and firm age (*Firm_Age*) are also controlled for. Moreover, we restrict the time effect by adding in time dummy variables, ensuring that firms in two comparing groups have the same base period. Several industrial dummy variables according to the industrial distributions are also set. In addition, the high-tech manufacture sectors (*Hi_Tech_ind*) defined by the National Bureau of Statistics are also controlled.

Table 6A.1 presents the results of the probit estimation using the full sample in the base period to estimate propensity scores (Model A1). 1-1 nearest neighborhood matching (1-1 NNM) without replacement is performed to identify the control group of firms. Meanwhile, we use a caliper with a pre-specified tolerance as 0.02 to avoid "bad" matches. Based on the PSM sample, we re-estimate the propensity scores, the result of which is presented in Table 6A.1 (Model A2). As shown in Table 6A.1, no single covariate remains significant and the pseudo-R2 drops sharply from 0.081 to 0.006 after matching on the base period. This means that the systematic differences in the distribution of covariates between the treatment and the control groups have been removed from our PSM sample.

Table 6A.1 The first-step Probit regression for PSM

	Model A1 Pre-matching	Model A2 Post-matching
Hi_Tech_ind	-0.119	-0.078
	(0.120)	(0.180)
RD_dpart	0.160*	0.066
	(0.087)	(0.127)
Firm_Size	-0.131***	-0.002
	(0.030)	(0.052)
Firm_Age	0.070	-0.006
	(0.053)	(0.086)
Cap_int	0.078***	-0.045
	(0.026)	(0.043)
Export	-0.014*	-0.005
	(0.007)	(0.012)
_cons	0.150	0.174
	(0.433)	(0.733)
N	1424	790
Firms	1424	790
Log pseudolikelihood	-1287.3858	-761.4030
Prob > chi2	0.0000	0.9998
Pseudo R^2	0.081	0.006

Notes: (1) Standard errors in parentheses; (2) *** p<0.01, ** p<0.05, * p<0.10; (3) All models include a set of industrial and year dummies (not reported)

We also provide a balance test for the means of covariates between the treatment and control groups (see Table 6A.2). According to the t-test statistic and the corresponding p-value on mean differences for covariates, the means of covariates are balanced between the treatment and control groups. In addition, the mean standardized bias (MSB) drops sharply after matching, which suggests that the matching is successful.

Table 6A.2 Balance test for PSM

	Means		t-test		MSB (%)	
Covariates	Treatment	Control	t-Stat	p>t	Before Match	After Match
Hi_Tech_ind	0.234	0.244	-0.41	0.683	9.8	-2.4
RD_dpart	0.860	0.875	-0.77	0.441	5.1	-4.3
Firm_Size	5.257	5.288	-0.46	0.642	-35.4	-2.7
Firm_Age	2.366	2.364	0.06	0.955	1.5	0.3
Cap_int	4.927	4.955	-0.41	0.685	-9.3	-2.3
Export	4.256	4.302	-0.19	0.853	-17.8	-1.1

6.6.2 Industrial and regional distributions

Table 6A.3 Industrial Distribution based on 2-digit industrial codes

2-digit industrial code	Industrial name	Firm number
17	Manufacture of Textile	10
26	Manufacture of Raw Chemical Materials and Chemical Products	64
27	Manufacture of medicines	52
28	Manufacture of chemical fibers	6
29	Manufacture of rubber and plastics	14
30	Manufacture of Non - metallic Mineral Products	30
31	Smelting and processing of ferrous metals	6
32	Smelting and processing of non-ferrous metals	4
33	Manufacture of metal products	20
34	Manufacture of General-Purpose Machinery	88
35	Manufacture of Special Purpose Machinery	206
37	Manufacture of Transport Equipment	26
38	Manufacture of Electrical Machinery and Equipment	82
39	Manufacture of communications and other electronic equipment	112
40	Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work"	62
41	Other manufacturing	8
Total		790

Table 6A.4 Area distributions in Jiangsu

Regions	Cities	Firm number
The north region of Jiangsu (Su' Bei)	Xuzhou, Lianyungang, Huai'an, Yancheng, Suqian	60
The central region of Jiangsu (Su' Zhong)	Yangzhou, Taizhou, Nantong	166
The south region of Jiangsu (Su'Nan)	Nanjing, Suzhou, Wuxi, Changzhou, Zhenjiang	564
Total		790

7. Discussion

In this dissertation, three empirical studies are arranged to answer one core research question about how public R&D subsidy influences the firm-level learning behaviors, which extends understanding of extant R&D subsidy related studies following the logic of neoclassical economics. The theoretical perspective of this dissertation echoes and follows the logic of Schumpeterian growth theory, which is an interdisciplinary theoretical system integrated by evolutionary economics, organizational learning perspective, and systematic theory.

