Corruption, Government Subsidies, and Innovation: Evidence from China

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May 25, 2018

Abstract

Governments are critical financiers of innovation by private firms around the world. While these public funds ideally ease capital constraints and information asymmetries, they can also introduce political distortions. We empirically explore these issues in China, where a quarter of firms' R&D expenditures come from government subsidies. Using a difference-in-difference approach, we find that the anti-corruption campaign that began in 2012 and the departures of local government officials responsible for innovation programs strengthened the relationship between firms' historical innovative efficiency and subsequent subsidy awards, and depressed the influence of their corruption-related expenditures. Subsidies were positively associated with future innovation, especially after the anti-corruption campaign and the departure of government innovation officials.

[1] INSEAD; Harvard University and NBER; Xiamen University; Xiamen University. We thank participants in seminars at Purdue University, the Toulouse Network on Information Technology, and the University of North Carolina for helpful comments, as well as Ufuk Akcigit, Nick Bloom, Sabrina Howell, and Andrei Shleifer. Harvard Business School's Division of Research and the Toulouse Network provided financial support. Wu and Zhang gratefully acknowledge the financial support from the National Natural Science Foundation of China (71722012, 71272082, 71232005, 71402156, and 71532012) and the Major Research Project of Philosophical and Social Sciences of China Education Ministry (15JZD019). All errors are our own.

Introduction

R&D activities are central to economic growth. But R&D is expensive and frequently engenders large positive spillovers to other entities, which can lead to under-investment by the private sector, as Nelson (1959), Arrow (1962), and many others have noted. As a result, governments frequently subsidize R&D to incentivize the private sector's investment in this important activity. In an ideal world, these funds can help firms overcome the capital constraints and information asymmetries that otherwise might impede such highly uncertain investments into intangible assets.

According to the OECD, R&D subsidies are ubiquitous across the major industrialized nations, ranging from 0.01% (Chile) to 0.47% (Russian Federation) of gross domestic product.[2] In the U.S., which is near the top end of this range, the role of the Defense Advanced Projects Agency in supporting the development of early computer firms and the National Institutes of Health in promoting the fledgling biotechnology industry have been well documented (e.g., Mazzucato, 2013). Similarly, the role of the Israeli Chief Scientist in catalyzing the creation of the nation's high-technology sector has been frequently emulated elsewhere (Senor and Singer, 2009). In recent years, economists have been increasingly interested in understanding the design of public subsidies for innovative firms (e.g., Howell, 2017; Wang, Li, and Furman, 2017).

At the same time, these subsidies can be distortive. The case studies assembled by Cohen and Noll (1991) indicate that political distortions can affect the decision to initiate, continue, and terminate public funding for private R&D projects. These distortions can have deleterious

[2] Organisation for Economic Cooperation and Development, "Financing Business R&D and Investment," https://www.oecd.org/sti/outlook/e-outlook/stipolicyprofiles/competencestoinnovate/financingbusinessrdandinnovation.htm.

consequences, not only leading to the misallocation of capital across firms but also harming society more generally.

There is a very large literature on the economics of corruption, which explores the ways that politically connected firms may exploit government ties to hamper rivals, lighten their own regulatory burdens, obtain financing, and generally maximize firm (though not social) value. (See for example, Khwaja and Mian, 2005 and Akcigit, Baslandze, and Lotti, 2017; Shleifer and Vishny, 1998, provide a thoughtful review.) But the extent of corruption in the allocation of public innovation subsidies and its implications has attracted relatively little attention from economists, as a review of the major papers in this literature suggest (e.g., Almus and Czarnitzki, 2003; Bond, Harhoff, and Van Reenen, 2005; Bronzini and Iachini, 2014; Jaffe and Le, 2015; Lach, 2002; Lerner, 1999; and Wallsten, 2000).

This paucity of research is striking given the importance of innovation for economic growth and the fact that firms' innovative activities leave a trail of patents and citations, which facilitates the assessment of the distortions associated with corruption in subsidy programs. In particular, a central question regarding the nature of corruption relates to its social consequences: to what extent does corrupt payments simply represent wealth transfers that "grease the wheels of commerce" or do they lead to permanent social harm? In a pioneering empirical analysis of this question, Bertrand and co-authors (2007) show that the Indian system leads to unqualified drivers who are willing to pay bribes being licensed, with clearly socially detrimental consequences.

