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Conference Paper

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2014: Evidenzbasierte Wirtschaftspolitik
- Session: R&D and Innovation, No. A03-V3

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Böing, Philipp (2014) : China's Technology Subsidies - Much ado about nothing?, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2014: Evidenzbasierte Wirtschaftspolitik - Session: R&D and Innovation, No. A03-V3, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/100536>

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China's Technology Subsidies – Much ado about nothing?

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February 2014

Abstract: This study investigates the allocation and effect of technology subsidies on R&D activities and technology acquisitions of Chinese domestic firms. We exploit novel firm data which includes information on subsidies, R&D, patents, trade, and balance sheet indicators. Conditional difference-in-difference estimation confirms that the innovation policy of China's government follows a picking-the-winner strategy. Technology subsidies are allocated to minority state-owned and privately owned firms which have high-tech inventions, high profitability, and compete with foreign firms in domestic industries. However, we find almost no evidence which confirms that technology subsidies incentivize an increase in R&D intensity or technology acquisition. There is weak evidence for a positive effect of consecutive treatments.

JEL Classification: O38, O32

Keywords: subsidies, R&D, technology acquisition, China, conditional difference-in-difference

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1 Introduction

After China's WTO-accession in 2001, its subsidies have received much attention. Hanley and Hanley (2013) analyze the allocation of subsidies across China's industries. In manufacturing, China's largest industrial sector, technology subsidies increasingly represent the largest category and account for 85% of total subsidies in 2005. Although the market failure and infant industry arguments provide a rationale for government support of firm R&D and technology acquisition, especially in developing economies, some observers argue that China's subsidy allocation has moved beyond legitimate policy (Atkinson 2012).

Following an economic roadmap of innovation and sustainable growth, the government allocates technology subsidies to stimulate R&D activities as well as acquisitions of advanced foreign technologies – two major strategies for technological catching-up (Li 2011). Throughout the time period 2001 to 2012, China's gross domestic expenditures for R&D (GERD) has increased from 0.95 to 1.98% and three quarters are accounted for by firms (NBS 2014, Worldbank 2014). Likewise, imports of China's high-tech industries were growing considerably in the past (Chen et al. 2014). Nonetheless, it remains unclear to which extent technology subsidies have incentivized increasing R&D intensities and technology acquisitions of domestic firms or if these trends emerged in parallel.

The previous literature provides only inconclusive evidence based on industry level data (Zhu et al. 2006). Moreover, aggregated industry data is considered less adequate for subsidy evaluation because it fails to account for the heterogeneity of treatments and firms (Alonso-Borrego et al. 2012). Obviously, the difficulties in accessing Chinese subsidy data and shortage of firm level data account for the lack of firm level studies (Hanley and Hanley 2013). This study is the first to fill this gap and provides firm level evidence on the allocation of China's technology subsidies and on their effect on R&D and technology acquisition.

In this study's time period 2001 to 2006, the accounting regulations for listed domestic firms provide the rare opportunity to access high quality subsidy data. We complement these data with balance sheet data and match further information on R&D, patents, trade, and state ownership. The result is an exceptionally rich data set that covers 1,461 firms from all industries and provinces in China. We introduce novel approaches of generating data on imports of capital goods encompassing advanced technologies and on citations for Chinese patent applications which are new to the literature.

For the econometric part of this study we rely on conditional difference-in-difference-estimation which allows for causal interpretation of results. This approach combines advantages of propensity score matching and difference-in-difference estimation and controls for the selection bias of receiving a treatment as well as observed and constant unobserved firm heterogeneity. With this method we first estimate which firm characteristics influence the allocation of technology subsidies. Hereafter, we create a quasi-experimental setting and estimate the treatment effect of technology subsidies on R&D intensity and technology acquisition.

R&D intensity is operationalized as annual R&D expenditures weighted with revenues. For the development of the technology-acquisition-variable we consider firm imports, exclude processing trade and identify the capital goods. Then, we use high and new product classifications of Chinese authorities to identify those capital goods which encompass advanced technologies. Finally, we calculate the stock of these imports and normalize it by the firm's capital stock. In this way, the variable proxies the firm's upgrading of production capacity. Further investigations take several treatment characteristics into account, including the size of treatment, consecutive treatments, sources of funding, and the effect of other subsidies.

Preliminary evidence confirms that the innovation policy of China's government follows a picking-the-winner strategy. Technology subsidies are allocated to minority state-owned and

privately owned firms which create high-tech inventions, have a high profitability, and compete with foreign firms in domestic industries. Majority state-owned firms and loss-making firms have a lower probability of receiving technology subsidies for obvious reasons. While loss-making firms do not fit to the governments focus on high performers, the strategies of majority state-owned firms follow innovation policies of the government more closely and are less responsive for additional forms of government intervention.

However, we find almost no evidence for significant effects of technology subsidies on R&D intensity or technology acquisition. Throughout the further investigations we discover some weak evidence for a positive effect of consecutive treatments on R&D intensity and to an even lesser extent on technology acquisition. Although the allocation of technology subsidies seems follows a reasonable pattern, firms are not responsive to the treatment. Since there is some weak evidence for a positive effect of consecutive treatments, this finding suggests that a predictable and continuous treatment pattern might provide better incentives.

The remainder of this study is structured as follows. Section 2 provides an overview of the theory and prior evidence. In addition, the institutional background is discussed and two hypotheses are derived. Section 3 explains the econometrical methodology. Section 4 introduces the data, operationalization of variables, and descriptive statistics. Section 5 presents the results and Section 6 concludes.

2 Literature Review and Hypotheses

2.1 Theory

Arrow's seminal work (1962) establishes the market failure argument and provides the rational for government intervention and public funding of firm R&D. Czarnitzki and Lopes-Bento (2013) summarize the main issues as follows. Firstly, the production of knowledge involves high fixed cost but the marginal cost for the production of an additional unit is below

the average costs. While from a welfare perspective the existing knowledge should become a freely available public good, private firms would have little incentives to invest in R&D again. Secondly, even though a firm bears the entire cost of its R&D, it cannot fully appropriate the related returns due to the non-rival and non-exclusive character of knowledge. Thirdly, due to the uncertainty related with R&D outcomes and the high sunk cost of R&D investments, risk-averse firms will seek for more predictable and recoverable investment opportunities. Governments aim to correct the market failure by granting subsidies to incentivize firm R&D expenditures until the social optimum is reached (Takalo et al. 2013).

