NBER WORKING PAPER SERIES

DOES "MADE IN CHINA 2025" WORK FOR CHINA? EVIDENCE FROM CHINESE LISTED FIRMS

Lee G. Branstetter
Guangwei Li

Working Paper 30676
http://www.nber.org/papers/w30676

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2022

Guangwei Li has acknowledged support from the ShanghaiTech Start-up Fund. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research and ShanghaiTech University.

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NBER Working Paper No. 30676
November 2022
JEL No. O25,O32

ABSTRACT

Rising concern over the impact of Chinese industrial policy has led to severe trade tensions between China and some of its major trading partners. In recent years, foreign criticism has increasingly focused on the so-called "Made in China 2025" initiative. In this paper, we use information extracted from Chinese listed firms' financial reports and a difference-in-differences approach to examine how the "Made in China 2025" policy initiative has impacted firms' receipt of subsidies, R&D expenditure, patenting, productivity, and profitability. We find that while more innovation promotion subsidies seem to flow into the listed firms targeted by the policy, we see little statistical evidence of productivity improvement or increases in R&D expenditure, patenting and profitability. This paper suggests that the “Made in China 2025” initiative may have not yet achieved its target goals.

Lee G. Branstetter
Heinz College
Hamburg Hall 2222
Carnegie Mellon University
Pittsburgh, PA 15213
and the Peterson Institute for International Economics
and also NBER
branstet@andrew.cmu.edu

Guangwei Li
ShanghaiTech University
Room 324, SEM Building
393 Middle Huaxia Road
Pudong, Shanghai 201210, China
ligw@shanghaitech.edu.cn

1. Introduction

Rising concern over the impact of Chinese industrial policy has led to the emergence of serious trade tensions between China and many of its major trading partners. These tensions are most visible in the US-China relationship, but other advanced industrial trading partners, leading multinationals, and foreign industry associations have voiced similar concerns.[1] In recent years, foreign criticism has increasingly focused on the so-called "Made in China 2025" (中国制造 2025) initiative.

"Made in China 2025" is a multi-pronged policy initiative of the People's Republic of China announced with considerable fanfare in May 2015.[2] The explicit aim of this initiative is to move China away from being the "world's factory" (producing cheap, low-quality goods due to lower labor costs and supply chain advantages) toward "innovation-driven" production of higher-value products and services. The Notice of the State Council on the Publication of "Made in China 2025" (国务院关于印发《中国制造 2025》的通知), the official announcement document of "Made in China 2025", specifies "being innovation-driven" as the central approach and notes that the country needs to "strive to achieve the strategic goal of becoming a manufacturing powerhouse through the 'three steps' (三步走)." The first step is up to 2025. By that time, China needs "greatly improve the overall quality of the manufacturing industry, significantly enhance

[1] The U.S.-China "trade war" launched by the Trump Administration was justified, in part, as a response to Chinese industrial policy. Bown and Kolb (2021)provide an updated description of the various aspects of this war, including the ones related to Chinese industrial policy. EU businesses recently put forward a wide-ranging critique of Chinese industrial policy (European Chamber of Commerce in China, 2017), and the investment agreement painstakingly negotiated between the EU and China over seven years has been recently frozen prior to implementation due to a range of Sino-European disputes, including some related to industrial policy.

[2] The State Council of China website provides an official description: "China to invest big in 'Made in China 2025' strategy," http://english.www.gov.cn/state_council/ministries/2017/10/12/content_281475904600274.htm, accessed April 6, 2020. McBride and Chatzky (2019) present a critical overview that emphasizes frequent foreign criticisms of the program. Rodrik (2020) provides a rare example of foreign praise for the program and Chinese industrial policy in general.

innovation capabilities, significantly improve the labor productivity of all employees, and bring the integration of industrialization and informatization to a new level." [3]

The policy targets ten key industries, including (1) next-generation information technology, (2) high-end digital control machine tools and robotics, (3) aerospace and aeronautic equipment, (4) oceanographic engineering equipment and high-technology shipping, (5) advanced rail transportation equipment, (6) energy-efficient and new energy automobiles, (7) electric power equipment, (8) agricultural machinery and equipment，(9) new materials, and (10) bio-pharmaceuticals and high-performance medical equipment.

The more controversial elements of the plan include the explicit goals of achieving independence from foreign suppliers in a broad range of high-tech products and services. Many other countries view the program as threatening because it is a state-led effort that uses government subsidies to mobilize Chinese enterprises (especially state-owned enterprises) to pursue intellectual property acquisition and catch up with—and then surpass—Western technological prowess in advanced industries.[4] Of special concern to many international trade experts is the conspicuous inclusion of specific domestic and international market share targets in the early versions of the plan, suggesting a heavy-handed attempt to determine market outcomes. In March 2018, a Trump Administration investigation—launched under Section 301 of the 1974 Trade Act—concluded that China's actions across a wide range of trade policies, including the "Made in China 2025" initiative, were "unreasonable and discriminatory." The

[3] http://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm, accessed April 6, 2020.
[4] An example of a critical overview of the policy initiative is provided by McBride and Chatzky (2019); see https://www.cfr.org/backgrounder/made-china-2025-threat-global-trade.

Trump Administration then used these findings as a partial justification for a far-reaching trade war against China that the Biden Administration has largely continued.

Despite the growing intensity of these debates, many of the claims advanced by “Made in China 2025” proponents and critics have yet to be subjected to serious empirical scrutiny. The lack of serious empirical research reflects, in part, the difficulty of accurately measuring the existence and incidence of “Made in China 2025” subsidies and supports at the firm level.

This paper will fill the gap using information extracted from Chinese listed firms’ financial reports and a difference-in-differences (DiD) approach to examine what impact the “Made in China 2025” initiative has had on firms' receipt of subsidies and outcome variables that measure the policy’s claimed goals by 2025, as described above. We find that while more innovation promotion subsidies seem to flow into the listed firms targeted by the policy, we see little statistical evidence of productivity improvement or increases in R&D expenditure, patenting, and profitability.

The remainder of this paper is organized as follows. Section 2 describes our data and empirical methods; Section 3 presents our main results. Section 4 provides robustness checks. Finally, Section 5 concludes and discusses the implications of our findings.

2. Data and Empirical Methods

2.1 Identifying firms affected by “Made in China 2025”

Despite the fanfare with which it was announced, the Chinese government has never publicly identified the firms that were designated to receive support under this program. Even for Chinese listed firms, whom are required by the law to disclose government subsidy amounts in their financial reports, only a few disclose that specific subsidies they received from the government are directly connected to the “Made in China 2025” program.[5]

To identify firms affected by the “Made in China 2025” policy, we perform a text search on all annual reports of Chinese listed firms from 2015 to 2018, and highlight the firms that mentioned “Made in China 2025” (in Chinese) at least once in their reports, even if they did not do so in the section that describes the subsidies they received. In this way, we identified 1,120 out of 3,486 firms that are potential beneficiaries of the “Made in China 2025” policy. A manual check of all such mentions indicates the reporting firms expected to *benefit* from this program. In our empirical analysis, we consider all manufacturing firms that mention the “Made in China 2025” policy in their annual reports in this way as ones “treated” by the policy. We acknowledge that our approach would be subjected to estimation bias if firms make misleading statements in their annual reports. That said, this kind of misconduct is likely to be rare as listed firms' financial statements are required by the law to be reviewed by independent auditors before they are released to the public.[6] As a robustness check, we also use an alternative method based on industry information to identify treated firms.