The Schumpeterian growth theory compensates for the insufficiency of neoclassical economics to a certain extent, regarding innovation as the endogenous determinant of economic growth (Aghion et al., 1998; Romer, 1986). On the one hand, Schumpeterian growth theory regards knowledge recombination as the key source of innovation, arguing that knowledge growth and technological advancement have a fundamental impact on economic development (Romer, 1986). At the micro-level, the accumulation of specialized and unique knowledge plays a key role in the enhancement of firms' competitive advantages, which is the fundamental reason for the differences in productivity among firms. The core competencies of a firm can be achieved through organizational learning (Levitt & March, 1988; March, 1991). Therefore, in Schumpeterian growth theory, knowledge is an important resource, learning is an important economic activity, and the firms can achieve sustainable growth through knowledge accumulation and learning (Lundvall, 1992; Romer, 1986).

On the other hand, the Schumpeterian growth theory breaks with the conclusion that growth is balanced and continuous development. Alternatively, the notion of "creative destruction" is the key to growth (Aghion & Howitt, 1992). During the process of destruction, innovations are constantly emerging, and the window of opportunity has been created, making it possible for catching up or even leapfrogging (Lee & Malerba, 2017). In the discontinuity generated by "creative destruction", appropriate public intervention is necessary to promote knowledge creation, break the existing pattern, and thus reshape social cognition on innovation and facilitate the formation of the legitimacy of innovation (Freeman, 1989; Nelson, 1993).

The design of innovation policies increasingly emphasizes the creation, accumulation, diffusion, and application of new knowledge through firms' learning behaviors under the logic of Schumpeterian growth theory. Accordingly, this dissertation complements and expands the innovation policy literature, especially the R&D subsidy studies by providing a new theoretical perspective for the government to formulate innovation policies and effectively improve firm-level R&D capabilities. At the same time, it also provides a new theoretical perspective for firms to allocate governmental resources for organizational learning, research and development activities, and thereby obtaining sustainable competitive advantages.

First, this dissertation extends the understanding of public R&D subsidy from the learning perspective, which strengthens the theoretical depth in the related research field (Clarysse et al., 2009; Gök & Edler, 2012; Zhou et al., 2019). More specifically, this dissertation analyzes and explores the changes in firm-level R&D behaviors under the sponsorship of R&D subsidy. This surpasses the R&D-subsidy-related extant studies which mainly focus on the logic of neoclassical economics. This research verifies the impact of public R&D subsidies on two kinds of learning behavior of firms, namely novel knowledge exploration and familiar knowledge exploitation. Especially, investigations into the impact of novel knowledge on R&D deepen the understanding of the changing learning behaviors of firms supported by the government. This may help us to better understand how R&D subsidy can underpin firms to overcome system failure.

Second, from a more comprehensive perspective, this dissertation further explores and portrays the heterogeneous factors of moderating the effects of R&D subsidies on firms' learning behaviors. This contributes to extant studies on organizational learning theory (Clarysse et al., 2009; Huber, 1991). Specifically, the dissertation integrates studies on firms' development stages and innovation novelty, explores the differences in the use of novel knowledge in firms at different stages of development and their underlying reasons, and supplements the research of Barbosa et al. (2014). From the perspectives of external tacit knowledge learning, and the learning curve with decreasing returns to experience, this dissertation tests and discusses the role of firms' congenital learning, inter-organizational learning and experiential learning in the interactions between R&D subsidy, firms' learning behaviors and R&D outputs. The conclusions of this dissertation demonstrate that firms' knowledge stock, which is developed from congenital learning, plays a key role in absorbing and adopting novel knowledge through inter-organizational learning by public support, but may potentially inhibit firms from changing their technological focus. This dual effect of congenital learning supplements extent studies.

At the same time, the experience of undertaking governmental R&D programs has eroded the effect of public funding on firms' learning behavior changes. This echoes and underpins related research in organizational learning theory (Clarysse et al., 2009; Jiang et al., 2018).

