The Allocation and Effectiveness of China's R&D Subsidies – Evidence from Listed Firms

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Abstract: In this study we investigate the allocation of China's R&D subsidies and their effectiveness in stimulating business R&D investments for the population of Chinese listed firms between 2001 and 2006. With respect to subsidy allocation, we find that firm selection is mainly determined by prior grants, high quality inventions, and minority state-ownership. Market-oriented provincial governments distribute grants less frequently, and firms located in developed provinces receive grants more often. Considering effectiveness, R&D subsidies instantaneously crowd-out business R&D investment but are neutral in later periods. In 2006, one public RMB reduces business R&D investments by half an RMB. However, crowding-out is not prevalent for repeated recipients of R&D subsidies, high-tech firms, and minority state-owned firms.

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1 Introduction

In global comparison, China’s business expenditures for R&D and the economy’s total R&D spending both rank second to the US (OECD 2014). Currently China contributes 20% of the global R&D expenditures and, assuming linear growth, will replace the US before 2020 to become the single largest contributor to global R&D spending. Within one decade, China has closed the gap with high income countries in terms of R&D. Given China’s formerly planned economy, an obvious question is to what extent China’s stunning rise as an innovation-driven economy has been influenced by governmental economic policies.

To provide an answer, we focus on the crucial time period at the onset of the millennium, when the State Council sought to encourage China’s economic development through innovation, high-technology, and industrialization (Liu et al. 2011). To increase China’s industrial R&D and to contribute to the economy’s technological sovereignty, R&D operations have been largely relocated from public research institutes to state and non-state firms (Liu 2009). Importantly, the government provided substantial funding in the form of R&D grants to incentivize firms’ R&D. In particular, these subsidies have targeted inventive high-tech firms, firms intended to become main drivers of China’s technological trajectory.

From 2001 to 2006, China’s public support for industrial innovation amounted to 450 billion RMB – two thirds of which came from R&D funds – and contributed 60% of all industrial R&D investments (Ministry of Finance (MOF) 2014). Over the same period, the industrial contribution to China’s gross expenditures for R&D increased from 60% to 71% and extended their contribution to GDP from 0.58% to 0.99%. Likewise, gross R&D expenditures to GDP grew from 0.95% to 1.39% (MOF 2014, National Bureau of Statistics (NBS) 2014).

Although these figures show increasing industrial R&D in relative and absolute terms, the effect of China’s R&D subsidies remains unclear. As pointed out by Arrow (1962), due to market failure in the production of knowledge, R&D investments of firms may remain below the social optimum and require correction by public subsidies. However, if government subsidies fail to increase firms' own R&D investments, i.e. R&D investments financed by firms' own funds, then the economic justification for public funding of business R&D is questionable. In other words, if grants allocated by the government do not result in additionality but instead are effectively neutral or even crowd-out firms' own R&D expenditures, the policy intervention cannot be considered a success. In China's case, the recurrent underachievement of national R&D targets throughout the first half of the last decade indeed questions the effectiveness of policy measures employed.[1] Thus, careful examination of the effectiveness of China's R&D subsidies on firms' own R&D expenditures is required.

Because prior studies of China's R&D subsidies are small in number and often suffer from methodological limitations, we aim to contribute new evidence to the literature. We estimate the effect of R&D subsidies by investigating changes in recipients' and otherwise comparable non-recipients' R&D investments over time. To estimate treatment effects and to control for potential selection bias in the distribution of grants, we derive robust estimates by combining non-parametric propensity-score matching (PSM) with a difference-in-differences (DID) estimator as the properties of both estimators are complementary.

This econometric strategy is employed to a unique panel on the population of Chinese listed firms, observed throughout the time period 2001 to 2006. We match firm level data from annual reports with numerous data sources, including patent data from the European Patent Office's Worldwide Patent Statistical Database (PATSTAT), and we match export data from Chinese Customs. An exhaustive set of variables is operationalized to capture the firm characteristics that determine the allocation of R&D subsidies. Because the government

[1] China's 9th and 10th "Science and Technology Development Plan" specify target ratios of 1.5% for gross R&D expenditures to GDP in 2000 and 2005 but actual ratios reached were 0.90% and 1.35%.

emphasized the importance of firms' inventiveness and the high-tech to accelerate China's technological trajectory, we place particular emphasis on these characteristics.

We briefly foreshadow our findings. For the allocation of R&D subsidies, our results show that the selection of recipient firms is mainly determined by high quality inventions whereas high-tech sector affiliation is less important. Further, we find that firms show persistence in receiving R&D subsidies. We also consider the consequences of China's transition from a centrally planned to a mixed market economy on grant distribution which, until now, have not been published in the literature. Regarding the influence of state-ownership, we find that minority state-owned firms are more likely to become subsidy recipients than majority state-owned and private-owned firms. Provincial variation in China's transition towards a market-driven economy reveals that R&D subsidies are less often distributed by more market-oriented provincial governments and that China's national innovation policy of "picking the winners" is more supportive to firms located in developed provinces.

Considering effectiveness, we find that R&D subsidies instantaneously crowd-out firms' own R&D investment but are neutral in later periods. For example, in 2006 one public RMB reduced firms' own R&D investments by half an RMB. This implies that public subsidies fail to correct business R&D towards the social optimum but instead cause partial crowding-out. However, for repeated recipients, high-tech firms, and minority state-owned firms, we identify neutral effects, i.e. firms' own R&D investments remain unchanged. Nonetheless, the economic justification for China's R&D programs between 2001 and 2006 is generally questionable since we fail to identify additionality effects.

The remainder of this study is structured as follows. In Section 2 we discuss the rational for R&D subsidies, review prior studies and derive consequences of China's institutional structure for the allocation and effectiveness of R&D subsidies. In Section 3 we explain the econometric methodology employed. Section 4 introduces the data and provides descriptive statistics. Section 5 contains the main results, robustness tests, and further investigations. We provide concluding remarks in the final section.

2 Previous Literature

The seminal studies by Arrow (1962) and Nelson (1959) provide the theoretical rationale for R&D subsidies: because externalities in the production of knowledge are difficult to appropriate, social and private returns to inventive activity differ. In combination with the risk and moral hazard involved in financing R&D, this difference in returns may result in systematic underinvestment in R&D. To avoid the suppression of economic growth through sub-optimal innovation rates, correction of business R&D by public subsidies is required.

Although this argument has been widely accepted by researchers and policy makers, a simple reading might be misleading. First, the optimum growth rate of R&D in a given economy, industry, or firm is unknown and may differ over time (David 2012). Second, it is difficult to identify those industries in which social returns exceed private returns on average (Hubbard 2012) or those particular R&D projects for which social returns are negatively correlated with private returns (Trajtenberg 2012). Third, as government failure in the selection of R&D projects may exceed market failure, neutral instead of targeted allocation of R&D grants might be preferable but is rarely found in practice (Foray 2012). Recent contributions by Acemoglu et al. (2013) and Akcigit et al. (2014) attempt to address some of these issues in theoretical models as to provide more nuanced approaches for policy making.

The most critical question at the micro level is whether the government is able to select those R&D projects with high social returns that firms would not fund by themselves, due to low private returns. R&D subsidies encompass two main policy instruments: tax incentives and direct subsidies (David et al. 2000). The primary difference is that the former allow the firm to select R&D projects while the government remains neutral, whereas the latter typically are accompanied by government selection.

In our study we are concerned with the effect of direct R&D subsidies on firms' R&D investments. Precisely, we consider the effect of accumulated R&D grants received by a firm in a given year on changes in the firms' own R&D investments. Own R&D investments (net R&D investments) correspond to gross R&D investments less the R&D subsidies received. We illustrate the differences between gross and net R&D expenditures and the taxonomy of subsidy effects – ranging from crowding-out over neutrality to additionality – in Figure 1.

Full crowding-out occurs when public funds are perfect substitutes for private funds and decrease firms' net R&D expenditure by the full amount of the R&D subsidy. Government failure, evident in the substitution of firms' own funds by public funds, occurs because it is unknown to the government whether the selected project would have been undertaken by the firm without support. To avoid crowding-out, in practice many R&D programs require that firms match public funds with private ones, e.g. one public USD with one private USD. However, even if the initiation of a firm's project was strictly conditional on the appropriation of public support and one-to-one matching of funds was demanded, the recipient may still readjust its portfolio of R&D projects and reallocate funds from dispensable projects to the publicly supported one. Thereby, the substitution of private funds for public funds is difficult to prevent as substitution takes place outside the supported project. Even though private funds released by R&D subsidies might be used totally for new R&D projects, i.e. the firms' net R&D investments remain generally unchanged, the firm may alternatively spend some these funds for non-R&D purposes – resulting in partial crowding-out.

The government's successful correction of market failure is achieved in the situation of additionality, that is, public grants are complementary to private funds and the net R&D expenditures of subsidized firms increase. This politically aspired outcome may be caused by several mechanisms. First, the obligation to match public funds with private funds necessitates that firms spend additional private funds on R&D. Second, a subsidized project (that would not have been carried out without governmental support) involves the establishment of research facilities, lowered fixed costs of other current or future projects, and the subsequent creation of profitable investments. Third, the expertise gained throughout a subsidized project might positively influence the profitability of non-subsidized projects. In conclusion, grants directly or indirectly close the gap between social and private returns and thereby incentivize private R&D.

Admittedly, using firm level instead of project data blurs insights into the rearrangements of project portfolios and thus limits the identification of the precise mechanism through which a firm changes its net R&D expenditure (Lach 2002). Nonetheless, at the firm level we can make inferences as to whether aggregate R&D subsidies cause changes in the aggregate net R&D investment of recipients, which is essential information for policy makers. In other words, if the direct effect of government grants on business R&D investment is negative or insignificant, then the economic justification for continuing public support of private R&D is considerably undermined. Based on these insights, policy makers may consider making adjustments to innovation policy in general and to R&D programs in particular.

2.1 Prior Studies

The literature has become increasingly focused on empirically examining the effects of R&D subsidies and provides conflicting evidence. David et al. (2000) report that one-third of those studies conducted before 2000 fail to reject crowding out. Similarly, Zuniga-Vicente et al. (2014) report that one-fifth of more recent firm level studies fail to reject crowding out, while 17% report neutrality and the remaining 63% find evidence for additionality. In summary, these findings indicate the existence of context specific effects of R&D subsidies, depending on the country, time period, and methodology applied.