The infant industry argument has first been codified by Hamilton in 1790. Adapting it to the economic situation of today's developing economies, Shin and Lee (2012) argue that latecomer economies, such as China, should import capital goods for the production of final or consumer goods. Based on this strategy, firms can increasingly catch-up with the manufacturing capacity of developed countries and produce more sophisticated and competitive goods for domestic and overseas markets. Because the import of advanced capital goods is (too) costly for the firm but beneficial for the economy's industrial upgrading, the infant industry argument speaks in favor of a proactive role of the government which support technology acquisition of domestic firms (Lee 2013).

2.2 Empirical Evidence

The empirical evidence on the effects of subsidies on R&D is inconclusive.¹ Alonso-Borrego et al. (2012) systematically survey 77 influential studies conducted between 1966 and 2011 and conclude that significant, mixed, and insignificant effects are found in the literature. While measurement issues, methodological differences, and variation in the unit of analysis as well as time periods might play a role, the results also reveal that different subsidy

¹ Hall and Van Reenen (2000), Klette et al. (2000), and David et al. (2000) provide comprehensive, but a bit dated, survey articles.

programs are differently effective. Because the majority of studies were conducted for the US or EU, the evidence for developing or emerging economies is scarce. But even for this smaller sub-set of studies, the heterogeneity of evidence prevails.

Only the study by Zhu et al. (2006) presents a focus on China. Covering the time period 1993 to 2002, the authors analyze the impact of subsidies on R&D expenditures of 32 industries in Shanghai. They fail to provide robust evidence but find that the effect of subsidies on R&D expenditures is ambiguous depending on the functional form. Because non-technology subsidies might also affect firm strategies, evidence on the impact of other subsidy categories also is relevant for this study. Investigating the impact of subsidies on export performance for loss-making state owned firms on China's provincial level for the time period 1995 to 1999, Eckaus (2006) identifies a significant and positive correlation. The analysis of Chinese manufacturing firms by Girma et al. (2009) confirms a positive relationship between subsidies and the intensive margin of exports for profitable firms, firms in capital-intensive industries, and firms located in non-coastal regions for the time period 1999 to 2005. In their study, the ownership structure of firms is found to be less important. For the time period 1994 to 2002 Claro (2006) finds that capital subsidies helped low-productivity state owned firms to co-exist with high-productivity non-state-owned firms. However, all these studies have the limitation of relying on industry level subsidy data.

2.3 Institutional Background and Hypotheses

Since the 1980s China's government has emphasized the importance of science and technology for the country's economic development. In the early transformation period R&D was mainly performed by research institutes while firms focused on production (Liu 2009). In line with China's transformation towards a market-driven economy, the concept of innovation appeared more regularly in the country's policy agenda since the late 1990s (Liu et al. 2011).

More recent policies have emphasized the central role of firms in China's innovation system – and extended the firm's activity scope from production towards R&D (OECD 2007).

Especially related to high priority issues, such as innovation, the Chinese government pursues active intervention to promote strategic goals.² Considering the time period 2000 to 2006, around 61 to 73% of the government's expenditures for science and technology were allocated to manufacturers in technologically advanced industries (Prud'homme 2012). The policies constituting China's innovation agenda differ by priority, duration, and reach. While Five Year Plans specify economy-wide priority targets for the respective planning period, the individual programs and associated funds have a more direct reach on the firm's strategy with considerable variation at the industry level.

In this study the subsidies income of firms is not linked to individual programs and funds but resembles the aggregated support received from the government's innovation policy. However, technology subsidies received throughout the time period 2001 to 2006 originating from the following major national programs: *key research* (1982-2006), *torch* (1988-), *863* (1986-), and *973* (1997-). Firms which are eligible for program participation often receive additional financial support from program-related support funds: *technology promotion* (1952-2002), *industrial technology R&D* (2002-), *applied technology R&D* (2004-), and *SME technology innovation* (1999-).³ A thorough examination of these programs and funds confirms that China's innovation policy follows a picking-the-winner strategy. In a nutshell, China's innovation policy support domestic firms which are (1) high-tech oriented, (2) inventive, (3) profitable, and (4) employ qualified human capital.

² See Liu et al. (2011) for an excellent survey of China's innovation policies.

³ The following administrative authorities are individually or collectively involved in the policies mentioned: Central Committee and State Council, National Development and Reform Commission, Ministry of Commerce, Ministry of Finance, Ministry of Information Industry, and Ministry of Science & Technology. The documents are accessible on the respective web-pages.

While the firm's high-tech industry affiliation might not be sufficient to receive technology subsidies, the high-tech content of a firm's inventions is more likely to have a positive effect. To consider different aspects of firm inventiveness, this study differentiates between the intensity and value of invention based on the firm's patent intensity per employee and citations received. The discrimination between intensity and value seems necessary, due to the high volume of junk-patent applications originating from China (Lei et al. 2013). Because the volume might be less representative for a firm's actual inventive capacity, a higher value of invention is likely to have a positive influence on receiving technology subsidies. Higher profitability and employment of qualified human capital are also expected to have a positive effect on the allocation of technology subsidies. It is difficult *ex ante* to predict which of these firm characteristics are more influential in the allocation of technology subsidies. However, this study assumes that firms exhibiting better performance in the allocation criteria addressed in China's innovation policy are more likely to receive technology subsidies.

H1a: Firms receive technology subsidies if they comply with allocation criteria addressed in China's innovation policy.

China's actual policy making is less coordinated and coherent than one might expect. Local governments have rather short term concerns in contrast to the central governments more strategic outlook and might use subsidies even to undermine, rather than reinforce, the central governments innovation policies (Oxford Analytica 2013). It is often beyond the capacity of the central government to monitor all policies and programs relevant for the allocation of subsidies at the local level (Eckaus 2006). Thus, this study also takes into account that the allocation of technology subsidies might also be influenced by criteria not determined in China's innovation policies.

For example, the priorities of local governments are rather biased towards short term economic targets, such as growth and employment, and the support of local firms. Deviating local policies might become even more relevant after China's WTO accession in 2001, which required the dismantling of much official protection for domestic firms and increased the exposure to foreign markets as well as domestic competition by foreign-invested firms (Cai and Tylecote 2008). Thus, local government might be inclined to allocate technology subsidies to domestic firms which are particularly affected by the WTO accession and exhibit high exposure to foreign markets or face rising domestic competition by foreign-invested firms.