Third, for the first time, this dissertation distinguishes the different influences of central and local governments in the study of the effects of R&D subsidy on firms' learning behaviors. Based on the theoretical framework of proximity by integrating administrative, economic and geographic proximity, this dissertation explains the differences between the central and local subsidy programs from three perspectives, including the provision of generic and specialized resources, interest alignments and information asymmetry. The results of this dissertation supplement the research of Li et al. (2018) and Zhou et al. (2018) that local governments can create a more stable institutional environment for firms to change technological focus changing and upgrade technologically. This supports the argument of Zhang et al. (2015). These findings provide a new perspective for R&D subsidy studies and expand the strategic research related to the government-industry relationship.

Fourth, this dissertation extends innovation policy studies in the context of China. By exploring and verifying the impact of Chinese government R&D subsidies on firms' learning behaviors, this dissertation provides both theoretical analysis and empirical evidence for Chinese governments to design R&D subsidy programs against the background of the innovation-driven development strategy. Based on the findings of this dissertation, the Chinese government is expected to provide effective R&D subsidy policies to enhance the firm-level R&D capabilities substantially, encourage firms' learning behaviors, and promote technological focus change as well as industrial upgrading. In addition, this dissertation has a deepened understanding of the role of the science parks in the R&D subsidy research within the Chinese context, which contributes to the studies on innovation systems.

Based on the discussion of the research findings, this Ph.D. dissertation further corresponds to Mazzucato's (2016) study and attempts to answer several of the key questions about the development of new innovation policy. First, this study supports Mazzucato's (2016) view that current innovation policies need to break out of the market failures framework but focus more on system failures. This study endorses and stresses the importance of innovation policy's enabling "*the directions picked to be broad enough to allow bottom-up exploration, discovery, and learning*" (Mazzucato, 2016; p. 150). In order to make this top-down learning efficient, this study argues that the role of governments is not only to provide R&D subsidies to promote firm-level R&D investment but also to create an external environment conducive to firms' learning and R&D collaborations. By this environment creation, firms are encouraged to learn and absorb external knowledge for exploration and innovation.

Second, the evaluation criteria for innovation policy are required to change from result-based to more process-orientation. The current evaluation indicators and methods on governmental R&D investment developed by market failure framework are usually estimated by cost-benefit analysis. In other words, current evaluation criteria on innovation policy are usually concerned about whether the benefits of public intervention can compensate for the costs associated with market failures and market interventions, as well as the implementation of policies. Mazzucato (2016) argues that these traditional and static evaluation criteria on innovation policy do not match the inherent dynamics of economic development under innovation. It also does not take into account that firms are often risk-averse and have a lower willingness to change existing technological patterns so as to create a new one. The studies of this dissertation support this argument of Mazzucato (2016). My research on the effects of R&D subsidies on firms' novel learning indicates that the government can promote firms' transformation and create new technological combinations that are entirely new to firms. Without indicators for such dynamic views, the static criteria will influence the government's ability to determine the novelty of innovation and the essential growth of firms' innovation capabilities. Therefore, this dissertation argues that it is essential to develop a new set of criteria to measure and evaluate the extent to which innovation policy has changed the firms' learning behaviors and technological fields. In my studies, the novelty of IPC code combinations is mainly adopted to evaluate the change of firms' innovation behaviors after receiving public R&D subsidies, which provides important enlightenment for the development of new evaluation criteria.

Third, Mazzucato's (2016) study suggests that governments should continue to learn and adapt to transformative processes of technologies and socio-economy in the designs of new innovation policies. On the one hand, governments need to be more patient with firms' innovation activities, so as to accept the failure and experimentation of firms under the R&D directionality shown by governments. On the other hand, governments require the potential to experiment and explore the environment. Thus, governments should learn, build relevant resources, capabilities, and structures in the process of investment, discovery, and experimentation to establish a symbiotic partnership with the private sector (Mazzucato, 2016). My studies further indicate that, based on more administrative, economic and geographic proximity to local firms, local governments have greater efficiency in learning through the interaction with local firms in the process of such policies' development. Thus, the central government needs to decentralize the authority of R&D subsidy investment to local governments. This echoes the arguments of Mazzucato (2016) that innovation "*is best achieved not through heavy top-down policies, but through a decentralized structure in which the organization(s) involved remain flexible, innovative, and dynamic from within*" (Mazzucato, 2016; pp 151).

8. Conclusion, Implications and Further Studies

Combining the knowledge-based view with an organizational learning perspective, this dissertation explores and analyzes empirically the interactions between R&D subsidy, organizational learning behaviors and firm-level R&D output in the context of China from a more evolutionary and systematic perspective. A set of exclusive panel data is applied as the basis for the empirical analysis, covering 7,928 manufacturing firms in Jiangsu Province observed from 2010 to 2014. Another primary data source is the official patent database of 2024 Jiangsu firms in the manufacturing sector from the State Intellectual Property Office of the People's Republic of China. The main econometric methods are comprised of propensity score matching, instrumental variables, Tobit regression model, Logit regression model, and Cox regression model.