More recently, the literature has started to consider temporal aspects of R&D subsidies, and it confirms persistence in grant distribution (Bloch & Graversen 2008, Gonzales & Pazo 2008). Persistence might arise due to several reasons. First, because prior recipients benefit from information advantages in subsequent applications, these firms not only select themselves more often into the application process but also exhibit higher probabilities of filing successful applications. Second, governments may repeatedly select prior recipients in order to maximize the success rate of a policy. Third, persistence may be stronger among R&D projects that span multiple time periods. However, investigations into the effectiveness of prior subsidies on R&D expenditures are still scarce. For German manufacturing firms, Hussinger (2008) confirms additionality effects and Aschhoff (2009) finds additionality for frequent recipients but neutral effects for first-time receivers.

There exist several reasons why a grant may show no instantaneous but instead a lagged effect on own R&D investments. First, the adjustment of a firm's R&D portfolio might be time consuming so that the full effect only emerges with delay. Second, a subsidized project may lower the fixed costs of future projects, thereby turning those into profitable investments. Third, learning throughout a subsidized project might increase the success of upcoming R&D projects. However, the prior evidence remains inconclusive for lagged effects. Investigating Israeli manufacturing firms, Lach (2002) finds an instantaneous crowding-out effect and a lagged neutrality effect. For Norwegian high-tech industries, Klette & Moen (2012) find weak evidence for both lagged additionality and lagged neutral effects, depending on the econometric specification.

Although R&D programs are not exclusively employed by governments of developed countries, the majority of studies thereof focus on the US and Europe. The few studies for emerging countries that do exist present equally inconclusive evidence (for examples see Kwon & Ko 2004 and Lee & Cin 2010 for Korea; Özcelik & Taymaz 2008 for Turkey). In the following, we review the evidence derived from Chinese firm-level data, including studies published by Chinese language journals.[2] Because we are interested in reactions at the firm level, we exclude studies at the industry level and disregard those firm level studies that only observe subsidy data at the industry level. Our review includes ten studies that are concerned with China, seven in Chinese and three in English, as summarized in Table 1. We briefly report the main insights of our survey. Surprisingly, only one of these ten studies fails to reject crowding-out in China. By comparison, one-third of the earlier studies surveyed in David et al. (2000) and one-fifth of the more recent literature surveyed in Zuniga-Vicente et al. (2014) fail to reject crowding out.

We are therefore skeptical of this one-of-ten result. At the macro level, such hesitation is shared by Naughton (2007, p. 368), who rejects overly positive results of China's innovation policy as counterintuitive given the economy's institutional setting, and Hu & Jefferson (2008), who are skeptical that the abrupt increase in industrial R&D investment observable throughout the early 2000s has been driven by government funding. At the micro level, the findings of Guan & Yam (2014) suggest instances of government failure in China as direct subsidies have failed to enhance innovative economic performance of firms in Beijing throughout the 1990s. Interestingly, Tian & Yu (2012) point out that the government or scientific community might influence Chinese journals to select politically satisfactory evidence for publication. Although we cannot observe ex ante selection, for those studies in our review, methodological issues – and not the journal's language – seem to be decisive.

As criticized by David et al. (2000), many studies ignore endogeneity problems by assuming random selection in grant distribution. Immediately evident, this assumption of random selection cannot hold as inventive high-tech firms are clearly selectively supported by China's R&D programs. Firstly, these firms are likely to have higher R&D spending than other firms. Secondly, there exist confounding characteristics that affect both R&D spending

[2] The heterogeneous quality of the Chinese literature has convinced us to focus on studies that are published in higher-quality journals listed in the *Peking University Ranking of Chinese Core Journals*.

and grant distribution. Thus, receiving a grant becomes endogenous to the firm's own R&D efforts. In other words, even in the hypothetical absence of government grants, the R&D expenditures of recipients are likely to be higher than those of non-recipients, leading to an overestimation of the actual subsidy effect.

Considering the estimators recommended by Blundell & Costa-Dias (2000) for policy evaluation in non-experimental settings, only the studies by Guo et al. (2014), Xie et al. (2009), and Cheng & Chen (2006) employ appropriate econometric strategies to address selection bias. To save space, we disregard studies with an obvious risk for selection bias from the subsequent discussion. Guo et al. (2014) conduct a single program evaluation for China's "Innovation Fund". However, their findings are only of marginal interest to us as the authors do not report whether the fund's official selection criteria are empirically confirmed, nor do they examine the effect on innovation inputs, e.g. R&D investments, but only consider innovation outputs. Xie et al. (2009) find a positive and significant effect of subsidies on R&D but remain unclear as to whether they observe net or gross R&D investments. Because their study employs a binary operationalization of R&D, the resulting specification allows for the conclusion that recipients have a higher likelihood of conducting R&D but limits more nuanced interpretations. Cheng & Chen (2006) examine the effect of R&D subsidies on own R&D investments and find neutrality for the average recipient. However, their study is restricted to private firms located in Zhejiang province which imposes limitations to the generalizability of their findings for China's economy and innovation policy.

As our review shows that prior studies fail to provide conclusive evidence for the allocation and effectiveness of China's R&D subsidies, we aim to fill this gap. In the following section, we derive implications of China's R&D subsidies and institutional background, which are addressed in the subsequent analysis.

2.2 China’s R&D Subsidies and Institutional Background

From 2001 to 2006, China’s innovation policy emphasized economic development through innovation, high technology, and business R&D (Liu et al. 2011). In the late 1990s, support was extended from the state- towards the non-state sector and private firms became beneficiaries of China’s innovation policies. Initiated between the mid-1980s and late 1990s, China’s major R&D programs were continuously administered by the Ministry of Science & Technology (MOST) – e.g. the Key Technologies Program or the National High Technologies Program (for details on individual R&D programs see Huang et al. 2004 and OECD 2008). There were no significant changes in China’s national innovation policy and R&D programs between the years under investigation. Only after 2006, the implementation of the “Medium- to Long-term Plan for Science and Technology Development” has provided considerable changes to China’s innovation policy.

Grant allocation occurred through an ostensibly competitive proposal process, and R&D activities that addressed the policy targets of the central government were preferentially selected (Ding et al. 2008). In addition to MOST, other central agencies and subnational governments were involved in grant allocation. However, these actors may display different bureaucratic preferences with respect to the selection of recipients. Further, essential technological expertise required for selection and monitoring of R&D programs may vary between actors (Springut et al. 2011). Because of China’s distinctive reforms, provincial governments have emerged as powerful regulators of firms in their jurisdictions (Tenev et al. 2002). Half of China’s spending for science and technology, including R&D programs, takes place at the subnational level – emphasizing the importance of provincial governments in implementing innovation policy (Springut et al. 2011). Therefore, de facto implementation of China’s R&D programs might deviate from the blueprints of the central government.

In Arrow’s (1962) and Nelson’s (1959) seminal model, the government should correct R&D investments through public subsidies and take the role of a regulator seeking to reduce market failure in the production of knowledge by private firms. However, given China's transition from a centrally planned to a mixed market economy, the government regulates privately-owned firms but also acts as a majority or minority shareholder within China's numerous state-owned firms.

During China's planned economy, the government directly commanded state-owned firms with little need for supplementary incentives (Holz 2003, p. 270). However, with respect to the ongoing separation of regulation, ownership, and management among state-owned firms throughout China's economic transformation, Lee and Hahn (2004) point to the potential rise of ownership-specific principal-agent and corporate governance issues. While the process of separation may, on one hand, increase the government's willingness to employ R&D subsidies within the state sector, it may also limit monitoring mechanisms and give rise to the abuse of public funds for non-R&D purposes (Ding 2000).

Meanwhile, many former majority state-owned firms have been transformed into minority state-owned firms with managers becoming owners, e.g. major shareholders. This transformation also corresponds with a reduction of direct governmental influence on firms but, unlike within majority state-owned firms, introduces managers as additional owners concerned with the long-term competitiveness of their firms (Tenev et al. 2002). Therefore, this transformation into a minority state-owned firm may increase the government's need to employ R&D subsidies in order to supplement weakening command of the firm. Furthermore, the corporate governance setting within minority state-owned firms appears to be beneficial for the effective use of R&D subsidies since major shareholders share the government's ambition to raise firms' R&D investments.

With respect to the increasing number of privately-owned firms operating in China's economy, the government's function is largely reduced to regulatory issues while mechanisms of direct command remain formally restricted to the state sector. In contrast to the state sector, the private sector is dictated by fierce competition as well as hard budget constraints, and private firms often pursue short-term profit maximization at the expense of uncertain R&D investments with high capital lockup (Naughton 2007, p. 309). Against this background, the private sector's potential to increase China's industrial R&D investments may appear insignificant and these firms' commitment to policy targets is relatively low. Although a privately-owned firm may be in greater need of financial support, uncertainty in the actual utilization of funds may decrease their attractiveness to a regulator. Conversely, privately-owned firms might also refrain from participation in public R&D programs because they seek to avoid government interference in their business operations. In summary, China's economic infrastructure offers the unique opportunity to study how the allocation and effectiveness of R&D subsidies are influenced by differences in firm ownership and related command mechanisms.

Progress in the transition from a planned to a market economy is not taking place uniformly but varies by province across China (Fan et al. 2007). Provincial governments follow different marketization strategies as observable in varied shares of governmental resource allocation to provincial GDPs. However, it remains unclear as to how increasing market-orientation will affect the distribution of grants. Since more market-oriented provincial governments are confronted with a higher probability of market failure within their jurisdiction, correction through frequent employment of R&D subsidies may be required. Alternatively, more market-oriented provincial governments might employ grants precisely less often in order to limit incidences of economic intervention. This pattern of provincial variation in China's economic transition between 2001 and 2006 allows us to study if marketization is accompanied by more or less frequent employment of R&D subsidies that target potential market failure in the production of knowledge.

Considering China's transformation process, marketization and economic development are related but not identical concepts (Fan et al. 2007). While intuition would suggest that marketization and development move in the same direction, it is interesting to note that in

Beijing and Shanghai, undoubtedly among the most developed places in China, governmental resource allocation in proportion to local GDPs is relatively high. In contrast, Anhui and Hebei allocate larger shares of resources through the market but these provinces are still less developed. Considering regional economic disparities, Xu (2011) argues that policies of the central government generally favor the support of China’s developed coastal regions. Indeed, firms located in developed regions may more easily access crucial resources required for successful R&D operations, making them more promising recipients than firms found in China’s backward regions. In conclusion, firm ownership, differences in the marketization strategies of provincial governments, and regional economic disparities may influence the allocation and efficacy of R&D subsidies in China beyond the explanatory scope of firm characteristics, i.e. inventiveness and high-tech orientation, specified in the central government’s policy blueprints.