Further, the implications of state vs. private firm ownership might also be relevant for the allocation of technology subsidies. Especially in the first decades after China's reform and opening, loss-making firms in the state sector were the main beneficiaries of subsidies. Local governments might still consider the support of loss-making state owned firms to prevent unemployment and to support local growth. To account for the particular firm ownership characteristics in the Chinese economy, this study follows the ownership classification by Cai and Tylecote (2008) and differentiates between majority state owned firms, minority state owned firms, and firms in private ownership. For state owned firms, we distinguish again between profitable and loss making firms. Profitable majority state owned firms are less likely to receive technology subsidies since they naturally follow government policies more closely (Li and Xia 2007). Since majority state-owned firms respond to different incentive structures than firms with minority state or private ownership, the government has a lesser need to use technology subsidies to adjust firm strategies according to policy targets. In contrast, minority state owned firms and private firms might receive more technology subsidies due to the lower

degree of direct government influence and firm strategies.⁴ Although these alternative allocation criteria are not addressed in China's innovation policies, this study considers the implications for the allocation of technology subsidies.

H1b: Firms receive technology subsidies if they comply with alternative allocation criteria not addressed in China's innovation policy.

Eventually, this study has the objective to investigate the effects of receiving technology subsidies on firm R&D expenditures and imports of advanced foreign technologies. Prior firm level evidence for developed and developing economies revealed significant, mixed, and insignificant effects. Unfortunately, there is no firm level evidence for China which could provide guidance in formulating a hypothesis. The industry level evidence for China in general speaks in favor of positive and significant effects but the effects on R&D are ambiguous and there is no evidence regarding the effect on technology acquisition. Consequentially, this study assumes that significant and insignificant effects are equally plausible.

H2a: Technology subsidies have a positive effect on R&D and technology acquisition of Chinese firms.

H2b: Technology subsidies have no effect on R&D and technology acquisition of Chinese firms.

3 Econometric Method

This section outlines the methodology of estimating the average effect of receiving technology subsidies (treatment) on firm R&D expenditures and technology acquisitions

⁴ State ownership is a sufficient but not a necessary condition for influence of the government. The strategy of a firm 100% owned by the state is obviously influenced by the government, but this does not allow for the reverse conclusion that a firm which is 100% in private ownership is free of the government's influence.

(outcome) – also known as the average treatment effect on the treated (*ATT*). *ATT* can be calculated as follows:

$$ATT = E(Y^T|S = 1) - E(Y^C|S = 1). \quad (1)$$

Y^T denotes the outcome of a treated firm and Y^C the outcome of a non-treated firm. S denotes the treatment status with 1 if the firm receives a treatment and 0 otherwise. *ATT* results from comparing the outcome of a treated firm with its hypothetical outcome given it had not received the treatment. While the treatment situation can be calculated as the mean outcome of treated firms, the counterfactual situation needs to be estimated. Assuming that the vector of firm characteristics $X = x$ is observable, the counterfactual situation can be estimated if the following equation holds:

$$E(Y^C|S = 1, X = x) = E(Y^C|S = 0, X = x). \quad (2)$$

In a non-experimental setting it is likely that vector $X = x$ determines the selection of treatment and the outcome. Thus, receiving a treatment is an endogenous variable in the firm's outcome function which introduces a self-selection bias and a possible overestimation of the treatment effect since the outcome of treated firms would differ even in the absence of treatment. To avoid this problem it is necessary to match every treated firm with a non-treated control firm, with both firms having the same probability of receiving a treatment with respect to a set of observables. This study uses the nearest-neighbor matching estimators to identify an appropriate control group for the treated group and require no assumption regarding the functional form and the distribution of the error term. The difference in mean outcomes can be attributed to the treatment effect and constitutes the *ATT*. For this exercise the conditional independence assumption by Rubin (1977) is introduced:

$$Y^T, Y^C \perp\!\!\!\perp S | X, \forall X. \quad (3)$$

It states that the selection of treatment is solely based on observables and that all firm characteristics X which influence treatment and outcome are simultaneously observed. A further requirement is the common support condition. It rules out that the treatment is perfectly predictable based on the observables X and ensures that firms with the same X values have a positive probability of receiving or not receiving the treatment (Heckman, LaLonde, and Smith 1999).

$$0 < P(D = 1|X) < 1 \quad (4)$$

Given that for each treated observation a non-treated control observation can be identified, the ATT can be estimated. However, in case of a high dimensional vector X it is difficult to find an exact control firm. Rosenbaum and Rubin (1983) overcome this “curse of dimensionality” by reducing the vector X to a single composite index – the propensity score.

$$ATT^{PSM} = E(Y^T|S = 1, P(X)) - E(Y^C|S = 0, P(X)). \quad (5)$$

The disadvantage of the propensity score matcher is that it only controls for observable differences between the treatment and control group. To overcome this problem, the propensity score matcher can be combined with a difference-in-difference estimator. Based on panel data the difference-in-difference estimator compares the mean outcome of treated firms in one period before the treatment with the mean outcome of treated firms after the treatment. Macroeconomic shocks are controlled for by calculating a second difference between the outcomes of treated and non-treated firms for the same time period. Consequently, the ATT based on the difference-in-difference approach is calculated as follows:

$$ATT^{DID} = E(Y_{t1}^T - Y_{t0}^T|S = 1) - E(Y_{t1}^C - Y_{t0}^C|S = 0). \quad (6)$$

By construction the difference-in-difference approach controls for constant individual effects and macroeconomic shocks. The combination of a propensity score matching estimator and a difference-in-difference estimator results in a so-called conditional difference-in-difference estimator. This estimator combines the advantages of the matching estimator with the advantages of the difference-in-difference estimator: (1) treated and non-treated firm have the same probability of receiving a treatment, (2) macroeconomic shocks, (3) constant individual unobservables, and (4) observable differences are controlled for:

$$ATT^{CDID} = E(Y_{t_1}^T - Y_{t_0}^T | S = 1, X = x) - E(Y_{t_1}^C - Y_{t_0}^C | S = 0, X = x). \quad (7)$$

4 Data and Variables

This study's time period 2001 until 2006 is chosen due to careful considerations of institutional and regulatory changes and their implications for data. China's WTO accession in 2001 required far reaching institutional adjustments and has implications not only for trade regulations but also for the allocation of subsidies and exposure to foreign competition. At the other end of the time period, the post-2006 global economic crisis again has far reaching implications for China's economy and is accompanied by structural adjustments on the industry level with implications for firm strategy. In addition, two important accounting regulations are amended after 2006. Firstly, the disclosure of subsidies received by a firm is not mandatory after 2006.⁵ Secondly, R&D related amendments of accounting rules after 2006 might affect the volume of firm level R&D expenses.⁶ Considering these implications, the years 2001 to 2006 are chosen as a stable time period for analysis in this study.