In our main specifications, we choose 2018 as the ending point of our sample because we observe a significant decrease in the frequency of “Made in China 2025” appearance in listed companies’ financial statements after 2018. This seems to be related to the change in the "Made in China" policy implementation, probably due to the pressure from the US-China trade war. Although the Chinese government never officially announced such a policy change, anecdotal

[5] Chinese listed firms disclose a total of 285,977 records of subsidies with meaningful descriptions by the end of 2018. Among them, only 109 records specify that the subsidy is given to the firm for a reason related to "Made in China 2025".

[6] This statement comes with the caveat that the quality of information disclosed by Chinese firms to the stock exchanges does not always meet the highest international standards (Chan et al., 2008).

evidence suggests that the Chinese government has significantly downplayed the initiative's role since the launch of the US-China trade war in March 2018. For example, the Chinese central government designated webpage for "Made in China 2025" (http://www.gov.cn/zhuanti/2016/MadeinChina2025-plan/index.htm) has not been updated since the trade war began. For another example, the Ministry of Industry and Information Technology issued a policy under the name of "Made in China 2025" in 2017, and then for the same policy in 2018, the words "Made in China 2025" were taken away from the document.[7] That said, the policy does not seem to be fully abandoned either. The words "Made in China 2025" still occasionally, though very rarely, appear in public media. This ambiguous situation brings extra challenges to our empirical analysis. It will likely make us misidentify hidden treated firms as controls after 2018 if we include the most recent years in our empirical analysis, making our estimated treatment effect biased downward. On the other hand, ending in 2018 makes our post-treatment exposure only four years at most, which may be too short to observe policy impacts. Recognizing this problem, we also extend the post-treatment period to include more recent years as a robustness check, assuming the firms that mention "Made in China 2025" in their disclosures during the 2015–2018 period are the only ones that are treated.

2.2 Estimation Model

We selected the firms self-identified as most likely to "benefit" from the "Made in China 2025" policy as described above and then tested the treatment effect on firm outcome measures using a DiD approach. The model is specified as follows:

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[7]For 2017, the document title is "Notice of the Ministry of Industry and Information Technology on Issuing the 2017 Industrial Transformation and Upgrading (Made in China 2025) Fund (Departmental Budget) Project Guidelines ("工业和信息化部关于发布 2017 年工业转型升级（中国制造 2025）资金（部门预算）项目指南的通知"); for 2018, the document title is "Notice of the Ministry of Industry and Information Technology on Issuing the 2018 Industrial Transformation and Upgrading Fund (Departmental Budget) Project Guidelines" ("工业和信息化部关于发布 2018 年工业转型升级资金（部门预算）项目指南的通知").

$$y_{it} = \alpha_i + \beta_1(P_t * T_i) + X_{it}^{'}\Gamma + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Here y_{it} represents an outcome measure of firm i during year t, including total subsidies received in logs, innovation subsidies in logs, the R&D/sales ratio, Chinese invention patent application counts, US utility patent application counts, labor productivity (calculated as sales divided by the number of employees) in logs, total factor productivity (TFP) and profit margin (calculated as profit divided by sales). X_{it}' are firm-level time-varying controls. Depending on specifications, we include all or some of the following controls: total assets, sales, employment and R&D sales ratio, all in log terms. The variables μ_i and λ_t are firm and time fixed effects. P_t is the post-treatment indicator, which equals 1 in the year in which the firm first mentions the words "Made in China 2025" and all years afterward, and 0 for years before the firm first mentions words "Made in China 2025". T_i is the policy treatment indicator, which equals 1 if firms ever mention the words "Made in China 2025" in their annual financial reports, and 0 if not. The coefficient on the interaction term $(P_t * T_i)$ enables us to discern the the impact of the "Made in China 2025" initiative. Since we include firm and time fixed effects, the traditional DiD coefficients of T_i and P_t are absorbed by these fixed effects.

We also use a panel event study design to examine the parallel trend assumption. The specification is as follows:

$$y_{it} = \sum_{j=\underline{j}}^{\bar{j}} \beta_j {b_{it}}^j + X_{it}^{'}\Gamma + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

where

$${b_{it}}^j = \mathbb{1}[t = Event_i + j]$$

Here y_{it}, X_{it}', μ_i, and λ_t are defined as before. $Event_i$ records the year when the firm mentions the words "Made in China 2025" for the first time, where $j = 0$. As is standard, the baseline omitted case is the first lead, where $j = -1$. The coefficients of β_j for $j \geq 0$ enable us to discern the impacts of the "Made in China 2025" initiative over time.

2.3 Data Source

We obtain the firm-level subsidies, R&D expenditure, and other financial information from the China Securities Markets and Accounting Research Database (CSMAR). CSMAR is analogous to Compustat in the US context. Scholars have frequently used this database to study Chinese listed firms. Our primary sample used for regression includes all manufacturing firms listed on the Shanghai and Shenzhen stock exchanges from 2011 to 2018 under the category code "C" of the China Securities Regulatory Commission (CSRC) industry classification.[8]

The patent data are drawn from Bureau Van Dijk's Orbis Intellectual Property, which allows us to aggregate all subsidiary-owned patents to the parent company level of the Chinese listed firms and trace patent grants both in China and the US. We count patents according to application years because they are much closer to the actual time of invention than grant years. As such, our patent counts are patent applications that have been granted as of May 2022 when we downloaded the data.

2.4 Estimation Firm-Level TFP

We use TFP as one of our key dependent variables. For its calculation, we use a longer time from 2006 to 2018. We estimate standard Cobb-Douglas production functions separately by industry, and compute total-factor productivity (TFP) as the residual calculated for each firm in each year. We aggregate the China Securities Regulatory Commission (CSRC) manufacturing

[8] There is a small number of firms that mention themselves as "Made in China 2025" beneficiaries but not under category code "C". We drop these firms because we want to focus on firms whose main business is manufacturing. The CSRC only assign one industry code to each listed firm according to their main business field.

industry codes into nine broader industry categories. The concordance of the CSRC codes and our classifications can be found in Appendix 1, Table A1.

One difficulty in estimating TFP is the potential occurrence of important demand or productivity shocks that are observable by managers of the firms but are unobservable to the econometrician. Firms may respond to these positive or negative shocks by increasing or decreasing their input levels. These sorts of responses cause ordinary least squares (OLS) estimates of the production function coefficients biased. To address this kind of endogeneity problem, Olley and Pakes (1996) and Levinsohn and Petrin (2003) proposed techniques that have been widely used in the empirical literature. Wooldridge (2009) offered an additional improvement, demonstrating that the Levinsohn-Petrin estimator can be obtained using the generalized method of moments (GMM) econometric framework. Wooldridge's approach leads to better inference and more efficient estimation. It avoids the potential identification issue highlighted by Ackerberg, Caves, and Frazer (2015). It is also easy to obtain robust standard errors that account for serial correlation and heteroskedasticity. Therefore, we rely on this method to estimate a firm's TFP as the residual of the firm-level regression. We estimate:

$$y_{it} = \alpha + \beta l_{it} + \gamma k_{it} + \delta m_{it} + \varepsilon_{it} \tag{3}$$

where y_{it} is the logarithm of the sales of firm i during year t, l_{it} is the logarithm of the number of workers of firm i during year t, and k_{it} is the logarithm of the total assets of firm i during year t, and m_{it} is the logarithm of the expenses for material and other inputs of firm i during year t.[9] Because we separately estimate production functions by industry, our estimate of TFP

[9] We use "cash payments for raw materials and services" in the cash flow statements of our sample firms to capture variation in materials and other variable inputs. Following the lead of other empirical researchers (e.g., Giannetti, Liao and Yu, 2015), we estimate production functions using "total assets" of the firm as proxy for our sample firms' capital stocks. The absence of an accurate investment series in the CSMAR data prevents us from building reliable capital stock measures using the standard perpetual inventory method. To the extent that we measure variations in capital services with error, this could lead to a systematic downward bias in the capital coefficient.

effectively captures a firm's deviation from the average TFP level within its industry. Following Wooldridge (2009), we use m_{it} as our proxy variable for unobserved productivity to obtain consistent estimates for coefficients of all input variables. All variables other than labor input are deflated by their appropriate deflators in each year published by China's National Bureau of Statistics (NBS).[10] We also use these deflated sales and total assets in the DiD and event study regressions.