3 Econometric Method

The crucial obstacle in evaluation studies is that grant distribution is mostly not random; that is, governments may select recipients according to political priorities, and certain types of firms might self-select into the application process. To avoid selection bias, the evaluation literature presents a variety of methods, such as instrumental variables techniques, selection models, PSM, or DID (for surveys see Blundell & Costa-Dias 2000, Cerulli 2010, and Heckman et al. 1999). We follow the suggestion of Blundell & Costa-Dias (2000) who argue that a combination of non-parametric PSM with a DID estimator is likely to provide robust results. Indeed, the properties are complementary, because the first relaxes the common trend assumption of the latter, while the DID estimator accounts for time-invariant unobservable firm heterogeneity which is neglected by PSM. With respect to the evaluation of subsidies, the conditional difference-in-differences (CDID) estimator has been applied by Goerg et al.

(2008) and Goerg & Strobl (2007) for panel data, as well as by Aerts & Schmidt (2008) for repeated cross-sections.

The average treatment effect on the treated can be expressed as

$$\alpha_{TT} = E(Y_i^T | S = 1) - E\left(Y_i^C \middle| S = 1\right) \quad (1)$$

where Y_i^T and Y_i^C denote the outcome variables, in our case R&D expenditures, in the treated 'T' and counterfactual 'C' situation. The treatment status – that is, the receipt or non-receipt of R&D subsidies – is indicated by $S \in \{0,1\}$. Thus α_{TT} is calculated as the difference of the actual outcome in the case of treatment with the potential outcome in the counterfactual situation.

While the actual outcome $E(Y_i^T | S = 1)$ can be calculated by the sample mean of the outcome in the treatment group, the counterfactual situation $E\left(Y_i^C \middle| S = 1\right)$ is not observed in the data. Naïvely assuming that the average outcome of the counterfactual situation equals the average outcome of the non-treated group

$$E\left(Y_i^C \middle| S = 1\right) = E\left(Y_i^C \middle| S = 0\right) \quad (2)$$

might lead to selection bias if the allocation of treatment is non-random. In our setting, China's "picking-the-winner" innovation policy aims to selectively support the inventive and high-tech firms that may have higher R&D expenditures than non-inventors or non-high-tech firms.[3] Therefore, the confounding variables that affect the distribution of R&D subsidies also affect the firm's R&D expenditures, and thus receiving a treatment becomes endogenous to the firm's R&D. Consequently, even in the hypothetical absence of treatment, the R&D expenditures of treated firms are likely to be higher than those of non-treated firms, leading to an overestimation of the actual treatment effect due to selection bias.

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[3] Indeed, the R&D intensity of inventive and high-tech firms in our sample is more than two times higher than the R&D intensity of non-inventive and non-high-tech firms.

3.1 Propensity Score Matching

PSM is a non-parametric estimator that requires no particular functional form. It matches treated and non-treated observations with similar confounders and thereby identifies a non-treated control group with the same likelihood of being treated as the actually treated group. Because the only remaining difference between both groups is the treatment, the difference in outcomes finally can be attributed to the treatment. However, PSM relies on relatively strong assumptions and is data-demanding with regard to the operationalization of relevant confounding variables.

First and most generally, the stable-unit-treatment-value assumption (SUTVA) is satisfied if the outcome takes a single value (instead of following a distribution) and if the treatment of one firm does not affect the treatment effect on another firm (Rubin 1990). Secondly, the conditional independence assumption (CIA) must be invoked. This assumption states that the receipt of treatment S and potential outcomes is independent ($\coprod$) for those firms with the same set of characteristics $X = x$ (Rubin 1977):

$$Y_i^T, Y_i^C \coprod \; S|X = x. \tag{3}$$

The CIA is only satisfied if all confounding variables are known and observable in the data. Unfortunately, the validity of SUTVA and CIA cannot be tested. However, based on the rich data observable to us we argue that enough information is given for the operationalization of confounders. Thirdly, the common support condition (CSC) demands that for all treated observations, a control-observation should be found in the sub-population of non-treated observations. In other words, CSC rules out that the treatment is perfectly predictable (0,1) based on the observables X and ensures that firms with the same characteristics X have a positive probability of receiving or not receiving the treatment (Heckman et al. 1999):

$$0 < P(S|X = x) < 1. \tag{4}$$

The CSC requires that there are no regions where either treated or control observations have zero probability to occur (for example if firms with a specific attribute included in X are strictly excluded from participation in R&D programs, e.g. foreign majority ownership). In addition, we can fulfill the CSC by removing observations on treated firms with probabilities larger than the maximum and smaller than the minimum probabilities of those observations in the potential control group. Consequently, the average treatment effect on the treated can be estimated:

$$\alpha_{TT} = E(Y_i^T | S = 1, X = x) - E(Y_i^C | S = 0, X = x). \tag{5}$$

The PSM estimator specifically addresses the issue of the CSC. Matching treated and non-treated observations might become complicated due to different dimensions or weighting schemes that may be applied for different firm characteristics in X. Fortunately, Rosenbaum & Rubin (1983) show that if CIA is satisfied, then the two treatments are independent not only of the assignment conditional on X, but also of specific functions of X, denoted as the propensity score $\hat{P}(X)$. Thus, the so-called 'curse of dimensionality' can be overcome by the use of propensity scores generated from modeling the probability of receiving a treatment.

The accuracy of matching can be improved by conditioning on a subset of X, also known as imposing stratification criteria, as done in our study. We perform nearest neighbor matching with replacement and allow the same control observations to be matched with different treated observations.[4] This replacement offers a large pool of potential controls but also causes a bias in the *t*-statistic on mean differences that is corrected for according to Lechner (2001). Our matching technique follows the routine by Czarnitzki & Lopes-Bento

[4] Considering different matching approaches, nearest neighbor is preferable to radius or kernel matching as nearest neighbor matching results in the smallest bias but largest variance. At the other end, kernel matching results in a larger bias but decreases the variance. Because we employ the most conservative matching approach, conducting other matching approaches as robustness tests is redundant.

(2013) – for further details see the Matching Protocol in the Appendix. Finally, after performing PSM we can estimate the average treatment effect on the treated:

$$\alpha_{TT}^{PSM} = E(Y_i^T | S = 1, P(X = x)) - E\left(Y_i^C \middle| S = 0, P(X = x)\right). \quad (6)$$

3.2 Conditional Difference-in-Differences Estimator

As argued in Blundell and Costa-Dias (2000), the PSM estimator still crucially rests on the CIA. Despite comprehensive data, it seems unreasonable to believe that we can observe all firm characteristics that determine the distribution of R&D subsidies and R&D expenditures. The CIA between the error term in the outcome equation and the treatment is quite strong if one considers that firms might select themselves according to their forecasted outcome. Consequently, we combine PSM with a DID estimator to control for selection bias based on observables and, in addition, time-constant firm-specific effects in the unobservables.

The DID requires panel data and compares the change in the outcome for treated observations with the change in the outcome of the counterfactual observations according to $\Delta Y_i^T - \Delta Y_i^C$, where Δ is a time-differencing operator over t_0 to t_1. The DID outcome equation can also be expressed as $\Delta Y_{it} = \alpha + \beta \Delta S_{it} + \varepsilon_{it}$, while the average treatment effect on the treated is estimated as follows:

$$\alpha_{TT}^{DID} = E\left(Y_{i,t1}^T - Y_{i,t0}^T \middle| S = 1\right) - E\left(Y_{i,t1}^C - Y_{i,t0}^C \middle| S = 0\right). \quad (7)$$

Finally, the CDID estimator combines the advantages of the PSM estimator with the advantages of the DID estimator. As such, we ensure that the treatment group and the control group are chosen according to observable confounders X, while common macroeconomic trends and constant firm-specific unobserved effects are controlled for as well. We estimate the average treatment effect on the treated according to our final specification:

$$\alpha_{TT}^{CDID} = E\left(Y_{i,t1}^T - Y_{i,t0}^T \middle| S = 1, P(X = x)\right) - E\left(Y_{i,t1}^C - Y_{i,t0}^C \middle| S = 0, P(X = x)\right). \quad (8)$$

Despite this considerable improvement, Goerg & Strobl (2008) point out that the CDID estimator might become inconsistent if firms apply for a R&D subsidy and also increase their

R&D expenditures regardless of the treatment. If this phenomenon is symmetrically distributed between recipients and non-recipients, then this issue should not be of concern. If, however, this is more common for recipients, then the subsidy effect is likely to be overestimated because the increase in R&D expenditures is not fully caused by the treatment. Even though this issue cannot be completely ruled out, we argue that our data is sufficiently rich so that correlation of time-variant unobservables with the treatment and the outcome is a minor concern. To further support this claim we provide two related robustness tests. First, we omit selected time variant variables in the matching process, thereby casting them as unobservables, and evaluate if mean differences in these variables remain after matching the treatment and control group. Second, we address selection bias as a specification error and investigate the correlation of residuals in the selection and outcome equation based on a Heckman two-step selection model.

4 Data and Descriptive Statistics

4.1 Data

Our raw data includes the population of firms listed at the two stock exchanges in mainland China between 2001 and 2006.[5] Until the mid-2000s, the central government determined stock issuance quotas in order to maintain a balance between regions in China's stock market (Pistor & Xu 2005). Provinces with sound economic performance obtained more quotas and provincial governments selected firms for initial public offerings (Du & Xu 2009). The resulting composition is an adequate reflection of China's economic development, with emphasis on better performing firms. The manufacturing industry from coastal provinces contributes the majority of firms while firms from remaining industries and provinces are included to a lesser extent. See Map 1 for an overview of firm locations.

[5] Only "domestic" firms are listed on the stock exchanges of Shanghai and Shenzhen. According to the definition of the China Securities Regulatory Commission (2006; 2002), a firm is considered "domestic" if the percentage of total shares held by foreign parties does not exceed 20%.