In this paper, we examine the presence of distortions in government subsidies for innovation in China, a natural testing ground for examining these issues for several reasons. First, the promotion of innovation has been a focus of intense policy interest in China. China's astounding growth has been historically achieved by relying on cheap labor, exports, and infrastructure investments. But as labor costs have soared and infrastructure investments saturated, China's leaders have increasingly focused on promoting innovation. China's most recent Five Year Plan, for example, singled out innovation as the key to future economic development.[3] This policy push has been accompanied by substantial subsidies. According to various issues of the *China Statistical Yearbook*, between 2005 and 2015, China on average spends about 1% of GDP on R&D subsidies. Nearly a quarter of China's total R&D spending in 2015 ($207 billion) was in the form of government subsidies ($46 billion).[4] These figures are likely understated. For instance, they do not include separate funds for government-backed venture capital investments: in 2015 alone, Chinese government bodies committed $338 billion to venture capital programs.[5]

At the same time, a major concern for China's political leaders has been the pervasiveness of corruption. The anti-corruption campaign waged by the Chinese President Xi Jinping in recent years, which has led to over one hundred thousand prosecutions (including the fall of a number of "tigers," or senior government officials), provides clear evidence that corruption is rampant in China, a point validated by many outside observers (Pei, 2016). Corruption is a first-order concern when it comes to innovation subsidies in China because decisions to grant subsidies are in the hands of individual government officials, rather than peer reviewers and expert panels, as in most western nations. Such a setting creates ample opportunities for government officials to accept

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[3] Five-year plans are China's top policy blueprints containing its social, economic, and political goals. As the name suggests, each plan covers a five-year period. The 13th Five-Year Plan (the most recent) covers 2016 to 2020. See Apco Worldwide, "The 13th Five-Year Plan: Xi Jinping Reiterates his Vision for China," http://www.apcoworldwide.com/docs/default-source/default-document-library/Thought-Leadership/13-five-year-plan-think-piece.pdf?sfvrsn=2 for information on and analyses of the most recent Five-Year Plan.

[4] This aggregate R&D subsidy rate (22.2%) is very close to the average (22.3%) we calculated from our sample firms' annual reports from 2007 to 2015 (see Table 1's summary statistics)..

[5] Shai Oster and Lulu Yilun Chen, "Inside China's Historic $338 Billion Tech Startup Experiment," https://www.bloomberg.com/news/articles/2016-03-08/china-state-backed-venture-funds-tripled-to-338-billion-in-2015.

bribes and extract rents from firms seeking R&D subsidies, particularly at the provincial and municipal levels.

Thus, the central questions that we empirically investigate are:

- How does firms' innovative capacity and corruption affect its ability to obtain government R&D subsidies?
- Are government subsidies associated with firms' future innovation?

We explore three alternative hypotheses concerning the relationship between corruption, government subsidies, and innovation, motivated by the framing of Bertrand, et al. (2007). In the first-best world, incorruptible government officials make subsidy decisions based on firms' merits (innovative ability). Under this hypothesis, subsidies should be positively related to firms' ability to innovate, and unrelated to corruption. If these subsidies significant reduce capital constraints or provide a signal to future investors (Lerner, 1999), the impact of the subsidies on subsequent innovation should be positive.

In contrast, under a system with pervasive crony capitalism, the allocation of R&D subsidies may be driven entirely by corruption. The more bribes that a firm pays, the more subsidies it would receive. Firms' innovative ability will have little or no bearing on the amount of subsidies received. There will likewise be little relationship between subsidies and subsequent innovations.

A third hypothesis is in between these two extremes, in line with Bertrand, et al.'s (2007) "grease the wheels" hypothesis. Government officials may try to allocate subsidies according to merit, but also care about private benefits that can be garnered through corruption. Under this hypothesis, firms' ability to innovate and corruption would both lead to more subsidies. The effect of subsidies on future innovation would depend on the relative weight given to merit or corruption by the government officials.