⁵ China Securities Regulatory Commission's (2000) "No. 2 disclosure guideline for the content and format of the annual report for the public offering of companies" specifies the position of subsidy income to be disclosed until 2006. The follow-up guideline enforced in 2007 does not list subsidy income anymore.

⁶ Before 2006 R&D expenses are fully expensed, The regulation "No. 6 enterprise accounting standards - intangible assets" is enforced in 2007 and implies that research related expenses should be accrued to the current

This study draws on firm balance sheet data from several data providers, including WIND, COMPUSTAT, and CSMAR. Additional balance sheet information on subsidiaries and ownership comes from RESSET. For information on R&D expenditures before 2006 a standardized screening process has been developed to manually collect data from the firms' annual reports accessible via CNINF. Firm import and export data has been obtained from Chinese Customs and is matched to the firm. For the identification of capital imports with advanced technologies, processing trade is excluded and capital goods are identified according to the UN BEC-4 classification. Hereafter, products encompassing advanced technologies are selected according to China's High and New Technology Product (HNTP) classifications. All monetary values used in this study are deflated.

PATSTAT⁷ is used to generate firm patent data. By exclusively considering invention patents this study focuses on technological inventions of higher value and simultaneously avoids double counting of invention and utility or design patents. The matching of accounting information to patent portfolios is based on the firm name. Because Chinese firms frequently change their names this study accurately accounts for historic firm names. Firm patent matches are performed in a semi-manual approach that takes 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. Patent families are compiled following the definition of the International Patent Documentation Center (INPADOC) and depreciated by the usual 15% annually to account for the fact that technology becomes obsolete over time (Hall, Jaffe, & Trajtenberg, 2005). For

profit and loss while development related expenses could be capitalized and recognized as intangible assets. For both activities a 50% deduction or amortization applies to encourage firm R&D.

⁷ April 2013 version of the EPO Worldwide Patent Statistical Database PATSTAT.

the classification of high-tech patents International Patent Class (IPC) definitions by EUROSTAT are used.

For the time period 2001 to 2006 the data includes 1,461 firms with 7,857 observations. Based on plausibility ratios the data is cleaned to correct for measurement errors. In addition, missing observations for R&D expenditures and ownership categories are excluded. Firm year observations for return on sales above the 99th percentile and average wages below the 1st percentile and above the 99th percentile are eliminated as outliers. After excluding financial holdings and firms from the financial sector the remaining firms are from 13 industries which all receive technology subsidies (see Table A1). Around 60% of firms are active in the manufacturing industry which confirms China's status as a manufacturing-oriented economy. Further, firms originate from all 31 provinces of Mainland China with a minimum of 0.61% coming from Tibet and maximum of 10.10% coming from Shanghai. Considering China's regional disparities this distribution is representative for the different levels of economic development. The final sample includes information for 1,236 firms with 5,407 observations.

4.1 Treatment

Data on Chinese subsidies is difficult to access. Even at the macro level, the position "total policy subsidy expenses" in China's national account is only reported until the year 2006 (NBS 2014). The studies surveyed in Section 2 make use of industry data available until 2005 while Hanley and Hanley (2013) estimate the volume of industry subsidies based on a price-gap approach. Although there are concerns regarding the quality of Chinese data in general, the quality of firm level data is regarded as more reliable than aggregated data because data fabrication on the firm level is more easily identified (Orlik 2011). One might expect that access to firm level data is even more difficult, but the accounting regulations for listed firms provide the rare opportunity to access data of relatively high quality. The quarterly and annual reports of listed firms are made public after scrutiny by accounting agencies. Thus, these data

provide relatively reliable information on different categories of subsidies and allows investigating the firm's total subsidy income differentiated into technology subsidies and other subsidies.⁸ Further, plausibility checks regarding the composition of subsidy data are done to exclude observations in those rare instances when the sum of individual subsidy categories exceeds the amount of total subsidies as reported by the firm.

4.2 Outcome

Based on annual R&D expenditures the firm's R&D stock is calculated, assuming an annual growth rate of 20% and annual depreciation of 15%. Firm technology acquisition is measured as the annual value of capital imports with advanced technologies. The stock of these imports is depreciated with 15 percent annually and weighted by the firm's net fixed assets. This ratio provides information to which extent the firm is advancing its production capacity through technology acquisition.

4.3 Covariates

Following the allocation criteria addressed in China's innovation policy six variables are operationalized. High-tech industry affiliation is built as a binary variable and follows the high-tech industry classification of China's National Bureau of Statistics. The high-tech content of a firm's innovations is operationalized as the share of patent applications in high-tech related IPC classes in the firm's patent application stock multiplied with 100. The ratio of the patent stock to employees multiplied with hundred controls for firm intensity of innovation. To control for the value of innovation the number of citations received by a patent applied for at the World Intellectual Property Office (WIPO) in three year period after publication is considered.

⁸ Subsidy categories include: technology subsidies, export subsidies, fiscal subsidies, tax refund, other subsidies, and total subsidies.

Because citation information is not made public by China's State Intellectual Property Office (SIPO), using WIPO citations is a novel approach which offers several advantages and has not been applied in the literature before. Firstly, it removes the home bias with regard to the choice of a patent office. Secondly, the costly WIPO application by the Chinese focal firm and the citation by third firms reveal information regarding the value of the patent's underlying invention. The share of WIPO citations is weighted by the firm's patent stock to control for a size induced citation bias and multiplied with one hundred. Firm profitability is calculated as the ratio of net profits to revenue. Finally, the quality of human capital is proxied by the average wages paid by the firm, following the rationale that more qualified human capital is paid higher wages on average.

Next, firm characteristics applying to alternative allocation criteria not specified in China's innovation policy are discussed. Exposure to overseas markets is operationalized as the firm's export intensity, total exports weighted by revenue, and indicates to which degree the firm depends on revenues generated abroad. For the operationalization of domestic competition by foreign invested firms the 3-digit industry level regulations for foreign direct investment are used. This binary variable indicates if a firm operates in an industry in which foreign investment is encouraged. Because firm industry affiliation is fixed at the year of entry the observed variation reveals regulatory trends and is not affected by firms switching industries.

The ownership categories discussed in Section 2 are built as follows. Majority state-owned firms exhibit a state ownership $x > 50\%$ and minority state-owned firms exhibit a state ownership $50\% \geq x > 25\%$. Private firms have a state ownership $x \leq 25\%$. In addition, majority and minority state-owned firms are split again in profitable and loss-making firms. Firms are classified as loss-making if they exhibit negative net profits in two consecutive years. Consequentially, five binary variables are operationalized as ownership categories.