With respect to data quality, Long et al. (1999) have suggested that the information efficiency of China's stock markets had reached a reasonable degree before the early 2000s.[6] In line with the enforcement of stricter governance requirements, the Chinese Securities Regulatory Commission has been obligating the disclosure of subsidies since 2001 (Jing 2009).[7] China's Accounting Standards define subsidies as monetary or non-monetary assets obtained by a firm from the government, excluding capital investments undertaken by the government as a partial owner of the firm.[8] Until the end of 2006, it was compulsory to report subsidy amounts as independent items in the income statement with additional information regarding the various types of subsidies and related amounts in the supplementary report of the financial statements (Lee et al. 2014).[9]

Considering the measurement of R&D, China's measure is more broadly defined than the typical R&D measure of the OECD's Frascati manual and most of the R&D literature (Jefferson et al. 2003). The broader concept applies to both R&D subsidies and expenditures and, in addition to typical R&D expenditures, involves a range of science- and technology-related expenses, e.g. expenditures for S&T affair management (Sun & Cao 2015). Against this backdrop, in the remainder of this study we continue to refer to R&D.

With respect to subsidies, we discriminate between R&D and non-R&D subsidies but disregard tax refunds as we are concerned with the effect of direct subsidies. Information on different types of subsidies is obtained from the Chinese database RESSET (sub-categories reported in the data are omitted here): science & technology subsidies and support funds, tax

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6 Data on Chinese listed firms has been widely used in high-quality publications (for examples see Fisman & Wang 2010, Kato & Long 2006, and Fernald & Rogers 2002).

7 China Securities Regulatory Commission (2000): "Regulation no. 2 disclosure guideline for the content and format of the annual report for the public offering of companies".

8 China Accounting Standard Committee (2006): "Accounting standards no. 16 – government subsidies".

9 The China Accounting Standard Committee (2006) regulation "Accounting standards no. 16 – government subsidies" is enforced in 2007 and implies amendments in the accounting regulations for subsidies. Before 2007, financial statements include a single account for subsidy income as well as mandatory notes on the different types of subsidies received. According to the regulation in force since 2007, subsidy income is included in the non-operating income and the available information on different types of subsidies is considerably reduced.

refunds, interest rate reduction for loans, export subsidies, financial subsidies, and other subsidies. Science & technology subsidies and support funds include all R&D-related governmental funds received by the firm and are the equivalent to aggregated R&D subsidies. The remaining subsidy categories are added up to aggregate non-R&D subsidies.

PATSTAT[10] is our source of patent data. We exclusively consider applications for invention patents as to identify technological inventions and simultaneously avoid double counting of Chinese invention patents and utility/design patents. In the context of this study, applications are preferable to patent grants because applications are closer to the time of invention. The matching of accounting information to patent portfolios follows the approach of Boeing et al. (2016), which is based on firm name and accounts for previous names. Firm patent matches are performed in a semi-manual approach to take care of spelling errors, systematical abbreviations, and names written in Chinese characters, Pinyin, or English wording. Based on all possible name variations, a computer algorithm is used to match firm and patent data, followed by manual checks to assure the correctness of the matching process. We base our measures on patent families instead of patent applications as the number of families more closely corresponds to the number of inventions, while applications for the same invention may be filed in more than one jurisdiction and thus become an inflated measure. Patent families are compiled following the definition of the International Patent Documentation Center.

Because patent citations are not disclosed by China's State Intellectual Property Office, we rely on a novel approach. Specifically, we calculate citations on the family level by counting forward citations received within the first three years after the publication of the priority application filed via the Patent Cooperation Treaty (PCT) at the World Intellectual Property Organization (WIPO). Thus, citations are counted during a three year time window

[10] April 2013 version of the EPO Worldwide Patent Statistical Database PATSTAT.

that opens 18 months after the priority date. An additional advantage of this approach is that we avoid a national citation bias. Because forward citations are often received from patentees located in the same national jurisdiction as the applicant of the cited patent, by exclusively counting forward citations received from applications filed via WIPO we largely rule out the bias resulting from filings at national patent offices.[11]

For the classification of high-tech industries we follow the definition by China's NBS.[12] Export data at the harmonized system 6-digit level is obtained from Chinese Customs and matched to the firm by also taking historic firm names into account. For the subsequent identification of high-tech exports, we exclude processing trade and filter the data based on the classification of China's High and New Technology Export Products Catalogues (issued by the Ministries of Foreign Trade and Economic Cooperation, MOST, MOF, the State Administration of Taxation and the General Administration of Customs in 2000, 2003, and 2006).

Since the majority of listed firms are former state-owned firms, annual information about the share held by the government informs us of the state of firm privatization. The respective ownership data is obtained from RESSET. To observe heterogeneity in provincial transitions towards marketization, we borrow the index for government allocation of resources in provincial GDP provided by China's National Economic Research Institute (NERI) (for details see Fan et al. 2007). To measure regional economic disparities in China's development, we observe GDP per capita on the provincial level. The source of this data is China's NBS.

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[11] See Boeing & Mueller (2015) for details on PCT citations.

[12] The high-tech definition of China's NBS includes the following industries: electronic component manufacturing, other electronic equipment manufacturing, medical device manufacturing, aerospace vehicle manufacturing, electrical machinery and equipment manufacturing, measuring instruments and office machinery, pharmaceutical manufacturing, communication and related equipment manufacturing, computers and related equipment manufacturing.

Fundamental balance sheet data is obtained from the global database COMPUSTAT and Datastream, and the Chinese databases WIND and GTA CSMAR. Complementary information on R&D expenditures is hand-collected from the universe of annual reports accessible via the Chinese CNINFO database. We manually screen all documents for an exhaustive set of R&D-related key words (see Appendix). As empirical studies have found that R&D investment is highly persistent (Peters et al. 2013, Antonelli et al. 2012), we interpolate missing observations for those firms with prior R&D expenditures and set observation with no prior R&D expenditures to zero. To avoid that this practice biases our findings, we perform a robustness test based only on those observation for which R&D expenditures greater zero are directly observed (reported in Section 5.2.1). All monetary values are deflated and expressed in RMB.

Initially, our raw data includes information about 1,458 firms in 7,853 observations. We exclude 11 firms with a holding structure and 12 firms from the financial sector. Hereafter, we first eliminate measurement errors and missing values, and then we exclude outliers above the 99th percentile for our R&D outcome variables. Our final sample includes1,331 firms and 7,008 observations. As required by our estimation strategy, we calculate first-differences for the outcome and treatment variables and then lag treatment variables by two time periods so that we estimate lagged effects of R&D subsidies for up to two time periods. After again eliminating observations with missing values, our estimation sample includes 1,155 firms with 4,139 observations.

Notably, we are aware of concerns regarding the quality of Chinese data in general and of subsidy data in particular (Haley & Haley 2013). As the firm-level data used in this study leaves less room for data fabrication than does aggregated data and the financial statements of listed firms are scrutinized by accounting agencies, we are less concerned with data quality (Orlik 2011). In addition, we test the quality of subsidy information based on the *ad valorem* distribution of China’s export subsidies; in other words, we know that the volume of the export subsidy should mainly be explained by the volume of exports. For exporting firms, we regress export subsidies on total exports and a set of controls. Indeed, we find that firms' export volume is positive and highly significant (*p*-value < 0.001) in explaining the amount of export subsidy received.[13] This result confirms the expected relationship between export subsidies and export volume and thus reassures us of the general quality of subsidy data.

4.2 Descriptive Statistics

Following the objectives of China's innovation policy, we consider firm inventiveness and high-tech orientation as important determinants for grant distribution. In addition to standard firm characteristics, we operationalize a set of controls for heterogeneity in ownership, marketization measured by resource allocation by provincial governments, and regional economic disparities. Table 2 provides descriptive statistics.

Subsidies are conceptualized as binary variables to meet our methodological requirements. R&D subsidies are distributed to 10% of observations. The median intensity of R&D subsidies to R&D expenditures is 10.4%, indicating that the magnitude of grants is not trivial. Acknowledging that prior literature has confirmed persistence in the allocation of subsidies, we separately control for firms that received R&D subsidies or other subsidies within that last 2 years prior to the treatment. Prior R&D subsidies have been distributed to 11% of observations while 44% of observations have received non-R&D subsidies throughout the last 2 years. These statistics inform us that R&D subsidies are allocated less often than non-R&D subsidies received by firms, which is reasonable considering the scope of China's non-R&D subsidies.

[13] We regress the log of export subsidies on the lagged log of export volume, log of the number of employees, capital intensity, profitability, log of age, and include controls for year, industry, and provincial GDP per capita.

A firm is identified as an inventor if it has a positive patent stock.[14] This might appear as a low benchmark but it sufficiently discriminates between Chinese inventors and non-inventors between 2001 and 2006. 607 out of 1,331 firms are classified as inventors while the mean value of their weighted patent stock is 0.007. Because, firstly, the distribution of the economic value of patents is generally highly skewed (Harhoff et al. 2003) and, secondly, the last decade has witnessed a flood of low value patent applications originating from China (Boeing & Mueller 2015, Lei et al. 2012), we separately control for the quality of inventions by calculating the mean of forward citations received per patent family. The average patent family of patenting firms receives 0.038 forward citations.

The general high-tech orientation of a firm is operationalized based on the industrial high-tech classification. In our sample, 16% of observations belong to high-tech industries. However, we expect considerable heterogeneity among the actual high-tech orientations of these firms. Therefore, we calculate the high-tech export intensity as non-processing high-tech exports weighted by the firm's revenue. Processing exports are excluded because Chinese firms often only assemble imported high-tech inputs for overseas export markets but add little value to the final product (Wang & Wei 2010). The average high-tech export intensity for exporting firms is 4%.

Based on ownership shares held by the government, we discriminate between majority state-owned firms ($x > 50\%$), minority state-owned firms ($50\% \geq x > 0\%$), and private-owned firms ($x = 0\%$). 33% of the observations are majority state-owned firms, while 39% are minority SOEs, and 29% are private-owned firms.[15]

[14] Precisely, the patent stock in year *t* is the patent filings of that year plus the patent stock in year *t*-1 depreciated by 15%. To control for firm size, we weigh the patent stock by the number of employees.

[15] For each ownership type we calculate the share of treated observations and find that majority state-owned firms are half as likely of receiving R&D subsidies as when compared to minority state-owned firms and privately-owned firms. We interpret this finding as preliminary evidence for our consideration that the government's direct influence on majority state-owned firms decreases the need for additional intervention by R&D subsidies.