To study corruption, we exploit a reporting rule in China that requires firms listed on the domestic A-share exchange to report "Entertainment and Travel Costs" (ETC) as an itemized sub-category of Sales, General and Administrative (SG&A) costs. Although ETC includes legitimate business expenses, firms and employees have significant latitude in using this line to expense corruption-related expenditures. For instance, banquets held at and gifts purchased from hotels are routinely added to room bills and expensed as business travel expenses. In China, social activities such as eating, drinking, entertainment, and gifting that develop "guan xi" (or relationships) are the ubiquitous lubricants for business transactions. These activities are among the most visible and obvious focuses of the anti-corruption campaign waged by the Chinese President Xi Jinping beginning in 2012.[6]

To establish the validity of ETC as a corruption measure, we conducted an event study of stock returns for firms with abnormally high and low amounts of ETC[7] during the ten trading days around (i.e., CAR [-5, +5]) Dec 4, 2012, the date that President Xi Jinping and the Central Committee of the Communist Party of China unveiled the "Eight Rules of the Central Politburo" that described the details of the anti-corruption campaign. We found that after controlling for size, age, leverage, ROA, and Tobin's Q, firms with high abnormal ETC experienced an average -4.38%

[6] A New York Times article in March 2013 likens the anti-corruption campaign to an austerity measure for the country's elite (https://www.nytimes.com/2013/03/28/world/asia/xi-jinping-imposes-austerity-measures-on-chinas-elite.html). Among other measures, President Xi Jinping required business meals to be limited to "four dishes and a soup". The article reports that 60% of restaurants surveyed in the two months after the start of the campaign reported reduced business reservations. Sales of shark fin, a Chinese delicacy, dropped by 70%. Mao Tai, the favorite Chinese spirit in business banquets, also reported slowing sales. The price of the 53-proof Mao Tai, a favorite among business people, fell from a peak of over 2300 RMB in 2012 (roughly 380 U.S.D at the then prevailing exchange rate), to less than 1000 RMB by 2014. See Chinese media reports such as "茅台酒价格或成腐败指数," http://money.163.com/10/1210/10/6NHKHQRR00253B0H.html and "告别腐败指数 茅台应让老百姓喝得起." http://business.sohu.com/s2013/others702/ for the price decline of Mao Tai after the anti-corruption campaign.

[7] Detailed definitions of abnormal ETC is found in Section 2.

market-adjusted abnormal return over the ten trading days, compared to an average abnormal return of -2.72% for firms with low abnormal ETC, a difference is significant at the 1% level.[8] Prior to our study, Cai, Fang, and Xu (2011) similarly established that the "Entertainment and Travel Costs" line item was a good proxy for corruption.

To investigate distortions in R&D subsidies due to corruption, we undertake difference-in-difference analyses, focusing initially on the inception of the anti-corruption campaign in 2012. We explore the changes in the innovative subsides offered to the firms that were more or less efficient at innovation, as well as those with abnormally high and low ETC expenditures. We also examine the changes in the impact of R&D subsidies on subsequent innovation.

One concern with such an empirical design is that other factors may have also changed in 2012, which led to shifts in the allocation of subsidies and innovative performance for reasons unrelated to the anti-corruption campaign. To address this concern, we undertake a second difference-in-difference analysis, focusing on the departures of provincial officials responsible for disbursing innovation funds. Routine official job rotations are an integral part of the Chinese Community Party's personnel management apparatus. These departures are staggered across time in different provinces, and they might lead to a rapid depreciation for the "gang xi" built up by certain players and a reallocation of awards. As such they serve as a strong identification instrument.

We present two main findings. First, firms' innovative capabilities and corruption both influence the amount of subsidies granted. The two inputs have roughly equal influence: a one standard deviation increase in either variable leads to a roughly 10% increase in subsidies (as a

[8] We use the median abnormal ETC in 2012 as the cutoff, and create a high and low abnormal ETC sample. We match firms in the high ETC sample with a firm in the low ETC sample that has the smallest total percentage difference in terms of firm size, age, leverage, ROA, and Tobin's Q. We use the CAPM as the normal return model. Betas are estimated using the 200-day window (event-day -210 to -11) prior to Dec 4, 2012.

percentage of revenue) obtained. However, as depicted in Figures 1 and 2, we find that both the government's anti-corruption campaign and the departures of provincial technology bureau officials sharply altered the relative impact of merit (R&D efficiency) and corruption on subsidy allocations. Both events increased the influence of merit (firms' R&D efficiency) on subsidies and simultaneously reduced the influence of corruption on subsidies. Our regression analyses indicate that the positive impact of R&D efficiency on subsidies is concentrated in the post anti-corruption campaign and post official departure years. In contrast, while corruption was an important determinant of subsidies prior to these events, its impact diminished afterwards.