Finally, this study controls for firm heterogeneity with two sets of basic and further control variables. Basic controls include the number of employees as a control for the firm's size, capital intensity, calculated as the ratio of net fixed assets by employee, and the firm's age. Further controls include time invariant binary variables for the firm's industry affiliation and province. Finally, years are included to control for general macro-economic shocks.

4.4 Descriptive Statistics

Table 1 provides the descriptive statistics. Starting with the treatment variables, the description reveals that 268 out of 1,236 firms receive a technology subsidy and 225 treated firms have received a previous treatment throughout the last three years. The volume of the treatment accounts for 1.9% of firm revenue on average of which 53% originate from support funds. Other, non-technology subsidies are received by 822 firms.

The outcome variables show that 400 firms conduct R&D and these firms' average R&D intensity is around 1.1%. Nonetheless, the maximum R&D intensity is as high as 20%. The variable technology acquisition reveals that 434 firms have imported capital goods containing advanced technologies. These imports' share of the firms' overall capital stock accounts for 10.2% on average.

Innovation policy related covariates display that 16% of firms affiliated with high-tech industries. 223 firms have applied for a high-tech patent. Of these firms, the share of high-tech patent applications to the depreciated patent stock is relatively high with a mean value of 0.92 and median of 0.42. This shows that firms with high-tech content in their innovation are concentrated on high-tech. 207 firms receive WIPO citation with an average of 0.48 citations and a maximum of 47 citation per depreciated patent application of the patent stock.

Considering the variables which apply to alternative allocation criteria of technology subsidies, the average firm has an export intensity of 4.2% and 52% of firms are located in industries with a higher level of competition due to encouragement of foreign investment. 445

firms are profitable majority state owned firms, while 35 are loss-making ones. 377 firms are profitable minority state owned firms and 49 firms are loss-making ones. 680 firms are profitable private firms. Because the binary ownership variables are time variant a firm can appear in multiple categories over time. For example, a loss-making majority state owned firm can become a profitable minority state-owned or private firm due to continuous privatization.

The basic controls reveal that firms are rather large and capital intensive with an average of 3,377 employees and a capital intensity of 0.55 million RMB per employee. The average firm is 9 years old but the maximum age is as high as 103 years. For information regarding industry composition and mean values of outcome variables across industries see Table A1 and Table A2.

5 Empirical Analysis

5.1 Probit Estimation

The allocation of technology subsidies is investigated based on the Probit estimations reported in Table 2. The parsimonious specification in Model (1) only includes the two sets of basic and further control variables. Firm size is positively significant and industry, province, and year groups are jointly significant. Based on this parsimonious specification, covariates related to allocation criteria addressed in China's innovation policies and alternative allocation criteria related to foreign exposure and competition, as well as firm ownership are individually tested for significance (results are not reported). In Model (2), those significant covariates are again jointly introduced into the final specification. Related to innovation policy, the high-tech content in firm innovation and profitability remain positively significant. Further, competing with foreign invested firms in domestic industries increases a firm's probability of receiving technology subsidies. Considering the implications of ownership,

profitable minority state-owned and private firms have a significantly higher probability of receiving technology subsidies as well.

These findings confirm that a firm's high-tech content in invention, the value of invention, and firm profitability are relevant in the allocation of technology subsidies. However, the value of invention is relevant only to a less significant extent. Thus, not only the allocation criteria of China's innovation policy but also alternative allocation criteria are relevant in the allocation process. In conclusion, the Chinese government's picking-the-winner strategy is largely confirmed while some extra support is granted to firms in industries with a high presence of foreign firms. However, also this finding might fit into the general strategy since foreign firms not only increase competition but are potential sources of spillover effects.

Model (3) complements the final specification with a control for treatments received by the firm during the last three years. Not surprisingly, this variable has a positive and highly significant effect. Once a firm qualified for technology subsidies it more easily receives consecutive treatments. Because treatment history implicitly controls for firm characteristics which positively affected treatment already in previous years, the significance of other covariates is reduced. Only the ownership categories remain explanatory power since these variables are time variant and capture information which is not controlled for by treatment history. In addition, the groups of industry and province controls remain significant. Based on Model (3) the propensity score is estimated.

5.2 Propensity Score Matching

In nearest neighbor matching, for each treated observation a control observation is identified. The group of potential control observations is restricted to common support – 100 treated observations with probabilities larger than the maximum and smaller than the minimum in the potential control group are deleted. Further, only potential control observations from the same year as the treated observation remain. The Mahalanobis-distance

is calculated and the control observation with the closest distance is chosen but remains in the group of potential control observations to become a control observation again for another treated observation. To avoid bad matches, caliper matching is imposed and avoids a match with a control observation which is too distant to the treated one. Consequently, 44 observations are dropped for which no neighbor is found. To take the appearance of repeated observation in the final control group into account, standard errors are calculated following Lechner's (2001) estimator for an asymptotic approximation of standard errors.

Table 3 and Table 4 show the groups before and after the matching. Before the matching, *t*-tests on mean differences between the treated group and potential control group reveal significant differences in treatment history, almost all other covariates of Model (3), and outcome variables. The means of R&D intensity and technology acquisition between the two groups are significantly different with the treated group exhibiting the higher means. Table 4 shows that after the matching the *p*-value of the *t*-tests on mean differences indicate that no significant mean differences remain. For the further controls including industry, province, and year, Chi2 tests reject joint explanatory power for each group. A comparison of Figure 1 and Figure 2 shows that propensity scores of both groups turn out to be graphically identical after the match. The matched sample has 385 firms with 828 observations and includes 239 treated and 234 untreated firms. This shows that only few control observations are used more than once. Further, firms appear as treated or untreated firms depending on the treatment status of the respective year. Since the propensity score considers a treated firm's treatment history, the control firm is a firm without a treatment in the actual year but with a similar treatment history.

5.3 Conditional Difference-in-Difference Estimation

Table 5 reports the treatment effect of receiving a technology subsidy on the outcomes variables R&D intensity and technology acquisition. These outcome variable captures the

variation over time and is specified in first and second differences, e.g. the difference in the outcome in the year before the treatment t_{-1} and in the year of the treatment t_0 as well as the difference in the outcome in the year before the treatment t_{-1} and in the year after the treatment t_1 . The first difference assumes an effect in the year of treatment while the second difference allows for a later significance the treatment effect. Because the second difference includes one more year, the number of firms and observations in specifications with this outcome variables is lower. All specifications also include two sets of basic and further controls for firm size, capital intensity, age and industry, province, and year to account for remaining firm heterogeneity in the matched sample. However, the effect of receiving a technology subsidy is not significant for firm R&D intensity or technology acquisition neither specified in first or second differences.