Heterogeneity in provincial transitions towards a market-driven economy is measured by the NERI index based on the resource allocation by provincial governments in proportion to provincial GDPs. For the base year 2001, the NERI index is normalized on a scale ranging from 1 to 10, with 10 indicating the province with the highest level of resource allocation by the market and 1 indicating the province with the highest level of resource allocation by the government. The remaining 29 provinces receive scores in between, according to their relative performances. In subsequent years the index may take values outside the base scale to account for differences between provinces and over time. Observations in our sample have a mean index of 7.93, suggesting that the majority of firms are located in provinces administered by more market-oriented governments. China's regional variation in economic development is measured by the log of provincial GDP per capita. Note that the market orientation of provincial governments and provincial economic development are interacting but different concepts as confirmed by the low correlation coefficient of 0.27.

We briefly summarize the operationalization of standard firm controls. Firm size is measured by the log of the number of employees while the capital intensity is measured by taking the log of net fixed assets divided by the number of employees. Profitability is a binary variable taking the value of 1 if the firm's net profits are positive. We classify a firm as an exporter if it exhibits exports in the respective year. The log of the number of years since establishment informs us of the age. In addition, we use 21 industry dummies to control for industry-specific characteristics. Because 62% of firms operate in manufacturing, we use a set of finer industry controls for the manufacturing sector. Table 3 shows the industry composition and the number of subsidized firms per industry.

Our main output variable is R&D intensity. We operationalize two R&D intensities, based on gross and net R&D expenditures weighted by revenue. For R&D performers the gross and net R&D intensity is 0.75% and 0.73% respectively, both of which are similar to the average gross R&D intensity of 0.76% for China's large- and medium-sized firms throughout this time period (NBS & MOST 2007). For later robustness tests, we also calculate the R&D stock according to the perpetual investment method.[16] The mean value for the R&D stock weighted by the capital stock is 6.64%.[17]

As an interim test, we want to examine whether firms' inventiveness and high-tech orientation is related to the decision to conduct R&D. Employing a Probit model with standard errors clustered at the firm level, we regress the decision to conduct R&D on our main confounders and standard firm characteristics. Indeed, we find that inventors and firms in high-tech sectors have a positive and highly significant ($p < 0.001$) probability to conduct R&D. In the following section, we continue with our examination of R&D subsidy allocation.

5 Empirical Results

5.1 Allocation

In Table 4, we present four Probit estimations for the likelihood of receiving R&D subsidies. All time-varying firm level regressors, except age which we consider as truly exogenous, are lagged by one time period to avoid simultaneity between (anticipated) grants and changes in firm characteristics. All provincial level regressors are included without lags since these are exogenous to the firm. Pairwise correlation between all regressors is around 0.4 or lower and standard errors are clustered at the firm level.

Model (1) presents a parsimonious specification without controls for prior subsidies and industry affiliation. Beginning with firm inventiveness, we find that the patent stock is negative but insignificant while the patent citation intensity is positive and significant at the 1% level. For high-tech industry affiliation, we find a positive effect at the 5% significance

[16] For the time period 2001-2011, we observe an average growth rate of 25% for R&D expenditure which is similar to Liu (2009) who find a growth rate of 22% for the time period 1999-2009. We use our growth rate to calculate the R&D stock in the first year and apply the standard depreciation rate of 15% to account for the fact that knowledge becomes obsolete.

[17] In comparison to the patent stock, it becomes obvious that not all patenting firms also conduct R&D. However, non-R&D invention is not unusual in developing countries and also exists in developed countries (Rammer et al. 2012).

level while the high-tech export intensity is negative and insignificant. These finding suggest that the quality – and not the quantity – of inventions determines selection and that affiliation with the high-tech sector instead of the intensity of high-tech exports is relevant.

For ownership, we find that both minority state-owned firms and privately-owned firms have a significantly higher probability, at the 1% level, of receiving grants compared to majority state-owned firms. Firms located in jurisdictions of provincial governments that are more market-oriented have a significantly lower probability of receiving grants. Conversely, firms located in more developed provinces have higher probabilities of receiving grants, both at the 1% significance level. For the set of standard controls, we find that profitability, export status, and age are positively and significantly correlated with receiving R&D subsidies. These findings fit well into China's innovation policy of "picking the winners" as inventive, high-tech oriented, and generally better performing firms have a higher likelihood of becoming recipients.

In Model (2), we include industry controls.[18] The results remain largely unchanged except that high-tech industry affiliation and export status turn insignificant. These changes are plausible, as both of these criteria are largely explained by industry characteristics which are now controlled for.

Model (3) presents our final specification and includes additional information on prior R&D subsidies and prior non-R&D subsidies. We confirm persistence in grant distribution for both subsidy categories at the 1% significance level. Note that the inclusion of prior subsidies increases the models' goodness of the fit *(pseudo R2)* from 0.08 in Model (2) to 0.28 in Model (3). As prior subsidies capture information about the firm characteristics that have previously led to successful applications, the explanatory power of the remaining regressors is

[18] Note that by including industry controls we lose 53 observations from mining and 12 observations from wood & furniture manufacturing since these industries have zero probability of receiving R&D subsidies in our regression sample.

reduced. This reduction also applies to industry controls, as revealed by an increase in the *p*-value of the *chi2-test* from 0.12 in Model (2) to 0.57 in Model (3).

In addition to prior subsidies, the following characteristics remain significant with respect to the probability of receiving R&D subsidies: patent citation intensity, minority state ownership, resource allocation by provincial governments, and provincial economic development. For these regressors we calculate average marginal effects as a change from 0 to 1 for discretely distributed variables and as an increase of one standard deviation from the mean for continuously distributed variables. Against an average probability of 11.67% to become a recipient, we calculate corresponding changes in percentage points: prior R&D 36.44, prior non-R&D subsidies 5.04, patent citations intensity 10.40, minority state-ownership 3.36, market orientation by provincial government -3.98, and provincial GDP per capita 2.87.

In line with the literature, we confirm persistence in receiving R&D subsidies. In addition, our findings suggest that grants are indeed distributed to firms with previous high quality inventions. Further, minority state-owned firms are more likely to become recipients. As discussed before, a large share of China’s spending for science and technology is allocated by subnational governments that often hold shares in minority state-owned firms (whereas majority state-owned firms are commonly associated with the central government). Minority state-owned firms may be frequent recipients because of the government’s lesser degree of direct influence, compared to governance by edicts in the case of majority state-owned firms, as well as because of the subnational governments’ preference to distribute its resources to those firms in which they held ownership shares. In addition, the regulator might anticipate a higher effectiveness of R&D subsidies in minority state-owned firms because owner-managers in these firms may share a long-term motivation to increase R&D investments (which differs from the short-term profit-orientation of private-owned firms).

On the provincial level, we can confirm that more market-oriented governments also limit the instances of intervention by R&D grants. Conversely, governments more directly involved in resource allocation also favor active regulation and employ R&D subsidies more often. Finally, firms located in more developed provinces indeed receive more support through China's innovation policy than firms in more backward regions, affirming the central government's strategy to support development of the coastal region. In addition, it is plausible that less developed provinces follow economic development targets that generate growth and employment more quickly and with less risk than based on industrial R&D investments.

Considering the interaction of provincial marketization and development over time, 11 of 31 provinces exhibit a negative correlation between the index of resource allocation by provincial government and provincial economic development in the time period under investigation. Considering a median marketization index of 8.02 and a median GDP per capita of 17,590 RMB as benchmarks, Beijing and Shanghai are actually less marketized but more developed than the benchmark. Conversely, provinces like Anhui and Hebei are more marketized but less developed than the benchmark. Consequently, firms in locations such as Beijing and Shanghai would receive R&D subsidies more often because of rather interventionist governments and because of higher economic development.

5.1.1 Matching of Treatment and Control Group

Based on the propensity scores obtained from Model (3), we perform nearest-neighbor matching and match every treated observation with the most similar control observation from the pool of potential control observations. As a common support is a necessary condition for the validity of the matching estimator, we exclude 6 treated observations because no common support could be found. To improve the accuracy of the match, we require exact matching for the following stratification criteria: time periods, prior R&D subsidies as well as inventor, high-tech, and ownership type. Because the *p*-value of the *chi2-test* in Model (3) confirms that industry controls have no joint significance in explaining the allocation of R&D subsidies, we only require a precise separation between manufacturing and non-manufacturing firms. For later analysis, by restricting the maximum distance between neighbors to a tolerance level of 0.1, we disregard another 134 observations. From the pool of control observations, 95% are used not more than three times and 68% are only used once throughout the matching process.

Table 5 and Table 6 present means, standard deviations, and the *p*-values of the *t*-test on mean differences for all regressors and propensity scores before and after matching. Before matching, 11 out of 15 regressors have significantly different means. After matching, the *p*-values of the *t*-tests on mean differences indicate that no significant differences remain. Accordingly, *t*-tests on mean differences between propensity scores show that *p*-values increase from < 0.001 to 0.992.

5.1.2 Robustness Tests for Matching

We conduct several robustness tests to scrutinize the quality of the matching.[19] First, Model (4) in Table 4 re-estimates Model (3) with the matched data and confirms that no single regressor remains significant in explaining the allocation of R&D subsidies, while *pseudo R2* is reduced from 0.28 to 0.02 accordingly. Second, we consider continuously distributed variants of the binary variables for ownership, profitability, and export intensity and we use a different control for the technological sophistication (low, low-medium, medium-high, and high) of industries based on standard industry classifications (SIC) (see Fu & Gong 2011). The comparison of the *p*-values of the *t*-tests on mean differences for these variables shows that there are no significant differences between means of the treatment and control group based on our initial matching.

[19] Estimation details can be obtained from the authors upon request.

Third, we investigate whether our matching fails to control for differences in time variant unobservables between the treatment and control group. For this exercise, we consider three important but quasi unobserved time variant variables for labor productivity (revenue by employees), research collaborations (the depreciated stock of joint patent applications with at least one domestic or foreign firm, university, research institute, or individual), and access to external finance (long term debt by total assets). These variables control for time variant changes that are not directly controlled for by observables. As those three variables are omitted in the matching process and thereby cast as unobservables, we can use them to test if our matching approach also controls for differences between time variant unobservables in the treatment and control groups. Reassuringly, no significant mean differences exist for these variables after the matching.