The production function estimation results are presented in Appendix Table A2. The TFP values obtained from these regressions are then used in the DiD analysis as well as the panel event study as a dependent variable.

2.5 Classifying Government Subsidies

We use the subsidy amount received by firms as one of our dependent variables. Starting in 2007, Chinese law has required listed companies to disclose government subsidy information in the notes to their financial reports.[11] The information includes the amount of the subsidies the company received during the relevant financial period, the breakdowns of the subsidies, and the reasons for those itemized subsidies.[12] Feeding this text information into Google BERT and using manual validation, we categorize subsidies into seven types (See Appendix 2 for the detailed methods and procedures).[13] We regard one of these seven types, R&D and innovation

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[10] Sales revenue (y_{ijt}) is deflated by the producer price index by industry, capital value (k_{ijt}) is deflated by the official capital price index, and intermediate material input (m_{ijt}) is deflated by the industrial producer input price index in each year. Note that we measure revenue, not physical output. As such, our productivity measures could be contaminated by the ability of some firms to price above marginal cost. However, given our data limitations (in particular, the absence of firm-specific price deflators), there is no practical way to account for this in our econometric estimation.

[11] Accounting Standards for Enterprises No.16–Government Grants 《企业会计准则第 16 号-政府补助》

[12] Notably, not all subsidies come with a meaningful reason. Many observations simply note "total subsidies", "government subsidies" and other vague descriptions.

[13] Branstetter et al. (2022) provides details and uses these data and techniques to undertake a more general analysis of the incidence and impact of Chinese government subsidies.

subsidies (hereafter referred to as innovation subsidies), as closely related to "Made in China 2025" and subsidy disclosures assigned to this category are used in our regressions as a separate dependent variable along with the total subsidies. Both total and innovation subsidy amounts are deflated by the Consumer Price Index deflator published by China's National Bureau of Statistics.

3. Results

3.1 DiD Results before Parallel Trends Assumption Check

As a starting point, we focus on the years from 2011-2018 and divide firms into two groups. The treated group includes manufacturing firms self-identified as the "Made in China 2025" policy initiative beneficiaries. The remaining firms are included in the control group. For the treated group, we drop firms that are newly listed or delisted in the year in which they first mention the words "Made in China 2025" in financial reports. As such, our treated firms have 1-4 years of pre-treatment and 1-4 years of post-treatment periods. Accordingly, we keep control firms that have observations at back to 2014 and 2015 to make them span across the year of policy launch (i.e., 2015) and have a similar number of observations as the treated firms (i.e., with 2-8 years of data). After these procedures, 1,657 firms are used for regression analysis, and among them, 718 firms are identified as treated. Table 1 shows the summary statistics of the variables we use for our DiD analysis and panel event study.

[Insert Table 1 about Here]

Table 2 presents the DiD results. Column 1 examines whether treated firms receive more total subsidies. Column 2 investigates whether treated firms receive more innovation subsidies. Column 3 considers the R&D/sales ratio as a measure of innovation input. Columns 4 and 5 use Chinese invention patents and US utility patents as measures of innovation output. We use

Chinese invention patents because China's patent system grants three types of patents: invention, utility model and design, and only invention patents go through substantive examination for utility, novelty, and non-obviousness. That said, even the quality of Chinese invention patents is not on par with international standards. Thus, we also use US utility patents as an alternative of high-quality innovation output measures. Columns 6 and 7 focus on labor productivity and TFP. Column 8 explores the impact of policy on profit margin, which we use as an indicator of product quality improvement. We used Ordinary Least Squares (OLS) regressions for all columns. All models include controls, as shown in the table, as well as firm fixed effects and year fixed effects.

It is notable that patents are count data. Scholars usually apply count models such as Poisson or Negative Binomial models to these data. However, many firms in our sample do not have any patents during the sample period, especially US utility patents. Poisson and Negative Binomial models with fixed effects automatically drop these firms because of all zero outcomes. As such, these models essentially compare patenting behaviors of firms only with patents. This is not our intention. We want to compare all firms. To address this issue, we instead use OLS with inverse hyperbolic sine transformed dependent variable and fixed effects as our primary model to examine firms' patenting activities.[14]

We find that our treated firms are indeed receiving more innovation subsidies than other firms after treatment. In addition, the policy appears to positively affect the R&D/sales ratio. However, there is no statistically significant evidence (at a 5% significance level) of positive effects of the "Made in China 2025" initiative on total subsidies, Chinese invention patents, US utility patents, log labor productivity, TFP, and profit margin.

[14] We also run the Pseudo-Poisson Maximum Likelihood (PPML) regressions as a robustness check, and present the PPML results in Appendix 1 Table A3.

[Insert Table 2 about Here]

3.2 Event Study Results

We next run event studies to examine the "parallel trends assumption" for the DiD analyses using the specification of equation (2). The sample we use is the same as in the DiD analyses. [15]

Table 3 presents the event study results, with columns responding to the columns of DiD analysis in Table 2. We plot the time period coeffects in Figure 1. First, the positive impacts of “Made in China 2025” initiative on innovation subsidies and R&D/sales ratio seem to be robust. There are no obvious positive pre-trends observed for the treated firms, and most of the post-treatment period coefficients are positive and statistically significant. Second, the event study results confirm the DiD results that there is no statistical evidence of positive effects (at a 5% significance level) of the “Made in China 2025” initiative on total subsidies, Chinese invention patents, US utility patents, log labor productivity, TFP, and profit margin.

[Insert Table 3 and Figure 1 about Here]

However, we observe an apparent violation of the “parallel trends” assumption for the Chinese invention patent DiD regression. This might not be surprising, as we find anecdotal evidence that the size of a firm’s patent portfolio is an important criterion for firms to be selected for the “Made in China 2025” program.[16] In Table 4, we use a linear probability model to examine whether firms’ inclusion in “Made in China 2025” is indeed influenced by patents. The dependent variable used here is a dummy variable which equals to 1 if the firm mentioned the

[15] We also run an event study for the full sample of 2007–20018 without considering individual firms’ pre-treatment and post-treatment exposure length. Results are consistent with the ones from the more refined DiD sample (See in Appendix Figure A1).

[16] For example, “Notice of the Ministry of Industry and Information Technology on Issuing the 2016 Industrial Transformation and Upgrading (Made in China 2025) Fund (Departmental Budget) Project Guidelines” (工业和信息化部关于发布 2016 年工业转型升级（中国制造 2025）资金（部门预算）项目指南的通知) clearly stipulates that applicants must provide “proof of the operating ability” including three years’ of audited financial reports and “proof of technical level” including intellectual property information in the application materials.

words “Made in China 2025” in its annual financial report, and 0 otherwise. The independent variables are as shown in the table and defined as the same in the DiD analyses but lagged for one year. Column 1 is the pooled sample from 2015-2018, and Column 2–Column 5 use yearly data. Both regressions suggest that patents are positively associated with treatment.

[Insert Table 4 about Here]

4. Robustness

4.1 Extending the post-treatment period beyond 2018

As mentioned before, we choose 2018 as the ending point of our empirical analysis as we observe a significant decrease in the frequency with which “Made in China 2025” appears in listed companies’ financial statements after the US-China trade war. However, dropping years after 2018 might make our post-treatment exposure too short to observe policy impacts.