Table 6 reports the effect of different sizes of technology subsidies on the outcome. The volume of treatment is classified into small, medium, and large technology subsidies and weighted by the firm's revenues. However, no significant effect can be reported. Next, the effect of consecutive treatments is analyzed. Table 7 reports the results of treatments when the firm's treatment history is controlled for. Even though treatment in t_0 and earlier treatments are individually not significant, the interaction term reveals a positive treatment effect with 10% significance for Model (1), (2), and (3). This finding provides weak evidence that a technology subsidy has a positive effect if the firm has already received a treatment in the past. However, an F -test reveals that the joint effect of the three covariates is not significantly different from zero.

In the next specification the composition of technology subsidies is analyzed. For treated firms, the share originating from support funds is expressed as a ratio to the subsidies total volume. However, the results reported in Table 8 indicate that the source of funding has not impact. Finally, the moderating effect of other subsidies is considered. For this exercise the treatment group and potential control group are matched again under the additional

stratification condition that treated observations and control observations must exhibit the same status with regard to receive other subsidies in t_0 . As Table 9 shows, there is weak evidence that receiving other subsidies has a negative effect on the outcome variables. Based on these results it can be concluded that technology subsidies have almost no statistically significant effect on R&D intensity and technology acquisition. There is weak evidence for a positive effect of consecutive treatments.

6 Conclusion

This study investigated the allocation and effect of technology subsidies on R&D activities and technology acquisitions of Chinese domestic firms. We exploit novel firm data which includes information on subsidies, R&D, patents, trade, and balance sheet indicators. Conditional difference-in-difference estimation confirms that the innovation policy of China's government follows a picking-the-winner strategy. Technology subsidies are allocated to minority state-owned and privately owned firms which have high-tech inventions, high profitability, and compete with foreign firms in domestic industries. However, we find almost no evidence which confirms that technology subsidies incentivize an increase in R&D intensity or technology acquisition. There is weak evidence for a positive effect of consecutive treatments.

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Tables and Figures

Table 1: Descriptive Statistics

Variables	Mean	Std. dev.	Median	Min.	Max.	No. firms[#]
Treatment						
Technology subsidy (binary)	0.103	0.304	0	0	1	268
Technology subsidy in last 3 years (binary)	0.105	0.306	0	0	1	225
Technology subsidy/revenue (%)	1.858	30,905	0.093	0.000	65.240	268
Support fund/ technology subsidy (%)	52.431	48,99	89.922	0	100	268
Other subsidy (binary)	0.452	0.498	0	0	1	822
Outcome						
R&D intensity (%)	1.075	1.956	0.468	0.001	20.711	400
Technology acquisition (%)	10.188	16.827	3.014	0.000	99.704	434
Covariates						
<i>Innovation policies</i>						
High-tech industry affiliation (binary)	0.158	0.365	0	0	1	1,236
High-tech patents/patent stock(*100)	92.696	203.25	41.812	0.782	2505.416	223
Patents stock/employee (*100)	0.621	2.49	0.127	0.002	41.606	498
WIPO citations/patent stock(*100)	135.506	388.646	44.878	0.444	4700	207
Profitability (net profits/revenue)	-0.045	1.837	0.06	-106.64	0.592	1,236
Human capital (avg. wages million RMB)	0.05	0.067	0.031	0.005	0.695	1,236
<i>Foreign competition</i>						
Export intensity (%)	4.248	12.668	0	0	98.914	1,236
Domestic competition by FDI (binary)	0.526	0.499	1	0	1	733
<i>Ownership</i>						
Maj. state-owned, profitable (binary)	0.3	0.456	0	0	1	445
Maj. state-owned, loss making (binary)	0.008	0.088	0	0	1	35
Min. state-owned, profitable (binary)	0.24	0.427	0	0	1	377
Min. state-owned, loss making (binary)	0.011	0.106	0	0	1	49
Privately owned, profitable (binary)	0.445	0.497	0	0	1	680
<i>Basic controls</i>						
Employees	3,377.266	13051.1	1,667	10	443,808	1,236
Capital intensity (million RMB/employee)	0.55	1.726	0.22	0.003	45.924	1,236
Age (years)	9.307	5.842	9	1	103	1,236

#Note: The statistics are calculated for 5,407 observations of 1,236 firms. Some variable are only applicable to a smaller sub-sample of firms.

Table 2: Allocation of Technology Subsidies

	(1)	(2)	(3)
	Parsimonious	Final	Final incl. historic technology subsidy
Technology subsidy in last 3 years			1.551*** (0.000)
<i>Innovation policies</i>			
ln(High-tech patents/patent stock)		0.058** (0.028)	0.011 (0.658)
ln(WIPO citations/patent stock)		0.035 (0.172)	0.037 (0.106)
Profitability		0.304** (0.031)	0.151 (0.167)
<i>Foreign competition</i>			
Domestic competition by FDI		0.181* (0.064)	0.101 (0.259)
<i>Ownership</i>			
Maj. state-owned, loss making		-0.405 (0.332)	-0.762* (0.096)
Min. state-owned, profitable		0.297*** (0.008)	0.203** (0.033)
Min. state-owned, loss making		0.259 (0.421)	0.089 (0.826)
Privately owned, profitable		0.237** (0.018)	0.121 (0.164)
<i>Basic controls</i>			
ln(Employees)	0.077** (0.038)	0.065* (0.087)	0.030 (0.328)
ln(Capital intensity)	-0.043 (0.270)	-0.047 (0.243)	-0.052 (0.145)
ln(Age)	0.149 (0.109)	0.105 (0.279)	0.063 (0.435)
<i>Further controls</i>			
Industry	(30)=126.26*** (0.000)	(30)=126.52*** (0.000)	(30)=99.41*** (0.000)
Province	(11)=28.12*** (0.003)	(11)=23.71** (0.014)	(11)=19.59* (0.051)
Year	(4)=11** (0.026)	(4)=10.04** (0.039)	(4)=5.74 (0.219)
Constant	-1.739	-1.827	-1.415
Pseudo	0.122	0.138	0.307
Observations	4,111	4,111	4,111
Firms	1,160	1,160	1,160

Notes: The dependent variable is the binary variable of receiving a technology subsidy. All time variant covariates except age are lagged by one year to control for simultaneity to the largest possible extent. Industries in which FDI is not encouraged are the reference category for domestic competition by FDI. Profitable majority state-owned firms are the reference category for ownership. Standard errors are clustered by firm. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels.