Finally, we employ a Heckman two-step selection model to investigate the selection bias due to actual unobservables. The selection equation resembles the Probit model (3) of Table 4 (using the same observations) and the outcome equation regresses net R&D intensity on treatment intensity (R&D subsidy by revenue) and all variables (except one) of the selection equation. For more robust identification we use the information whether a firm had received a prior non-R&D subsidy as an exclusion restriction. The economic intuition is that prior recipients of non-R&D subsidies benefit from information advantages in subsequent applications for R&D subsidies due to accumulated knowledge of how to deal with subsidy applications and government agencies in general. However, prior non-R&D subsidies have no direct impact on present R&D investments. Statistically, a prior non-R&D subsidy indeed has a non-trivial and positive effect at the 1% significance level on selection. As expected, ρ confirms a positive correlation of residuals in the selection and outcome equation. Nonetheless, the coefficient of λ, which is the error covariance, is not significant. This finding confirms the relevance of those observables included in the selection equation and shows that additional unobservables are unlikely to induce significant selection bias. In conclusion, our robustness tests show that for the matched treatment and control group selection on observables can indeed be considered as random, with observables, rather than unobservables, being relevant confounders that significantly affect both R&D spending and grant distribution.

5.2 Effectiveness

After studying grant allocation, we investigate the effect of R&D subsidies on own R&D investment of firms based on the following outcome equation: $Y_{it} = \alpha + \beta S_{it} + \varepsilon_{it}$. In accordance with our econometric strategy, outcome is measured by net R&D intensity while treatment enters the equation as a binary operationalization of R&D subsidies.[20] This setting enables us to estimate the subsidy effect for recipients in comparison to non-recipients with a similar probability of receiving the subsidy. Because we are methodologically intrigued by the question in how far the reduction of selection bias changes the perceived effectiveness of the treatment, we start with an OLS estimator (Table 7).[21] Under the naïve assumption of random selection and without considering relevant controls, we identify a positive effect of R&D subsidies, which is significant at the 5% level. This result reflects the finding of additionality reported by prior studies on China, with these studies ignoring the issue of selection bias by assuming random allocation of R&D grants.

Hereafter, we re-estimate the outcome equation with the matched sample to rule out selection on observables.[22] The effect of R&D subsidies turns negative and insignificant –

[20] Although we observe the amount of R&D subsidy, we only consider the incidence of treatment instead of treatment intensity. Calculating the subsidy effect for *K* different levels of treatment intensity would require a split of recipients' observations into *K+1* treatment groups and corresponding control groups. However, for this exercise the number of available observations is too small and would result in poor matching results as well as less robust DID estimations.

[21] Note that the OLS estimation is based on the complete sample with 7,008 observations.

[22] All following estimations rely on the matched sample with 686 observations. This sample has non-missing observations for first-differences of the outcome and treatment variable as well as non-missing observations for 1 and 2 period lags of the treatment variable. By performing all estimations with the same sample we rule out that results are influenced by the selection of observations. For all following estimations we calculate bootstrapped standard errors (using 500 replications) as suggested by Lechner (2002), since the repeated use of control

suggesting neutrality. This result is similar to the findings of Cheng & Chen (2006), who draw the same conclusion for private firms in Zhejiang province after performing nearest-neighbor matching. Based on the matched sample, we finally adjust the outcome equation by taking first-differences $\Delta Y_{it} = \alpha + \beta \Delta S_{it} + \varepsilon_{it}$ to rule out selection on observables and on time-constant unobservables. We obtain a negative treatment effect, significant at the 1% level, which suggests partial or full crowding-out. Speaking in favor of our econometric strategy, starting from a naïve OLS estimation the stepwise elimination of selection bias based on observables by PSM and additionally on time-invariant unobservables by CDID considerably changes the results of the three specifications. The following analysis relies on the last specification to eliminate selection bias to the largest extent.

In Table 8 we focus on potential differences between instantaneous and lagged effects. The coefficients for R&D grants lagged by one and two periods turn positive but insignificant and decline in magnitude, suggesting neutrality in later periods. These findings are similar to the results presented by Lach (2002) for Israel and Lv & Yu (2011) for China. Thus, it seems that public funds instantaneously reduce own R&D investment of firms but have no effect on the funding of R&D projects in later periods – suggesting that firms use R&D subsidies for an immediate reduction of their own expenses for R&D while keeping their R&D portfolio unchanged.

5.2.1 Robustness Tests for Effectiveness

Having obtained these results, we conduct several robustness tests. First, as reported in Table 9, we use the R&D stock divided by the capital stock as an alternative outcome variable. This stock measure is more reflective of the firm's long-term R&D strategy and less sensitive to annual changes than the flow measure R&D intensity. Nonetheless, our results are

observations in the matching procedure makes the calculation of the actual estimation variance more complicated.

confirmed as we find a negative instantaneous effect, significant at the 5% level, and positive but insignificant lagged effects. Second, we re-estimate our original specification but exclude non-manufacturing firms. As we have required a precise separation between manufacturing and non-manufacturing firms in our matching approach, we can split the sample accordingly. Again, our results are confirmed as we find a negative instantaneous effect, significant at the 1% level, and positive but insignificant effects in the following periods.

Third, we only keep observations for which we directly observe R&D expenditures greater zero in the annual reports, perform the identical matching routine as before, and re-estimate the main CDID specifications.[23] As with our full sample, we find a negative instantaneous treatment effect, significant at the 5% level, but insignificant lagged effects. These results reassure us that interpolation of R&D expenditures has not biased our findings.

As a final test we investigate the effect of R&D subsidies, while controlling for selection based on observables and unobservables, based on the two stage Heckman selection model specified in Section 5.1.1. Recall that the selection equation resembles the Probit model (3) of Table 4 (using the same observations) and in the outcome equation net R&D intensity is regressed on the treatment intensity (R&D subsidy by revenue) and all variables of the selection equation (except prior non-R&D subsidy, which is the exclusion restriction). Reassuringly, an instantaneous crowding-out effect, significant at the 5% level, is confirmed.

5.2.2 Further Investigations

In the remainder, we report two lines of further investigations based on our CDID estimator. First, in Table 10 we examine whether treatment effectiveness differs between firm types. Since our matching routine imposes an exact match of stratification criteria, we can split the sample accordingly. Considering repeated R&D subsidies, we investigate whether

[23] To save space, estimation results for robustness test three and four are not reported but can be obtained upon request.

effects differ between repeated recipients and recipients that have not received R&D subsidies throughout the last 2 years. Indeed, we confirm a negative effect for firms that have not received R&D subsidies in the preceding 2 years, significant at the 5% level, but a negative and insignificant effect for repeated recipients. This difference in effectiveness is in line with Aschhof (2009) and Hussinger (2008) who report an increase of effectiveness for repeated receivers in Germany. In the Chinese context, this finding suggests that continuous grants do not substitute own R&D expenditures of firms but are used for additional R&D projects.

Next, we consider if the target recipients of China's R&D programs, inventive and high-tech firms, experience a higher effectiveness of treatment. As before, we split the sample between inventors and non-inventors and re-estimate our standard specification. However, we fail to confirm a difference since both coefficients are negative and significant at the 10% level. We perform the same exercise for high-tech and non-high-tech firms. For the latter group, we find a negative treatment effect, significant at the 5% level, indicating crowding-out. Nonetheless, we find no significant crowding-out effect for high-tech firms and conclude neutrality. This result indicates a comparatively better use of grants, which is quite plausible given that the competitiveness of high-tech oriented firms largely depends on R&D and makes these firms more likely to invest R&D grants in additional R&D projects instead of scaling down own R&D.

Finally, we investigate implications of ownership. We find negative and significant effects, at the 5% level, for private-owned firms and majority state-owned firms. In contrast, we identify neutrality effects for minority state-owned firms. These findings are largely in line with our previous considerations and suggest again that minority state-owned firms are indeed superior recipients in comparison to the other ownership types.

Second, as policy makers are typically interested in the magnitude of the average crowding-out effect, we conduct a back-of-the-envelope calculation based on our complete sample for the year 2006. R&D expenditures of all firms amount to 7.66 billion RMB while subsidized firms contribute 1.10 billion RMB. Dividing the coefficient of our standard specification by the mean of net R&D intensity (-0.054 / 0.24), we calculate that public R&D funds repel 22.31% of net R&D expenditures of recipients. Thus, the net R&D of treated firms in the hypothetical situation of non-treatment was 1.10 billion RMB × 122.31% = 1.34 billion RMB. Therefore, grants decrease net R&D by 0.30 billion RMB (1.34 billion RMB × -0.223). R&D subsidies received by firms in our sample amount to 0.62 billion RMB. On average, 1 RMB of R&D subsidies substitutes 0.49 RMB of net R&D (-0.30 billion RMB / 0.62 billion RMB). Thus, we can conclude that China's R&D subsidies are causing an average partial crowding-out effect with the proportion of 2:1.

6 Conclusion

This study investigates the allocation of R&D subsidies and the effect on firms' own R&D investments for the population of Chinese listed firms between 2001 and 2006. For allocation, we find that firm participation is positively determined by prior grants, high quality inventions, and minority state-ownership. Provincial variation in grant distribution reveals that R&D subsidies are less often employed by market-oriented provincial governments and that China's innovation policy is more supportive of firms located in developed provinces. Considering effectiveness, we find that R&D subsidies instantaneously crowd-out own R&D investment of firms but are neutral in later periods. In 2006, one public RMB reduces own R&D investments of firms by half a RMB. For repeated recipients, high-tech firms, and minority state-owned firms, crowding-out cannot be confirmed. To a large extent, these firm characteristics reflect those characteristics that seem influential in the allocation of grants.

With respect to policy implications, the targeted allocation of grants to high-tech firms and minority state-owned firms seems reasonable but the effectiveness of China's R&D subsidies could potentially be improved by requiring a more rigorous matching of public funds with own funds – as prevalent in international best practice – and by stricter monitoring of allocation and use of R&D grants. Overall, the economic justification for China's R&D programs is questionable as we fail to identify additionality effects of R&D grants on firms' own R&D investments. However, one should be careful to generalize our findings as our analysis is limited to Chinese listed firms observed between 2001 and 2006. A methodological limitation of our study is that we cannot fully control for selection bias by unobservable time variant firm characteristics that are not symmetrically distributed between the treatment and control group.

Our results affirm the more general observation by Hu & Jefferson (2008) that the influence of government grants on increases in China's business R&D is most likely not significant. China's recent increases in business and gross R&D expenditures suggest that the incidence of market failure in the production of knowledge may be less severe than in other (developed) economies, making public support of business R&D a less decisive factor.