Three core research questions are answered in this dissertation: 1) How does R&D subsidy influence high-tech SMEs' collaborations with universities? What are the moderating roles of science parks and human resources? 2) How does public R&D subsidy influence firms' exploratory learning? Are the effects of public R&D subsidy diverse at different firm development stages? 3) By participating in public R&D subsidy programs can this enable firms to adopt novel knowledge to change their core technological focus? Do R&D subsidies from central and local governments have different effects on firms' novel knowledge exploration and the change of their core technological focus?

The main findings are as follows:

First, the R&D subsidy promotes the high-tech SMEs' investment in R&D collaborations with universities, and it also promotes SMEs' citations of knowledge from universities in the invention patent applications. At the same time, SMEs' highly-educated R&D human resources are found to positively moderate R&D subsidy to promote the firms' citations of knowledge from universities in invention patents. Surprisingly, the empirical results imply that antagonistic effects exist between the science parks and R&D subsidy, which may be due to the overlapping of public resources. Therefore, R&D subsidies can help the high-tech SMEs outside the science park to collaborate with universities but failed to be "the icing on the cake" for SMEs in the science park.

Second, R&D subsidy cannot stimulate firms' novel knowledge exploration behaviors. Furthermore, the effects of R&D subsidy on firms' exploratory learning behaviors vary at different development stages. R&D subsidy significantly reduces the probability of firms in the declining stage to explore, absorb and adopt novel knowledge in innovation. For firms at growth and mature stage, R&D subsidy has no impact on firms' exploratory learning behaviors.

Third, public R&D subsidy has no significant effect on firms' general behaviors of novel knowledge exploration, which reinforces the results of Chapter 5. While firms participating in public R&D subsidy programs have a higher probability of changing their core technological focus with novel knowledge than other firms, we further distinguish the different effects of R&D subsidy programs of local and central governments. R&D subsidies from local governments have significant effects on firms' core technological focus change, while those from the central government have no such effects. Moreover, the empirical results show that the firms' existing knowledge stock has a significant negative effect on their novel knowledge exploration and the change of firm-level technological focus, even though the firms are sponsored by governments. In addition, prior experience of participating in public subsidy programs has a significant negative impact on firms' novel knowledge exploration and the change of technological focus.

8.1 Implications

This dissertation attempts to produce practical enlightenment for both the government and firms.

For the government, this dissertation at first provides new essential insights for the design of R&D subsidy policy. Initially, according to the discussion on R&D subsidy's effects on firms' learning behaviors of this dissertation, the focus of its R&D subsidy policy had to change from being result-based to process-orientation. The government needs to pay attention to the change in firms' innovation behaviors after receiving R&D subsidies. Second, based on the results of Chapter 5, the timing of R&D subsidy allocation is also important. The government can consider giving R&D subsidies to firms in the growth stage. However, for firms in the maturity stage, and especially in the decline stage, the government should withdraw intervention and no longer grant R&D subsidies. Especially for firms in the decline stage, R&D subsidies will damage their innovation novelty, and even cause them to miss the opportunity to enter a new life cycle by using novel knowledge. Third, the study of Chapter 6 indicates that firms' motivation to undertake R&D with novel knowledge and further change technological focus is reduced with previous experience of working with the government. Thus, the government should set an appropriate interval between obtaining R&D subsidy by the same firms, in order to avoid the weakening of the positive effects of R&D subsidy caused by the declining in the learning experience and repeated investment. Fourth, based on the discussion on designing the new innovation policy, the government's R&D subsidy should take into account the novelty of patents in setting the criteria for final acceptance, rather than only using the number of patents as the single threshold. Additionally, since direct subsidies are deemed less effective in promoting novel knowledge invention, subsidy with more incentive mechanisms, such as subsidized loans, might be a better option.

In order to promote the learning behaviors of firms, the government should also help shape the external learning environment of firms. Governments should make efforts to build regional innovation systems to support the local firms and the spillover of novel knowledge, as the complicated novel tacit knowledge tends to be localized and disseminated within the region (Fritsch, 2002). Within perfect regional innovation systems, the government can help to link firms with universities and encourage knowledge sharing among firms via R&D subsidy. At the same time, the transfer and use of external new knowledge to generate technological output comes down to the improvement of internal absorptive capacities. In this way, governments, besides giving direct R&D subsidies, need to encourage firms to enhance internal congenital learning capabilities through specific behaviors and activities, for example, recruiting highly educated R&D employees. In addition, according to the findings of this dissertation, the R&D subsidy should be more allocated to the firms outside science parks.