Table 3: Potential Control Group and Treatment Group

Variables	Unsubsidized firms, N=1200		Subsidized firms, N=268		<i>t</i> -test on mean differences
	Mean	Std. dev.	differences	Std. dev.	
Technology subsidy in last 3 years	0.057	0.232	0.519	0.500	***
<i>Innovation policies</i>					
ln(High-tech patents/patent stock)	0.272	1.028	0.539	1.445	***
ln(WIPO citations/patent stock)	0.393	1.252	0.679	1.642	***
Profitability	-0.377	1.991	0.047	0.236	
<i>Foreign competition</i>					
Competition by FDI	0.515	0.499	0.571	0.495	**
<i>Ownership</i>					
Maj. state-owned, loss making	0.006	0.081	0.002	0.046	
Min. state-owned, profitable	0.240	0.427	0.280	0.449	*
Min. state-owned, loss making	0.010	0.102	0.006	0.080	
Privately owned, profitable	0.418	0.008	0.501	0.500	***
<i>Basic controls</i>					
ln(Employees)	7.342	1.221	7.487	1.147	**
ln(Capital intensity)	12.396	1.079	12.255	0.897	***
ln(Age)	2.074	0.539	2.219	0.507	***
<i>Outcome</i>					
R&D intensity	0.174	0.871	0.351	1.289	***
Technology acquisition	2.783	9.907	4.455	12.145	***

Note: ***, **, * indicate significance levels of 1%, 5%, 10%. Chi2-test for *further controls*: industry (11) = 19.59*, p = 0.014; province (30) = 99.41***, p = 0.000; year (4) = 10.04**, p = 0.039.

Figure 1: Propensity Scores of Potential Control Group and Treatment Group

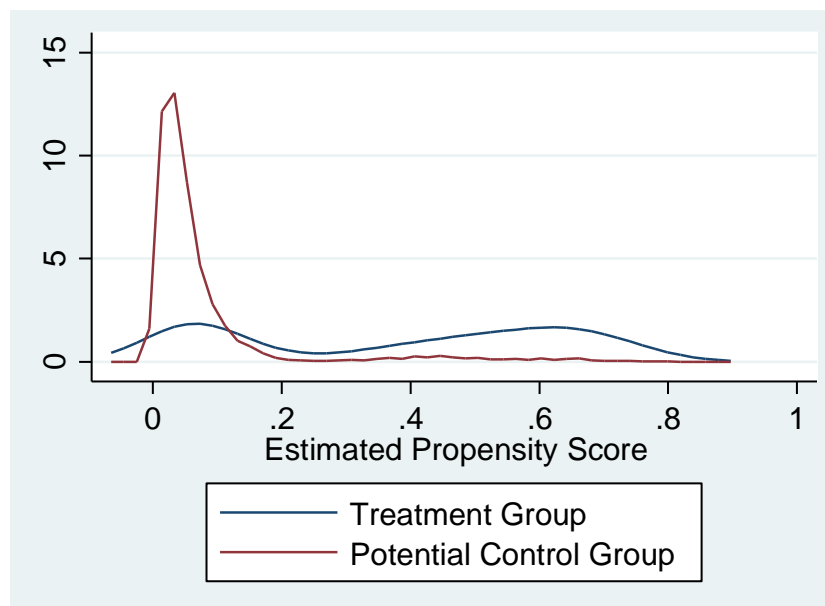


Table 4: Control Group and Treatment Group

Variables	Unsubsidized firms, N=234		Subsidized firms, N=239		<i>p</i> -value of <i>t</i> -test on mean differences
	Mean	Std. dev.	differences	Std. dev.	
Technology subsidies in last 3 years	0.591	0.492	0.586	0.492	<i>p</i> =0.910
<i>Innovation policies</i>					
ln(High-tech patents/patent stock)	0.517	1.389	0.510	1.423	<i>p</i> =0.469
ln(WIPO citations/patent stock)	0.769	1.695	0.614	1.601	<i>p</i> =0.284
Profitability	0.019	2.994	0.048	0.239	<i>p</i> =0.234
<i>Foreign competition</i>					
Domestic competition by FDI	0.582	0.493	0.574	0.494	<i>p</i> =0.865
<i>Ownership</i>					
Maj. state-owned, loss making	0	0	0.002	0.049	<i>p</i> =0.317
Min. state-owned, profitable	0.297	0.457	0.282	0.450	<i>p</i> =0.713
Min. state-owned, loss making	0.007	0.084	0.007	0.084	<i>p</i> =1.000
Privately owned, profitable	0.461	0.499	0.492	0.500	<i>p</i> =0.468
<i>Basic controls</i>					
ln(Employees)	7.435	1.154	7.479	1.147	<i>p</i> =0.658
ln(Capital intensity)	12.252	1.021	12.257	0.891	<i>p</i> =0.957
ln(Age)	2.232	0.459	2.250	0.455	<i>p</i> =0.657
<i>Outcome</i>					
R&D intensity	0.251	0.900	0.306	1.07	<i>p</i> =0.508
Technology acquisition	4.324	11.082	4.513	3.411	<i>p</i> =0.845

Note: ***, **, * indicate significance levels of 1%, 5%, 10%. Chi2-test for *further controls*: industry (8) = 11.64, *p* = 0.168; province (30) = 23.22, *p* = 0.806; year (4) = 0.13, *p* = 0.997.