Considering future research, we briefly point out three interesting topics. First, the "Medium- to Long-term Plan for Science and Technology Development" has provided considerable changes to China's innovation policy after 2006 and the Chinese economy has changed in numerous dimensions. Against this background, future research should examine if post-2006 R&D subsidies have improved in effectiveness and also address tax incentives and individual R&D programs. Second, reports have identified cases of substantial misuse of grants by recipients (e.g. 60% of R&D grants being used for non-R&D purposes (Science Net 2016); fraud due to insufficient control mechanisms (MOST 2014)) as well as managers of R&D programs (e.g. withholding 30% of grants handled (The Economist 2014)). Thus, it seems meaningful to examine how new approaches to fund management and the government's recent anti-corruption investigations have improved the effectiveness of R&D funds. Finally, multivalued, heterogeneous, and lagged treatment effects are fertile grounds for methodological advancements in future evaluation research.

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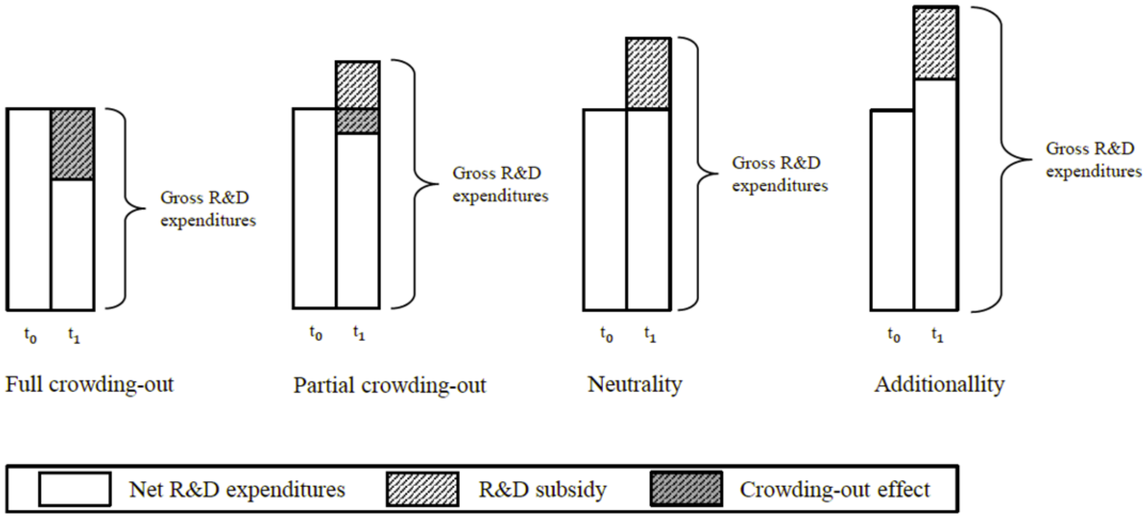
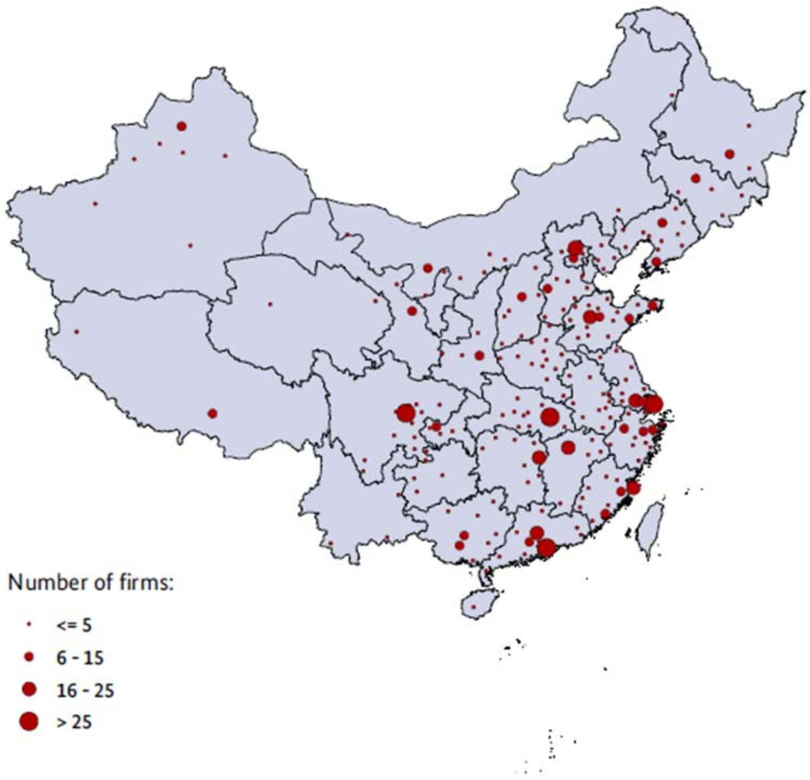
Appendix: Figures and Tables

Figure 1: Taxonomy of Subsidy Effects



Source: Own illustration.

Map 1: Location of Firms



Source: Own illustration.

Table 1: Firm-level Studies on China

Authors	Literature	Period	No. obs.	Firm selection	Dep. var.	Subsidy-level	Prior Subsidy	Lagged Subsidy	Method	Effect
Cheng & Chen (2006)	EN	2001-2003	6,732	Private-owned	R&D expenditures	Firm-level	Yes	Yes	PSM	Neutrality
Cheng & Zhao (2008)	CN	2004-2005	324	Private-owned	R&D expenditures	Firm-level	No	Yes	OLS	Additionality
Guo et al. (2014)	EN	1997-2007	~70,000	Tech-SMEs	New products, exports, annual patent grants	Project-level	No	No	PSM, Heckman	Positive
Hu & Zhou (2008)	CN	1999-2004	6,038	Tech-SMEs	R&D expenditures	Project-level	No	No	OLS	Additionality
Huang et al. (2013)	EN	2007	500	Private-owned	Innovation expenditure intensity	Firm-level	No	No	CLM	Positive
Liu (2009)	CN	2005-2007	507	Tech-firms	R&D intensity	Firm-level	No	Yes	OLS	Additionality
Liu et al. (2012)a	CN	2009-2011	165	Tech-start-ups	R&D expenditures	Firm-level	No	Yes	OLS	Additionality
Liu et al. (2012)b	CN	2007-2009	n/a	Listed firms	R&D intensity	Firm-level	No	Yes	Logit, Probit	Inverse U-shape
Lv & Yu (2011)	CN	2007-2008	1,442	Listed firms	R&D intensity	Firm-level	No	Yes	OLS	Crowding-out
Xie et al. (2009)	CN	2003-2005	3,890	Listed firms	R&D binary	Firm-level	No	Yes	Logit, Heckman	Positive

The Matching Protocol

Step 1	Specify and estimate a probit model to obtain the propensity score $\hat{P}(X)$
Step 2	Restrict the sample to common support: delete all observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. (This step is also performed for other covariates that are possibly used in addition to the propensity score as matching arguments)
Step 3	Choose one observation from the subsample of treated firms and delete it from that pool
Step 4	Calculate the Mahalanobis distance between this firm and all non-subsidized firms in order to find the most similar control observation. $MD_{ij} = (Z_j - Z_i)'\Omega^{-1}(Z_j - Z_i)$ where Ω is the empirical covariance matrix of the matching arguments based on the sample of potential controls. We use caliper matching, first introduced by Cochran and Rubin (1973). The intuition of caliper matching is to avoid "bad" matches (those for which the value of the matching argument Z_j is far from Z_i) by imposing a threshold of the maximum distance allowed between the treated and the control group. That is, a match for firm i is only chosen if $\left\lVert Z_j - Z_i \right\rVert < \varepsilon$, where ε is a pre-specified tolerance
Step 5	Select the observation with the minimum distance from the remaining control group. (Do not remove the selected controls from the pool of potential controls, so that it can be used again.) If the control group is empty after applying the caliper threshold, the treated firm is dropped from the sample and is not taken into account in the evaluation
Step 6	Repeat steps 3–5 for all observations on subsidized firms
Step 7	Using the matched comparison group, the average effect on the treated can thus be calculated as the mean difference of the matched samples: $\widehat{\alpha}_{TT} = 1/n^T \left(\sum_i Y_i^T - \sum_i \widehat{Y}_i^C \right)$ with $\widehat{Y}_i^C$ being the counterfactual for i and n^T is the sample size (of treated firms)
Step 8	As we perform sampling with replacement to estimate the counterfactual situation, an ordinary t-statistic on mean differences is biased, because it does not take the appearance of repeated observations into account. Therefore, we have to correct the standard errors in order to draw conclusions on statistical inference. We follow Lechner (2001) and calculate his estimator for an asymptotic approximation of the standard errors

Source: Czarnitzki & Lopes-Bento (2013).

Set of R&D-related Keywords

Chinese	English
开发设计费	Development and design expenditures
技术开发费	Technology development expenditures
新产品试制费	New product trial expenditures
研发投入	Research and development investments
研发支出	Research and development expenditures
研发费	Research and development expenditures
研发费用	Research and development expenditures
研究开发费	Research and development expenditures
科技开发成本	Science and technology development costs
科研开发费	Scientific research and development expenditures
科研经费	Scientific research expenditures

Table 2: Descriptive Statistics

	Mean	Min.	Max.	Median	Std. dev.	Obs.	Firms
R&D subsidy	0.104	0	1	0		7,008	1,331
Prior R&D subsidy	0.111	0	1	0		7,008	1,331
Prior non-R&D subsidy	0.436	0	1	0		7,008	1,331
Patent stock	0.007	0	0.416	0.001	0.026	2,325	607
Patent citation intensity	0.038	0	7.34	0	0.195	2,325	607
High-tech industry	0.16	0	1	0		7,008	1,331
High-tech export intensity	0.043	0	0.871	0.001	0.108	2,390	649
Majority state-owned firm	0.325	0	1	0		7,008	1,331
Minority state-owned firm	0.386	0	1	0		7,008	1,331
Private-owned firm	0.289	0	1	0		7,008	1,331
Market-orientation provincial govs.	7.929	-16.4	10.48	8.17	2.316	7,008	1,331
ln(provincial GDP per capita)	9.692	8.108	10.959	9.664	0.651	7,008	1,331
Provincial GDP per capita	20,098	3,320	57,480	15,746	13,984	7,008	1,331
ln(size)	7.329	2.303	13.003	7.423	1.262	7,008	1,331
Size	3,398	10	443,808	1,674	12,450	7,008	1,331
ln(capital intensity)	12.487	9.072	19.333	12.347	1.138	7,008	1,331
Capital intensity	829,478	8,712	248,917,376	230,231	5,800,353	7,008	1,331
Profitability	0.861	0	1	1		7,008	1,331
Exporter	0.341	0	1	0		7,008	1,331
ln(age)	2.134	0	4.644	2.197	0.527	7,008	1,331
Age	9.664	1	104	9	5.794	7,008	1,331
Gross R&D intensity of R&D performer (%)	0.751	0.001	4.938	0.406	0.899	1,707	460
Net R&D intensity of R&D performer (%)	0.731	0	4.92	0.39	0.892	1,707	460
Net R&D stock/capital stock of R&D performer (%)	6.639	0	54.98	3.207	9.056	1,707	460