As a robustness check, we assume that the treatment and control status of firms remain unchanged after 2018 and then extend the post-treatment period to 2021.[17] The DiD results from these alternative specifications are presented in Appendix 1 Table A4, which correspond to the specifications of Table 2. The event study plots are shown in Appendix 1 Figure A2, which correspond to Figure 1. As can been seen from these tables and figures, our main findings hold.

4.2 Alternative way to identify treated firms

As an alternative way to identify treated firms, we match the ten key industries targeted by the “Made in China 2025” policy to firms’ CSRC industries (the concordance of the key industries “Made in China 2025” and the CSRC industries can be found in Appendix 1, Table A5.). We regard all firms in these matched CSRC industries as treated firms and run event studies following equation (2), where $Event_i$ is defined to be 2015 when “Made in China 2025”

[17] Due to data availability, subsidy information can only be extended to 2020.

started. The time period coefficients from the event study are shown in Appendix 1, Figure A3. The results from these specifications are broadly consistent with the ones from the keyword search method (Figure 1), except that the post-treatment period coefficients are no longer significant for innovation subsidies.

5. Conclusion

Despite the enormous international controversy generated by China's "Made in China 2025" policy, no prior research has used firm-level data to assess the impact of this program on the productivity and performance of the targeted firms. This paper seeks to address this gap in the literature by using computer text analysis of the annual reports of publicly traded Chinese firms to identify firms supported by this program. Using a DiD approach, we find evidence that participation enables firms to receive more innovation subsidies, appears to induce increases in R&D intensity. However, there is no evidence that participation increases domestic and foreign patenting, labor productivity, TFP, or profitability of participating firms, suggesting the most important goals of the policy are still unrealized.

These results must be interpreted in light of a number of caveats and limitations. Our analysis is limited to the publicly traded firms disclosing the key data we need to identify participants, and we can say little about the impact of participation on privately held firms. Our tests of the impacts of policy on patenting are likely to be confounded by the clear existence of pre-trends and the known use of patenting as selection criterion for inclusion in the program. On the other hand, because our analysis only covers the first few years of the program (seven year at most), it is conceivable that substantial productivity impacts could emerge over a longer time horizon but are not yet visible in the data. Despite these caveats, our results cast doubt on the view that this controversial Chinese government policy has yet achieved its key objectives. Our results are consistent with the main findings of the recent work of Cao et al., (2022). They develop a Schumpeterian growth model and decompose quantity-based innovation subsidies' impact on growth and welfare into quantity and quality channels and shows that quantity-based subsidies in China actually suppress the country's TFP growth rate.

The absence of evidence that these benefits have been realized sits uncomfortably against strong evidence that implementation of "Made in China 2025" has generated significant costs for the Chinese economy. While rising trade friction between China and its principal trading partners has many causes, there is little doubt that the "Made in China 2025" policy has been a major contributor. As tariffs, restrictions, and export controls enacted against Chinese firms proliferate, and China responds with trade restrictions of its own, these costs mount. Given the current state of the evidence, it seems reasonable to conclude that China's benefits, net of these costs, have been limited at best.

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Table 1. Sample Summary Statistics

Variable	N	Mean	SD
Log total subsidy (Yuan)	11633	15.72	2.82
Log innovation subsidy (Yuan)	8399	13.74	1.95
R&D sales ratio (%)	11431	3.86	4.67
CN invention patents	11540	13.37	85.37
US utility patents	11540	0.97	19.06
Log labor productivity	11626	13.56	0.78
TFP	11619	1.09	1.82
Profit margin	11632	0.04	1.17
Log total assets	11633	21.74	1.19
Log sales	11632	21.27	1.43
Log employment	11627	7.71	1.18

Table 2. DiD Results before Parallel Treads Assumption Check

VARIABLES	(1) Log Total Subsidy	(2) Log Innovation Subsidy	(3) R&D sales ratio (%)	(4) CN Invention Patents	(5) US Utility Patents	(6) Log Labor Productivity	(7) TFP	(8) Profit Margin
Post x Treatment	-0.100	0.182*	0.451**	0.0437	0.0336+	-0.0263	0.0110	0.0336
	(0.0833)	(0.0712)	(0.161)	(0.0371)	(0.0174)	(0.0185)	(0.0180)	(0.0370)
Log total assets	0.844***	0.507***	1.478***	0.0758*	0.0303*	0.220***	-0.380***	0.139
	(0.146)	(0.105)	(0.432)	(0.0372)	(0.0144)	(0.0279)	(0.0348)	(0.235)
Log sales	0.232	0.0521	-2.436***	0.0764**	0.0241*		0.469***	0.0837
	(0.142)	(0.0886)	(0.454)	(0.0279)	(0.0105)		(0.0256)	(0.198)
Log employment	0.283*	0.228**	0.581***	0.0380	0.0317**		-0.125***	-0.180
	(0.114)	(0.0741)	(0.134)	(0.0244)	(0.0110)		(0.0214)	(0.125)
R&D sales ratio	0.0379**	0.0198***		0.00882+	0.00384+	-0.0246***	-0.00473	-0.0515+
	(0.0135)	(0.00598)		(0.00520)	(0.00197)	(0.00638)	(0.00416)	(0.0305)
Constant	-9.867***	-0.213	18.98***	-2.100***	-1.320***	8.868***	0.342	-3.176
	(2.413)	(1.638)	(3.697)	(0.623)	(0.333)	(0.607)	(0.521)	(2.426)
Firm FE & Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,423	8,161	11,423	11,330	11,330	11,423	11,416	11,423
R-squared	0.553	0.585	0.664	0.803	0.762	0.789	0.970	0.219

Note: All columns are OLS regressions. Patent counts are inverse hyperbolic sine transformed in Column (4) - (5). Data include Chinese listed firms from 2011 to 2018. Treatment group include firms with 1-4 years of pre-treatment and 1-4 years of post-treatment periods. Robust standard errors are clustered at firm level. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 3. Panel Event Study Results