Another important implication for policymakers is that the central government needs to decentralize the authority of R&D subsidy investment to local governments for the technological upgrading of local firms. Local governments should strengthen their interaction with local industries and leveraging systemic flexibility in order to promote the local firms' acquisition and adoption of regional specialized resources for exploratory learning and technological upgrading.

For firms, the results of this dissertation provide implications for strategic decisions on when and how to participate proactively in governmental projects in relation to the exploration of novel knowledge for the enhancement of their own innovative capabilities and technological upgrading. This dissertation also suggests that firms should emphasize the improvement of R&D capabilities and related absorptive capacities for novel knowledge through upgrading human capital and knowledge base renewal. At the same time, firms should design flexible organizational forms to efficiently absorb and adopt relevant specialized resources and knowledge when utilizing R&D subsidy. In addition, firms need to maintain close interaction with local governments to reduce information asymmetry when undertaking R&D subsidy programs.

8.2 Limitations and Further Studies

This dissertation also raises several questions for further research directions. First, the data employed in this dissertation has a comparatively short observation period, and cannot capture the impact of R&D subsidies on long-term learning behaviors and performance. As extant research stressed, firms' high level of learning behavioral additionality generated by R&D subsidies does not necessarily guarantee the success of the policy (Georghiou & Clarysse, 2006). This policy may lead firms to surpass their own capabilities, moving in wrong directions of technological development. This may lead to higher failure risks in firms' R&D activities, which is not conducive to sustainable competitive advantage. More specifically in the context of China, the evaluations of R&D subsidy projects are usually undertaken within three or four years after providing support. Therefore, in further research, the observation period of the sample can be extended with more than five years' observation to capture not only the legacy effect but the persistent effect of R&D subsidy on firms' learning behaviors as well.

Second, the sample employed in this dissertation comes from Jiangsu Province, which is a leading province of innovation in China. The R&D capabilities of Jiangsu firms are in the leading position. For other provinces, especially those with relatively backward innovation capabilities, whether R&D subsidies have the same impact is unverifiable in this dissertation. Thus, further research can compare the impact of R&D subsidies on firms' learning behaviors in different regions with different technological development stages in China. The effects of knowledge flow formed by cross-regional linkages on firms' R&D behaviors can be also explored (Qiu, Liu, & Gao, 2017).

Third, because there are differences in the relationship between firms' development stages and innovation novelty in different industries and technologies (Barbosa et al., 2014; Sorensen & Stuart, 2000), R&D subsidies designed for firms in other industries can be one of our future explorations. In addition, the effects of different types of R&D subsidy, such as subsidized loans and tax incentives on firms' learning behaviors, can be further investigated.

Fourth, this study cannot capture the effect of R&D subsidy on firms' collaborations with other industrial partners, even though Li et al. (2018) argue that interactions with suppliers, users, and even competitors have a profound effect on a firm's innovation performance. Thus, another future research direction can measure firms' organizational learning behaviors with industrial partners, and further study the effect of R&D subsidy on learning behaviors in such collaborations.

Fifth, exploring effects from types of R&D subsidy should be one of the critical directions for further study. Currently, in China, various types of R&D subsidies have been designed, including direct grants, subsidized loans, tax incentives, and even public guidance funds. As argued by Mazzucato (2016), governments can learn from the experience of private venture capitalists to design portfolios of different types of R&D subsidy by considering opportunity costs and risk tolerances. For example, the research question could be valuable about how direct grants can be used by combining subsidies with more market-orientation mechanisms, such as subsidized loans, to achieve higher efficiency. Thus, research related to finding the optimal solution for the different proportions of various R&D subsidy types could be another promising research direction.

In terms of research methodology, to further confirm the causal relationship between R&D subsidy programs and the change of firms' learning behaviors, a qualitative research technique can be designed to identify the changing directions of the technological focus of sponsored firms, thereby verifying the extent to which R&D subsidies affect firms' learning behaviors. The data envelopment analysis (DEA) method can be adopted as well to find the optimal proportion of R&D subsidies on firms' R&D investment in different regions. At the same time, the DEA method can also help to explore the optimal solution for the different proportions of various R&D subsidy types, and thereby provide guidance for the government to formulate more effective R&D subsidy policies.

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