Table 3: Industry Composition

	All firms		Subsidized firms	
Industry	No. firms	(%)	No. firms	(%)
Agriculture	33	2.48	9	2.74
Mining	23	1.73	1	0.30
Manufacturing: food & beverages	63	4.73	15	4.56
Manufacturing: textiles & apparel	58	4.36	22	6.69
Manufacturing: wood & furniture	5	0.38	1	0.30
Manufacturing: paper & printing	29	2.18	6	1.82
Manufacturing: petro-chemistry & plastics	156	11.72	34	10.33
Manufacturing: electronics	39	2.93	7	2.13
Manufacturing: metal & non-metals	135	10.14	23	6.99
Manufacturing: machinery & instruments	239	17.96	79	24.01
Manufacturing: pharma & biological products	85	6.39	28	8.51
Manufacturing: other	12	0.90	2	0.61
Utilities	58	4.36	6	1.82
Construction	20	1.50	4	1.22
Transportation and Warehousing	74	5.56	18	5.47
Information Technology	38	2.86	5	1.52
Wholesale and Retail	102	7.66	26	7.90
Real Estate	42	3.16	16	4.86
Social Services	56	4.21	4	1.22
Communication and Culture	4	0.30	1	0.30
Conglomerates	60	4.51	22	6.69
Total	1,331	100	329	100

Table 4: Probit Estimations on the Allocation of R&D Subsidies

	(1) Parsimonious excl. industry controls	(2) Parsimonious incl. industry controls	(3) Final specification before matching	(4) Final specification after matching
Prior R&D subsidy			1.462***	-0.034
			(0.079)	(0.125)
Prior non-R&D subsidy			0.344***	-0.000
			(0.067)	(0.128)
Patent stock by employees t-1	-0.023	-0.035	-0.042	0.091
	(0.028)	(0.036)	(0.04)	(0.118)
Patent citation intensity t-1	1.135***	1.049**	0.749**	-0.831
	(0.414)	(0.425)	(0.332)	(0.994)
High-tech industry t-1	0.207**	0.07	0.11	0.095
	(0.104)	(0.128)	(0.105)	(0.199)
High-tech export intensity t-1	-0.251	-0.041	-0.153	0.427
	(0.64)	(0.622)	(0.565)	(1.041)
Minority state-owned firm t-1	0.337***	0.331***	0.238***	0.071
	(0.100)	(0.101)	(0.081)	(0.157)
Private-owned firm t-1	0.292***	0.265***	0.133	0.018
	(0.103)	(0.103)	(0.088)	(0.171)
Market-orientation provincial govs.	-0.044***	-0.052***	-0.029**	-0.017
	(0.015)	(0.015)	(0.012)	(0.026)
ln(provincial GDP per capita)	0.421***	0.438***	0.209***	0.075
	(0.068)	(0.068)	(0.056)	(0.093)
ln(size) t-1	0.024	0.046	0.008	0.07
	(0.035)	(0.039)	(0.032)	(0.062)
ln(capital intensity) t-1	-0.042	-0.004	-0.019	0.083
	(0.036)	(0.044)	(0.039)	(0.068)
Profitability t-1	0.149*	0.171**	0.063	-0.189
	(0.081)	(0.082)	(0.087)	(0.16)
Exporter t-1	0.19**	0.121	0.068	-0.085
	(0.076)	(0.078)	(0.069)	(0.122)
ln(age)	0.177*	0.201**	0.079	-0.061
	(0.093)	(0.724)	(0.086)	(0.166)
Industry		chi2(18)=25.09	chi2(18)=16.35	chi2(18)=7.43
		p>chi2=0.122	*p*>chi2=0.568	*p*>chi2=0.986
Year	chi2(3)=1.97	chi2(3)=1.96	chi2(3)=6.52*	chi2(3)=0.13
	p>chi2=0.578	*p*>chi2=0.58	*p*>chi2=0.089	*p*>chi2=0.988
Constant	-5.506	-6.063	-3.616	-1.924
Pseudo R2	0.066	0.083	0.284	0.019
Observations	4,118	4,053	4,053	686
Firms	1,150	1,129	1,129	385

Notes: The dependent variable is the binary operationalization of receiving R&D subsidies. ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels.

Table 5: Potential Control Group and Treatment Group before Matching

Variables	Unsubsidized obs., N=3,656 Mean	Unsubsidized obs., N=3,656 Std. dev.	Subsidized obs., N=483 Mean	Subsidized obs., N=483 Std. dev.	*p*-value of *t*-test on mean differences
Prior R&D subsidy	0.080	0.272	0.629	0.483	$p<0.001$
Prior non-R&D subsidy	0.376	0.484	0.708	0.455	$p<0.001$
Patent stock by employees	0.231	1.566	0.220	0.740	$p=0.787$
Patent citation intensity	0.008	0.053	0.021	0.105	$p=0.008$
High-tech industry	0.146	0.354	0.208	0.407	$p=0.002$
High-tech export intensity	0.013	0.062	0.017	0.065	$p=0.308$
Minority state-owned firm	0.367	0.482	0.450	0.498	$p<0.001$
Private-owned firm	0.286	0.452	0.344	0.475	$p=0.012$
Market-orientation provincial govs.	7.896	2.447	7.825	2.568	$p=0.564$
ln(provincial GDP per capita)	9.760	0.618	10.072	0.680	$p<0.000$
ln(size)	7.356	1.265	7.382	1.322	$p=0.567$
ln(capital intensity)	12.553	1.147	12.458	1.068	$p=0.072$
Profitability	0.841	0.365	0.878	0.328	$p=0.025$
Exporter	0.322	0.467	0.414	0.493	$p<0.001$
ln(age)	2.287	0.419	2.383	0.396	$p<0.001$
P(X)	0.085	0.127	0.367	0.241	$p<0.001$

Table 6: Control Group and Treatment Group after Matching

Variables	Unsubsidized obs., N=343 Mean	Unsubsidized obs., N=343 Std. dev.	Subsidized obs., N=343 Mean	Subsidized obs., N=343 Std. dev.	*p*-value of *t*-test on mean differences
Prior R&D subsidy	0.501	0.501	0.501	0.501	$p=1.000$
Prior non-R&D subsidy	0.665	0.473	0.659	0.475	$p=0.888$
Patent stock by employees	0.156	0.530	0.190	0.701	$p=0.522$
Patent citation intensity	0.011	0.055	0.008	0.037	$p=0.570$
High-tech industry	0.152	0.359	0.152	0.359	$p=1.000$
High-tech export intensity	0.016	0.064	0.015	0.064	$p=0.868$
Minority state-owned firm	0.510	0.501	0.510	0.501	$p=1.000$
Private-owned firm	0.289	0.454	0.289	0.454	$p=1.000$
Market-orientation provincial govs.	7.974	0.139	7.85	0.144	$p=0.589$
ln(provincial GDP per capita)	9.951	0.657	10.005	0.678	$p=0.348$
ln(size)	7.339	1.128	7.361	1.354	$p=0.836$
ln(capital intensity)	12.39	1.031	12.466	1.09	$p=0.411$
Profitability	0.883	0.321	0.857	0.35	$p=0.368$
Exporter	0.449	0.498	0.402	0.491	$p=0.283$
ln(age)	2.388	0.408	2.282	0.377	$p=0.851$
P(X)	0.293	0.235	0.293	0.235	$p=0.992$

Table 7: Comparison of Estimators

Method	Dep. Var.	Treatment Effect	Obs.
OLS	R&D intensity	0.070** (0.032)	7,008
PSM	R&D intensity	-0.025 (0.042)	686
CDID	R&D intensity	-0.054*** (0.021)	686

Notes: (1) standard errors are in parenthesis. (2) standard errors are generated via bootstrapping (500 replications) and are clustered at the firm-level. (3) ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels.

Table 8: Comparison of Treatment Lags

Treatment Lag	Dep. Var.	Treatment Effect	Obs.
Not lagged	R&D intensity	-0.054*** (0.021)	686
1 period	R&D intensity	0.035 (0.026)	686
2 periods	R&D intensity	0.009 (0.043)	686

Notes: Estimation method employs CDID. (1) standard errors are in parenthesis. (2) standard errors are generated via bootstrapping (500 replications) and are clustered at the firm-level. (3) ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels.

Table 9: Robustness Tests

Firm Selection	Treatment Lag	Dep. Var.	Treatment Effect	Obs.
All	Not lagged	R&D stock / capital stock	-0.400** (0.175)	686
All	1 period	R&D stock / capital stock	0.146 (0.140)	686
All	2 periods	R&D stock / capital stock	0.163 (0.208)	686
Manufacturing	Not lagged	R&D intensity	-0.084*** (0.031)	432
Manufacturing	1 period	R&D intensity	0.049 (0.040)	432
Manufacturing	2 periods	R&D intensity	0.030 (0.065)	432

Notes: Estimation method employs CDID. (1) standard errors are in parenthesis. (2) standard errors are generated via bootstrapping (500 replications) and are clustered at the firm-level. (3) ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels.

Table 10: Further Investigations

Firm Selection	Dep. Var.	Treatment Effect	Obs.
R&D subsidy in last 2 years	R&D intensity	-0.030 (0.030)	344
No R&D subsidy in last 2 years	R&D intensity	-0.092** (0.042)	342
Inventor	R&D intensity	-0.090* (0.052)	238
Non-inventor	R&D intensity	-0.032* (0.017)	448
High-tech	R&D intensity	-0.100 (0.065)	104
Non high-tech	R&D intensity	-0.050** (0.021)	582
Private-owned	R&D intensity	-0.058** (0.029)	198
Minority state-owned	R&D intensity	-0.034 (0.030)	350
Majority state-owned	R&D intensity	-0.093** (0.045)	138

Notes: Estimation method employs CDID. (1) standard errors are in parenthesis. (2) standard errors are generated via bootstrapping (500 replications) and are clustered at the firm-level. (3) ***, **, * indicate statistical significance at the 1, 5, and 10 percent levels.