VARIABLES	(1) Log Total Subsidy	(2) Log Innovation Subsidy	(3) R&D sales ratio (%)	(4) CN Invention Patents	(5) US Utility Patents	(6) Log Labor Productivity	(7) TFP	(8) Profit Margin
Log total assets	0.844***	0.507***	1.473***	0.0747*	0.0297*	0.221***	-0.380***	0.138
	(0.146)	(0.105)	(0.432)	(0.0371)	(0.0144)	(0.0279)	(0.0348)	(0.235)
Log sales	0.233	0.0519	-2.434***	0.0759**	0.0241*		0.469***	0.0837
	(0.142)	(0.0888)	(0.454)	(0.0278)	(0.0105)		(0.0256)	(0.198)
Log employment	0.284*	0.229**	0.576***	0.0373	0.0315**		-0.125***	-0.180
	(0.114)	(0.0743)	(0.134)	(0.0243)	(0.0110)		(0.0214)	(0.125)
R&D sales ratio	0.0379**	0.0198**		0.00871+	0.00374+	-0.0246***	-0.00474	-0.0517+
	(0.0135)	(0.00601)		(0.00517)	(0.00195)	(0.00639)	(0.00417)	(0.0306)
t = -4	0.110	0.141	-0.322*	-0.170**	-0.0388+	0.0108	-0.00953	-0.0393
	(0.115)	(0.103)	(0.160)	(0.0535)	(0.0230)	(0.0270)	(0.0242)	(0.0348)
t = -3	0.0265	0.117	-0.0144	-0.0559	-0.0273	0.00957	-0.0105	-0.0666
	(0.0947)	(0.0926)	(0.123)	(0.0458)	(0.0196)	(0.0218)	(0.0156)	(0.0425)
t = -2	0.0612	0.0452	-0.0644	-0.0255	0.0157	0.0105	-0.0290*	-0.0255+
	(0.0828)	(0.0807)	(0.0979)	(0.0393)	(0.0166)	(0.0175)	(0.0121)	(0.0136)
t = 0	-0.0566	0.237**	0.202*	-0.0230	0.0102	-0.0154	0.00290	-0.0112
	(0.118)	(0.0789)	(0.0952)	(0.0377)	(0.0139)	(0.0141)	(0.0117)	(0.0238)
t = 1	-0.0841	0.203*	0.354*	0.0520	0.0283	-0.0205	-0.00621	-0.00796
	(0.119)	(0.0936)	(0.167)	(0.0480)	(0.0212)	(0.0201)	(0.0160)	(0.0360)
t = 2	0.00330	0.285*	0.753*	-0.0455	0.0447+	-0.0263	0.000468	0.0527
	(0.188)	(0.120)	(0.365)	(0.0611)	(0.0266)	(0.0267)	(0.0238)	(0.0479)
t = 3	-0.109	0.291+	0.705**	-0.0379	0.0551+	-0.0292	0.00400	0.0773
	(0.112)	(0.158)	(0.256)	(0.0748)	(0.0321)	(0.0326)	(0.0281)	(0.0817)
Constant	-9.908***	-0.255	19.09***	-2.039**	-1.303***	8.860***	0.349	-3.146
	(2.419)	(1.638)	(3.695)	(0.623)	(0.332)	(0.608)	(0.524)	(2.433)
Firm FE & Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,423	8,161	11,423	11,330	11,330	11,423	11,416	11,423
R-squared	0.553	0.585	0.665	0.803	0.762	0.789	0.970	0.219

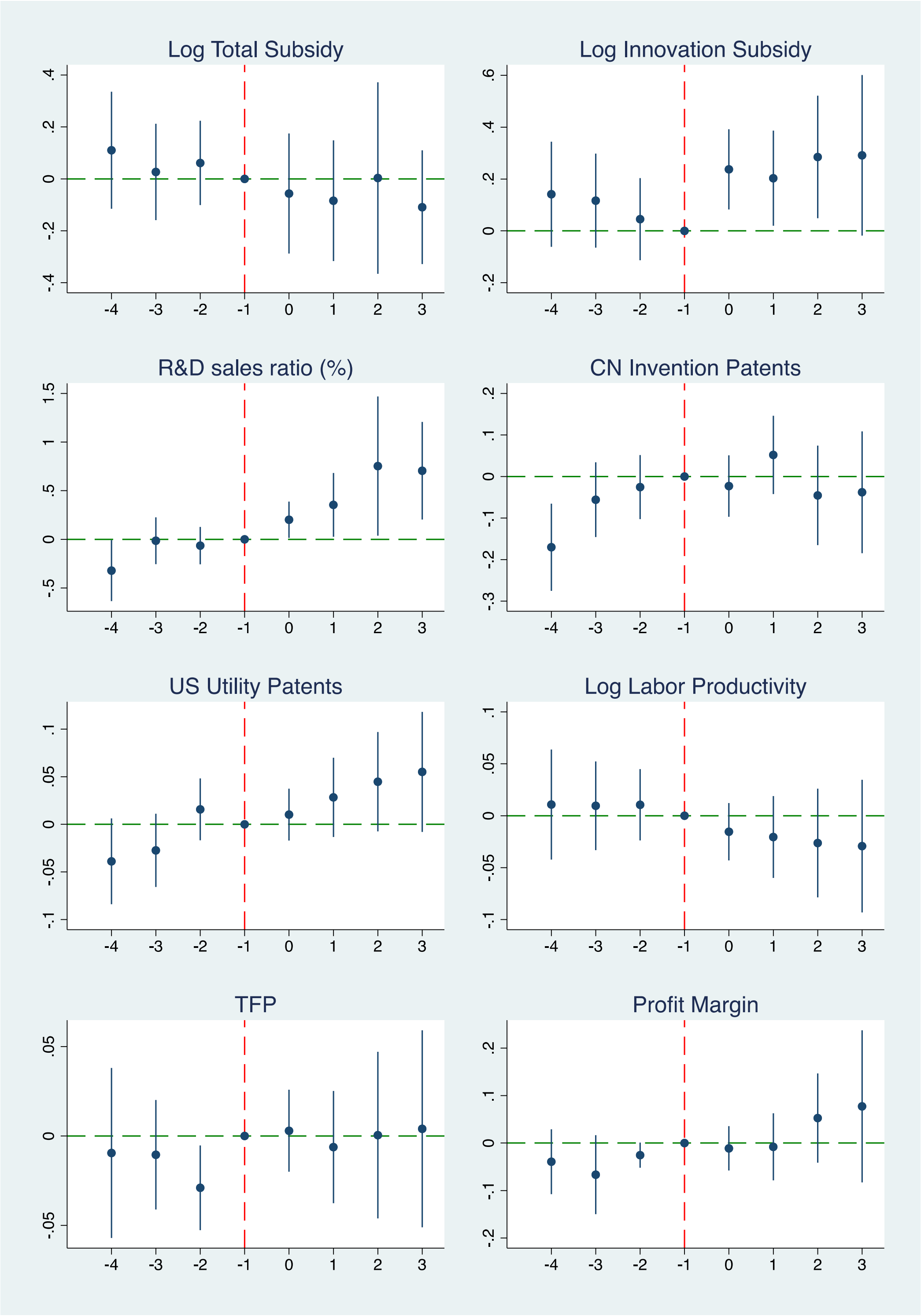
Note: All columns are OLS regressions. Patent counts are inverse hyperbolic sine transformed in Column (4) - (5). Data include Chinese listed firms from 2011 to 2018. The time of event is t=0. Treatment group include firms with 1-4 years of pre-treatment and 1-4 years of post-treatment periods. Robust standard errors are clustered at firm level. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 4. Linear Probability Regressions of "Made in China 2025" on Patents

VARIABLES	(1) Made in China 2025 Dummy	(2) Made in China 2025 Dummy	(3) Made in China 2025 Dummy	(4) Made in China 2025 Dummy	(5) Made in China 2025 Dummy
L1.R&D sales ratio	0.00127	0.00319	0.00401	0.00485+	0.00201
	(0.000999)	(0.00277)	(0.00261)	(0.00286)	(0.00212)
L1. CN Invention Patents	0.00950**	0.0401***	0.0416***	0.0345***	0.0161*
	(0.00343)	(0.00780)	(0.00730)	(0.00777)	(0.00765)
L1. US Utility Patents	0.0120	-0.00882	-0.0415**	-0.00180	-5.34e-05
	(0.00925)	(0.0238)	(0.0159)	(0.0199)	(0.0184)
L1. Log total assets	0.0164	-0.00170	0.0242	0.0658***	0.0110
	(0.0103)	(0.0189)	(0.0182)	(0.0192)	(0.0195)
L1. Log sales	-0.00342	0.00194	-0.0259+	-0.0567**	-0.0341*
	(0.00744)	(0.0156)	(0.0151)	(0.0175)	(0.0165)
L1. Log employment	0.0102	0.0113	0.000234	0.00356	0.0171
	(0.00757)	(0.0137)	(0.0136)	(0.0170)	(0.0142)
Constant	-0.277+	0.0401	0.142	-0.0810	0.535*
	(0.166)	(0.231)	(0.232)	(0.258)	(0.230)
Firm FE & Year FE	Y	N	N	N	N
Observations	15,276	1,617	1,750	1,831	1,805
R-squared	0.418	0.031	0.028	0.028	0.007

Note: All columns are OLS regressions. Patent counts are inverse hyperbolic sine transformed. All independent variables are lagged for one year. Column 1 includes include Chinese listed firms from 2015 to 2018. Column 2–5 present yearly results of 2015, 2016, 2017, and 2018, respectively. Robust standard errors are clustered at firm level. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Figure 1. Event Study Plot



Note: This figure plots the time period coefficients from Table 2. 95% CIs are shown.