Figure 2: Propensity Scores of Control Group and Treatment Group

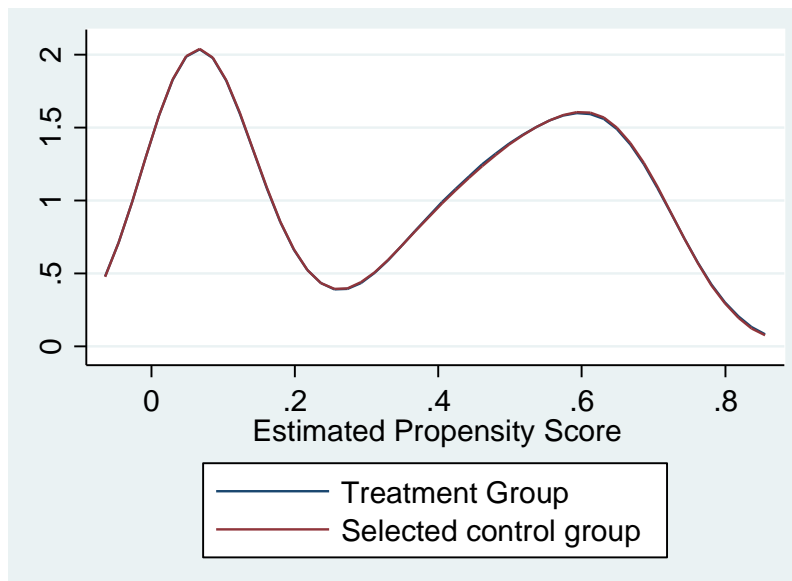


Table 5: Effect of Technology Subsidy

	(1)	(2)	(3)	(4)
<i>Outcome</i>	R&D intensity	R&D intensity	Technology acquisition	Technology acquisition
<i>Difference</i>	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$
Technology subsidy (binary)	0.072 (0.385)	0.118 (0.400)	0.530 (0.233)	0.444 (0.492)
<i>Basic controls</i>	yes	yes	yes	yes
<i>Further controls</i>	yes	yes	yes	yes
Constant	-0.298	0.974	0.494	-1.830
R2	0.083	0.091	0.053	0.079
Observations	815	572	828	765
Firms	379	295	385	364

Table 6: Effect of the Size of Technology Subsidy

	(1)	(2)	(3)	(4)
<i>Outcome</i>	R&D intensity	R&D intensity	Technology acquisition	Technology acquisition
<i>Difference</i>	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$
Technology subsidy (small)	0.120 (0.300)	0.189 (0.279)	0.903 (0.193)	0.742 (0.389)
Technology subsidy (medium)	0.064 (0.519)	0.176 (0.356)	-0.030 (0.957)	-0.299 (0.749)
Technology subsidy (large)	0.017 (0.788)	-0.012 (0.932)	0.584 (0.215)	0.776 (0.115)
<i>Basic controls</i>	yes	yes	yes	yes
<i>Further controls</i>	yes	yes	yes	yes
Constant	-0.257	1.054	0.240	-2.336
R2	0.084	0.095	0.056	0.081
Observations	815	572	828	765
Firms	379	295	385	364

Note: The technology subsidy's volume is decomposed into the following centiles: small: $0 < x < 33.33$; medium: $33.33 < x < 66.66$; large: $66.66 < x < 100$. Technology subsidy with volume 0 is the reference category.

Table 7: Effect of Consecutive Technology Subsidies

	(1)	(2)	(3)	(4)
<i>Outcome</i>	R&D intensity	R&D intensity	Technology acquisition	Technology acquisition
<i>Difference</i>	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$
Technology subsidy (binary)	-0.097 (0.152)	-0.135 (0.204)	-0.406 (0.393)	-0.246 (0.667)
Technology subsidy in last 3 years	-0.141 (0.112)	-0.229 (0.104)	-1.189* (0.069)	-0.652 (0.494)
Interaction	0.290* (0.056)	0.443* (0.052)	1.607* (0.083)	1.192 (0.333)
<i>Basic controls</i>	yes	yes	yes	yes
<i>Further controls</i>	yes	yes	yes	yes
Constant	-0.112	1.171	1.427	-1.153
R2	0.092	0.103	0.059	0.08
Observations	815	572	828	765
Firms	379	295	385	364

Note: F-tests on joint significance of the three technology subsidy covariates reveal joint insignificance.

Table 8: Effect of Share of Support Fund for Treated Firms

	(1)	(2)	(3)	(4)
<i>Outcome</i>	R&D intensity	R&D intensity	Technology acquisition	Technology acquisition
<i>Difference</i>	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$
Support fund/technology subsidy (%)	-0.002 (0.134)	-0.001 (0.566)	-0.005 (0.404)	-0.005 (0.520)
<i>Basic controls</i>	yes	yes	yes	yes
<i>Further controls</i>	yes	yes	yes	yes
Constant	-1.542	0.435	10.619	5.273
R2	0.117	0.133	0.11	0.134
Observations	407	279	414	381
Firms	236	177	239	225

Table 9: Effect of Technology Subsidy and Other Subsidy

	(1)	(2)	(3)	(4)
<i>Outcome</i>	R&D intensity	R&D intensity	Technology acquisition	Technology acquisition
<i>Difference</i>	$\Delta(t_1 - t_{-1})$	$\Delta(t_1 - t_{-1})$	$\Delta(t_0 - t_{-1})$	$\Delta(t_1 - t_{-1})$
Technology subsidy (binary)	-0.082 (0.339)	0.013 (0.931)	0.025 (0.968)	0.157 (0.881)
Other subsidies (binary)	-0.064 (0.422)	-0.149 (0.174)	-1.150* (0.071)	-1.590 (0.125)
Interaction	0.121 (0.260)	0.083 (0.659)	0.565 (0.513)	0.198 (0.876)
<i>Basic controls</i>	yes	yes	yes	yes
<i>Further controls</i>	yes	yes	yes	yes
Constant	-0.529	0.836	3.878	1.896
R2	0.092	0.095	0.071	0.088
Observations	767	532	780	726
Firms	371	290	377	360

Note: F-tests on joint significance of the three technology subsidy covariates reveal joint insignificance.

Appendix

Table A1: Industry Composition and Allocation of Technology Subsidies

Industry	All firms		Firms with ITS	
	No. firms	(%)	No. firms	(%)
Agriculture	30	2.42	5	1.84
Mining	20	1.62	1	0.37
Manufacturing	781	62.93	182	66.91
Utilities	53	4.27	3	1.10
Construction	16	1.29	2	0.74
Transportation and Warehousing	54	4.35	4	1.47
Information Technology	54	4.35	22	8.09
Wholesale and Retail	97	7.82	23	8.46
Real Estate	36	2.90	5	1.84
Social Services	37	2.98	5	1.84
Communication and Culture	4	0.32	1	0.37
Conglomerates	59	4.75	19	6.99
Total	1,241	100	272	100

Note: The industries are specified according to industry classification for listed firms as specified by China Regulatory Stock Market Commission.

Table A2: Outcome Variables across Industries

Industry	R&D intensity	Technology acquisition
	(%)	(%)
Agriculture	0.075	0.937
Mining	0.035	1.143
Manufacturing	0.239	3.39
Utilities	0.004	0.561
Construction	0.006	3.507
Transportation and Warehousing	0.043	0.062
Information Technology	0.86	8.696
Wholesale and Retail	0.012	2.855
Real Estate	0.023	0.124
Social Services	0.032	0.973
Communication and Culture	0	0
Conglomerates	0.021	1.962
Total	0.192	2.954

Note: The industries are specified according to industry classification for listed firms as specified by China Regulatory Stock Market Commission.