Appendix 1

Table A1. Concordance of CSRC Industries to Aggregate Industries Categories used in TFP Estimation

CSRC Industry Code	Industry Name	Collapsed Industry Name
C13	Agricultural and sideline food processing industry	Food
C14	Food manufacturing	Food
C15	Liquor, beverage and refined tea manufacturing	Food
C16	Tobacco products industry	Food
C17	Textile industry	Apparel
C18	Textile, clothing and apparel industry	Apparel
C19	Leather, fur, feathers and articles thereof and footwear	Apparel
C20	Timber processing and wood, bamboo, rattan, palm and straw products	Other manufacturing
C21	Furniture manufacturing	Other manufacturing
C22	Paper and paper products	Printing
C23	Printing and recording media reproduction	Printing
C24	Culture, education, beauty, sports and entertainment products manufacturing	Printing
C25	Petroleum processing, coking and nuclear fuel processing industries	Gas and chemistry
C26	Chemical raw materials and chemical products manufacturing	Gas and chemistry
C27	Pharmaceutical manufacturing	Pharmaceutical
C28	Chemical fiber manufacturing	Gas and chemistry
C29	Rubber and plastic products	Gas and chemistry
C30	Non-metallic mineral products industry	Mineral products
C31	Ferrous metal smelting and rolling processing industry	Metal products
C32	Non-ferrous metal smelting and rolling processing industry	Metal products
C33	Metal products industry	Metal products
C34	General equipment manufacturing	Machinery
C35	Special equipment manufacturing	Machinery
C36	Automotive Manufacturing	Transportation equipment
C37	Railway, ship, aerospace and other transportation equipment manufacturing	Transportation equipment
C38	Electrical machinery and equipment manufacturing	Machinery
C39	Computer, communications and other electronic equipment manufacturing	Electronic
C40	Instrument manufacturing	Electronic
C41	Other manufacturing	Other manufacturing
C42	Comprehensive utilization of waste resources	Other manufacturing
C43	Repair of metal products, machinery and equipment	Other manufacturing

Table A2. Wooldridge GMM Estimation of Production Functions at Industry Level

Industry	Apparel	Electronic	Food	Gas and Chemistry	Machinery	Metal Products
lnl	0.118***	0.180***	0.146***	0.0528***	0.185***	0.113***
	(0.0129)	(0.00769)	(0.0120)	(0.00839)	(0.00578)	(0.00935)
lnk	0.281***	0.335***	0.368***	0.320***	0.356***	0.258***
	(0.0372)	(0.0209)	(0.0470)	(0.0229)	(0.0173)	(0.0280)
lnm	0.559***	0.482***	0.742***	0.592***	0.569***	0.585***
	(0.0277)	(0.0161)	(0.0274)	(0.0157)	(0.0125)	(0.0174)
Observations	833	2,537	1,062	2,811	3,879	1,363
No. of Groups	132	466	153	442	649	201

Industry	Mineral Products	Other Manufacturing	Pharmaceutical	Printing	Transporta tion Equipmen t
lnl	0.204***	0.172***	0.291***	0.0316	0.145***
	(0.0143)	(0.0126)	(0.0119)	(0.0219)	(0.0124)
lnk	0.399***	0.0909**	0.496***	0.0837	0.253***
	(0.0369)	(0.0404)	(0.0409)	(0.0592)	(0.0369)
lnm	0.507***	0.821***	0.433***	0.637***	0.663***
	(0.0238)	(0.0343)	(0.0214)	(0.0319)	(0.0282)
Observations	792	380	1,605	485	1,213
No. of Groups	118	96	249	73	202

Table A3. PPML Estimation of Patenting

VARIABLES	(1) CN Invention Patents	(2) US Utility Patents
Post x Treatment	0.230*	0.354
	(0.0989)	(0.238)
Log total assets	0.418**	0.745*
	(0.158)	(0.334)
Log sales	0.173	0.0297
	(0.124)	(0.0854)
Log employment	0.0146	-0.265
	(0.0659)	(0.208)
R&D sales ratio	-0.00145	0.0284
	(0.0135)	(0.0245)
Constant	-9.494***	-11.87+
	(2.699)	(6.749)
Firm FE & Year FE	Y	Y
Observations	9,516	1,648

Note: Pseudo-Poisson Maximum Likelihood (PPML) regressions are used. Data include Chinese listed firms from 2011 to 2018. The time of event is t=0. Treatment group include firms with 1-4 years of pre-treatment and 1-4 years of post-treatment periods. Robust standard errors are clustered at firm level. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A4. DiD Results (2011-2021)

VARIABLES	(1) Log Total Subsidy	(2) Log Innovation Subsidy	(3) R&D sales ratio (%)	(4) CN Invention Patents	(5) US Utility Patents	(6) Log Labor Productivity	(7) TFP	(8) Profit Margin
Post x Treatment	-0.0800	0.143*	0.768**	-0.0360	0.00198	-0.00948	0.0161	-0.0276
	(0.0726)	(0.0706)	(0.254)	(0.0379)	(0.0145)	(0.0193)	(0.0172)	(0.0746)
Log total assets	0.765***	0.471***	1.814**	0.0594+	0.0112	0.202***	-0.416***	-0.517
	(0.141)	(0.0971)	(0.652)	(0.0352)	(0.0124)	(0.0207)	(0.0246)	(0.816)
Log sales	0.186	0.0169	-3.489***	0.0450+	0.0140+		0.465***	1.270
	(0.131)	(0.0816)	(0.898)	(0.0255)	(0.00818)		(0.0231)	(0.878)
Log employment	0.316**	0.256***	0.857**	-0.0262	0.00115		-0.119***	0.0151
	(0.102)	(0.0703)	(0.330)	(0.0251)	(0.00852)		(0.0196)	(0.257)
R&D sales ratio	0.0164**	0.0193***		0.00235	0.000624	-0.0157***	-0.00167	-0.0351
	(0.00540)	(0.00548)		(0.00185)	(0.000727)	(0.00467)	(0.00130)	(0.0238)
Trend x Treatment	-7.273**	1.093	32.35**	-0.745	-0.456+	9.293***	0.967*	-15.89+
	(2.216)	(1.573)	(10.06)	(0.587)	(0.259)	(0.453)	(0.433)	(8.485)
Constant	-0.0800	0.143*	0.768**	-0.0360	0.00198	-0.00948	0.0161	-0.0276
	(0.0726)	(0.0706)	(0.254)	(0.0379)	(0.0145)	(0.0193)	(0.0172)	(0.0746)
Firm FE & Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,643	9,691	16,121	16,028	16,028	16,121	16,112	16,121
R-squared	0.540	0.568	0.512	0.745	0.677	0.767	0.954	0.202

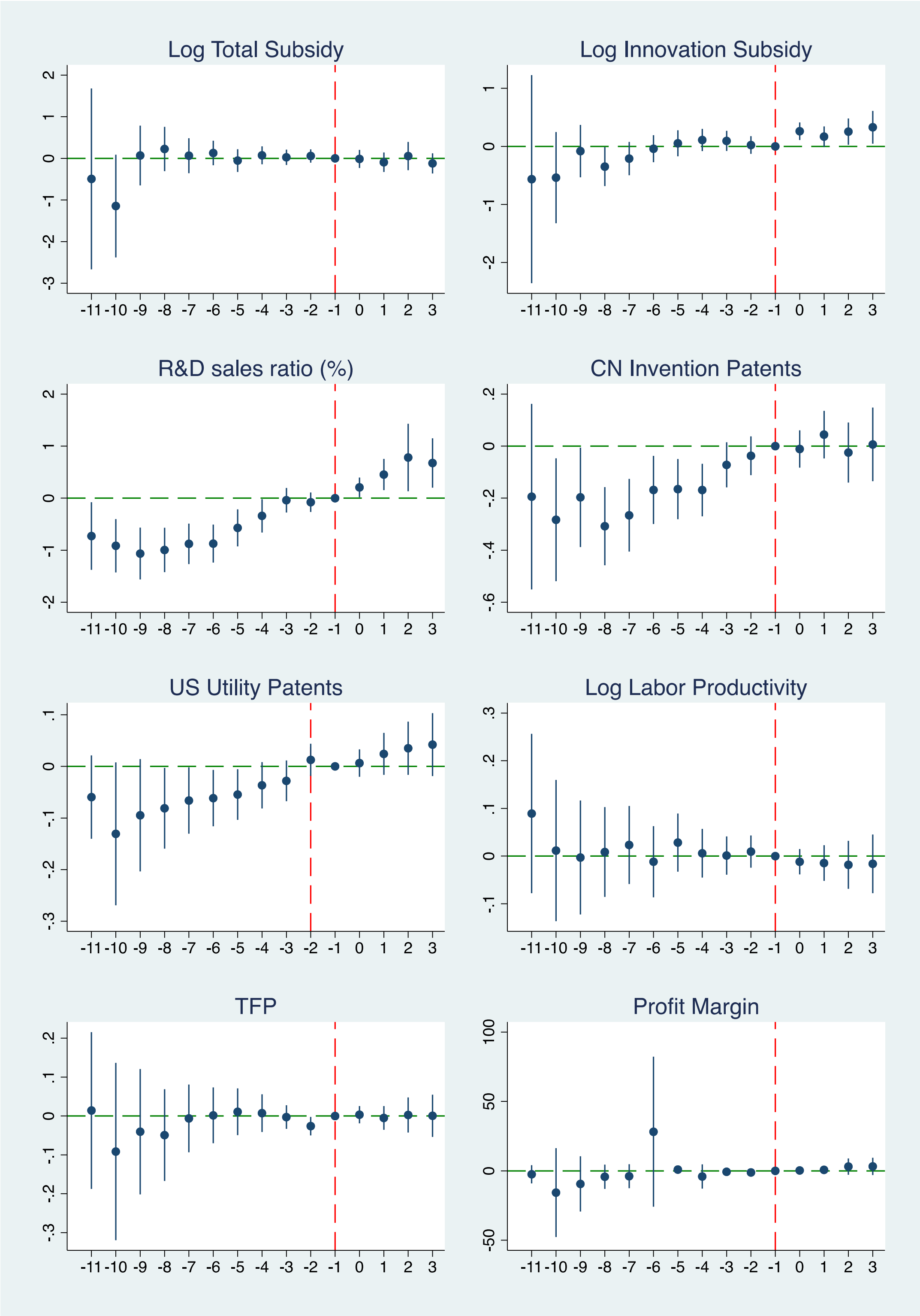
Note: All columns are OLS regressions. Patent counts are inverse hyperbolic sine transformed in Column (4) - (5). Data include in Column (1) are from 2011 to 2020, and other columns are from 2011 to 2021. Treatment group include firms with 1-4 years of pre-treatment and 1-4 years of post-treatment periods. Robust standard errors are clustered at firm level. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A5. Concordance of “Made in China 2025” Targeted Key Industries to CSRC Industries

Made in China Key Industry	CSRC Industry Code	CSRC Industry Name
new materials	C26	Chemical raw materials and chemical products manufacturing
bio-pharmaceuticals and high-performance medical equipment	C27	Pharmaceutical manufacturing
new materials	C28	Chemical fiber manufacturing
new materials	C29	Rubber and plastic products
high-end digital control machine tools and robotics	C34	General equipment manufacturing
agricultural machinery and equipment bio-pharmaceuticals and high-performance medical equipment	C35	Special equipment manufacturing
energy-efficient and new energy automobiles	C36	Automotive Manufacturing
aerospace and aeronautic equipment oceanographic engineering equipment and high-technology shipping advanced rail transportation equipment	C37	Railway, ship, aerospace and other transportation equipment manufacturing
energy-efficient and new energy automobiles electric power equipment	C38	Electrical machinery and equipment manufacturing
next-generation information technology	C39	Computer, communications and other electronic equipment manufacturing

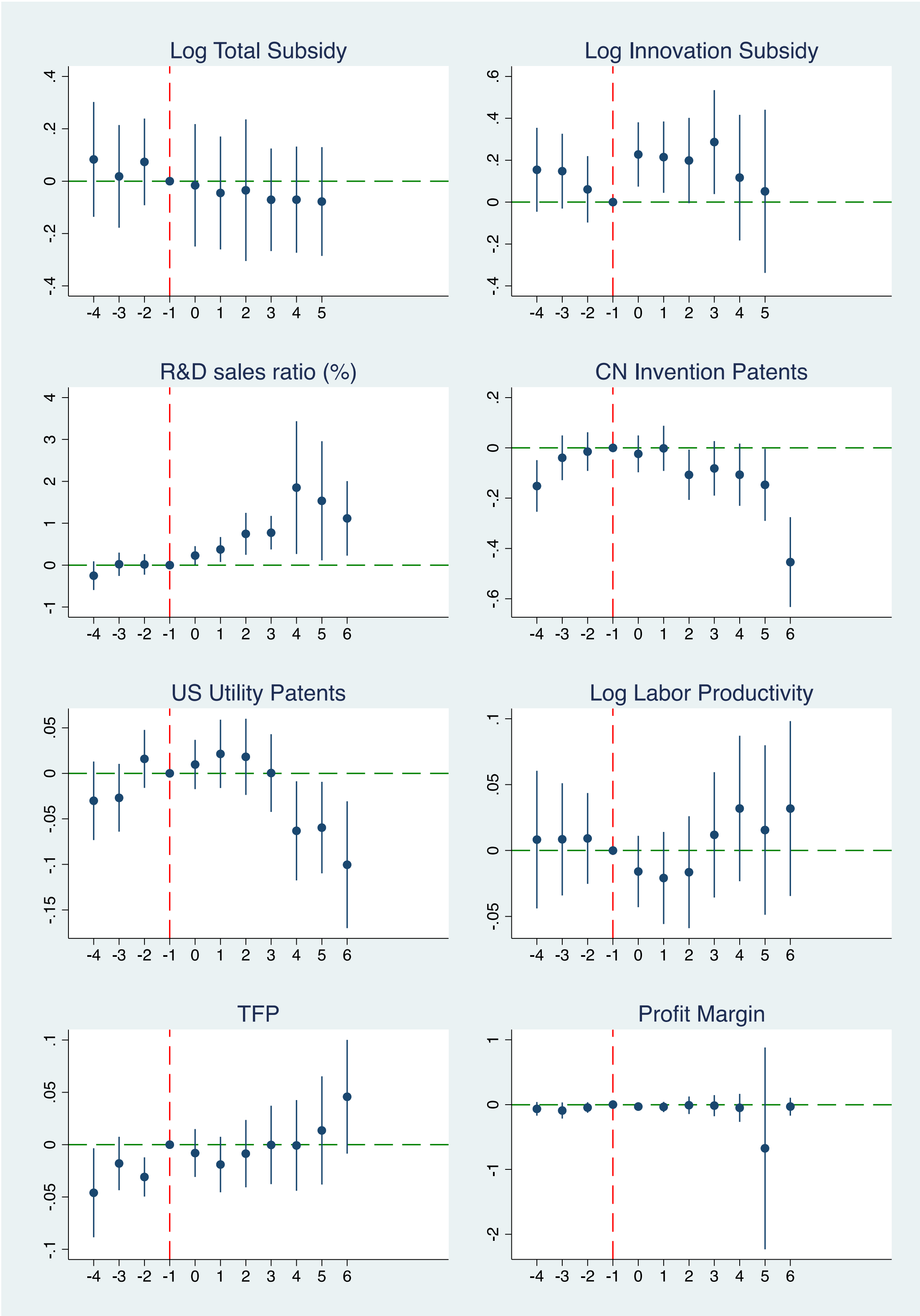
Note: CSRC industry codes can be directly linked to the Industrial Classification for National Economic Activities industry codes (the Chinese version of ISIC). However, the Industrial Classification for National Economic Activities has more disaggregated/detailed industry information than the CSRC industry classification. We use this more disaggregated/detailed industry information a bridge to construct this concordance.

Figure A1. Event Study Plot Based on Full Sample from 2007-2018



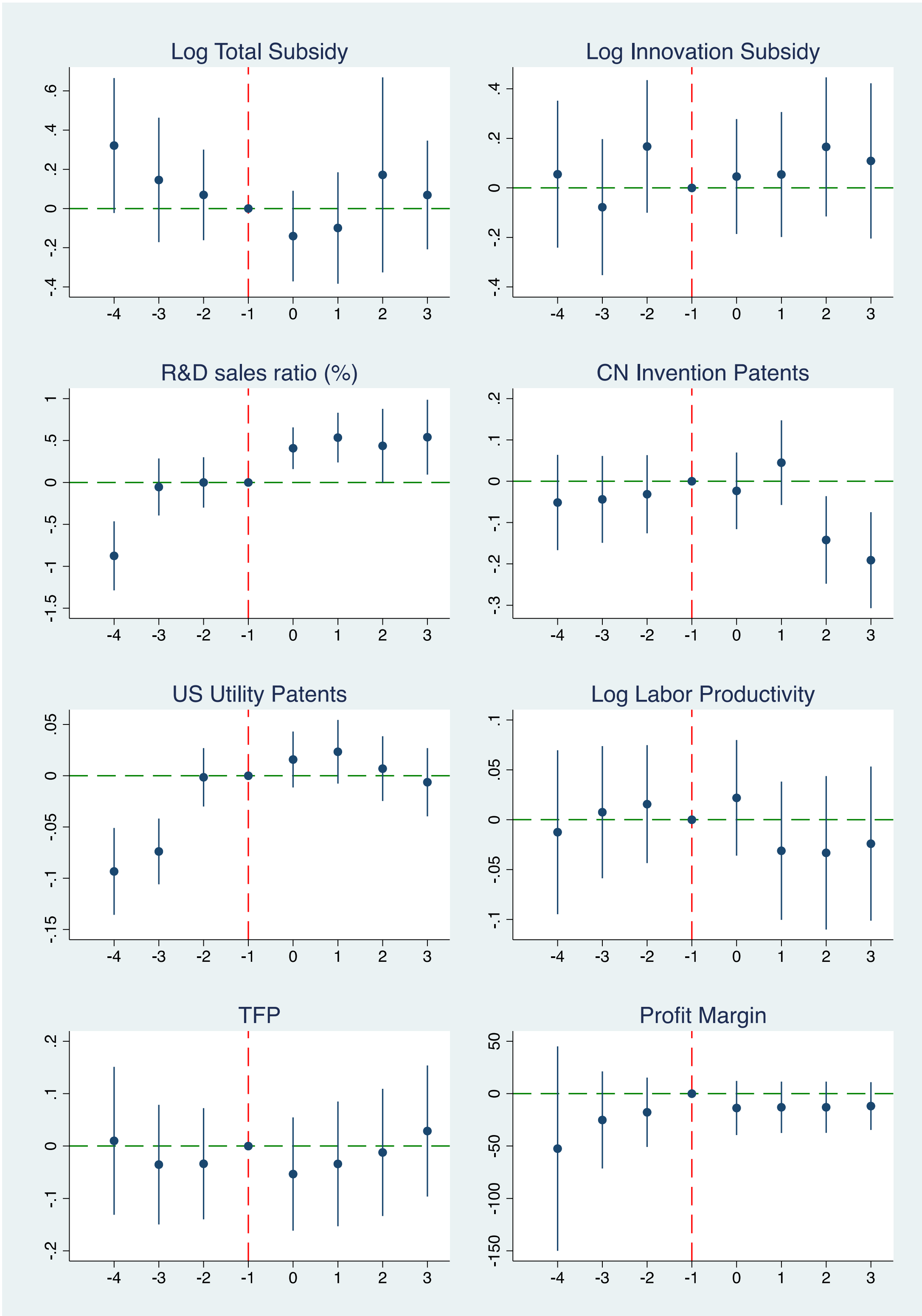
Note: 95% CIs are shown.

Figure A2. Event Study Plot (2011-2021)



Note: 95% CIs are shown.

Figure A3. Event Study Plot Using Industry Information to Identify Treated Firms



Note: 95% CIs are shown.

Appendix 2

Classifying subsidy types

We classify subsidies into seven major categories, including:

1. R&D and innovation subsidies;
2. Industrial and equipment upgrading subsidies;
3. Employment stabilization and promotion subsidies;
4. Business operation subsidies;
5. Environment protection subsidies;
6. Unknown;
7. Others.

The classification combines the artificial intelligence classification method with human intervention. It takes three main steps:

Step 1: Manual classification of training data

Two rounds of simple random sampling were undertaken before the classification. The first round randomly selected 12,000 observations from the whole dataset. The second round randomly selected four sets of 2,500 observations (without repetition) from the above 12,000 observations. Each set was then given to four research assistants for manual classification.

Whenever an individual encounters unclear or ambiguous text content that cannot be easily classified, the record will be bought to a team discussion. Whenever there was a two-two split during the discussion, a fifth individual would be brought in for another round of discussion so that a majority vote could reach the final classification criteria. Through these procedures, the team could grasp the database's overall characteristics. This information was then used to frame the meaning and boundaries of each category. Common keywords of each category based on the 10,000 observations were also summarized.

The team then linked the keywords from the above procedure with the keywords from the remaining dataset. Keywords with strong corresponding relationships were used for batch classification. Any keywords with more than one likely corresponding relationship were excluded. This step resulted in more than 60,000 extra observations both with a clear classification and a sufficient number of observations in each category. These observations were then combined with the original 10,000 observations from the manual classification and used as the training data for artificial intelligence (AI) deep learning in the next step.

Step 2: Artificial intelligence deep learning classification

Google Bert model was used in this step. A validation testing dataset was randomly selected from the remaining dataset for AI classification. After AI classification, the research assistant team judged the effect of AI classification and made necessary corrections. Then, the Bert model was run for the second time according to the corrected data. After three rounds of "AI classification-manual correction-AI reclassification," the statistical accuracy rate of AI for the testing dataset reached more than 88%. Then the algorithm was applied to the whole dataset.

Step 3: Manual review

After classifying all the data by the Bert model, a research assistant team manually reviewed all results and made the final round of manual corrections. The team consisted of four original research assistants and three newly entered research assistants. These new research assistants conducted the review after a formal training session given by the team leader among the original four research assistants.

Through these procedures, a total of 500,735 records of subsidies were classified for all Chinese listed firms.