Our second finding is that government subsidies are generally positively associated with future innovation, and this positive role is significantly stronger—doubling or more—in the years after the anti-corruption campaign and the years after the departure of provincial innovation officials than before. These patterns hold when we use patent-based metrics such as successful applications (either un-scaled or scaled by sales) and relative citations to measure innovation outcomes. Patents and citations are commonly used but imperfect measures of innovation outcomes and this concern may be particular relevant for Chinese patent data. Our results hold not only for Chinese patent data, but also U.S. patent and citation data. In addition, they also hold when we use the export share of firms' revenue as an alternative innovation outcome measure, based on the assumption that export revenue is likely to be associated with the innovativeness of the firms' offerings.

Our results are robust to an array of robustness and placebo tests. They are stronger in regions that were more corrupt to begin with, and they are more pronounced for smaller firms and firms that rely more heavily on external financing.

Overall, our findings indicate that anti-corruption efforts reduced the influence that corruption had on subsidy allocation and increased allocational efficiency. Departures of local government officials which abruptly end the relationships between firms and individual bureaucrats have a similar effect.

The plan of this paper is as follows. In Section 1, we summarize the institutional features and preview the empirical design. Section 2 presents the data employed in the study. The results regarding the allocation of subsidies is presented in Section 3; Section 4 undertakes a series of robustness tests, while Section 5 examines the consequences of these awards. The final section concludes the paper.

1. Institutional Setup and Empirical Design

The government plays a controlling role in resource allocation in China, and the allocation of R&D subsidies is no exception. Since the 1990s, each level of China's government – central, provincial, and municipal—has run bureaus that are responsible for matters related to technology development and innovation. The labyrinth of technology bureaus offer a wide variety of subsidies, including direct monetary subsidies for the development and testing of new products, for major R&D projects, for the commercialization of new technologies, for small and medium-sized technology enterprises, and for patent application fees and associated costs. The funding source is in each case a combination of central, provincial, and municipal budgetary resources, with the mixture differing with the category of award. While tax credits are also used as a form of R&D subsidy by the Chinese government, we focus on direct, typically discretionary monetary R&D subsidies in this paper.

All applications are initially filed at the municipal level. Provincial- and central-level applications need the approval of lower-level technology bureaus. That is, a provincial application will only be submitted and considered if the officials in the municipal technology bureau approve and endorse the application for submission. Likewise, an application to the central government will need to be approved by the provincial-level technology bureau.

This pyramidal structure of the approval process means that the local (municipal and provincial) technology bureau officials play an important role as gate keepers and referees of firms' applications for innovative subsidies. This creates a strong incentive for firms to cultivate good relationships with these local officials, potentially including through gifting and entertaining at the companies' (and ultimately shareholders') expense.

At the same time, local officials have powerful incentives to select the firms most likely to succeed. An extensive political science literature (e.g., Li and Zhou, 2005) has suggested that officials' future promotion prospects depend on local economic performance in the region for which they are responsible. Career concerns thus create incentives for the government officials responsible for innovation programs to reward the most promising firms.

Consequently, officials' decisions on applications can be affected by both the innovative capability of the company and by the presence of corruption. In order to identify causal relationships between innovative ability, corruption, and subsidies, we rely on exogenous events that allow us to implement a difference-in-differences approach. Specifically, we exploit two types of exogenous events. The first is the sweeping anti-corruption campaign waged by President Xi Jinping, starting in 2012. While the program officially began with the 18th National Congress in November 2012, at which Xi assumed the reins of power from outgoing General Secretary Hu Jintao (and which was followed by the abrupt sacking of Sichuan Deputy Party Secretary Li

Chuncheng for abuse of power), these moves were telegraphed by increasing media discussions of corruption and its deleterious impact over the course of 2012.

Figure 3 illustrates the timeline of this event by tracing the frequency of articles in Chinese news media with the phrase "anti-corruption" in the title.[9] It shows a distinctive and steady increase in media mention of anti-corruption from 2012, the first year of the campaign. The timing and sweeping nature of this campaign was outside the control of both firm managers and local government officials, making it an exogenous shock to the amount of corruption that firms could engage in. We use this discontinuity to examine the *difference* in subsidies obtained before and after the anti-corruption campaign, by firms with high and low historical innovative efficiency and firms with high and low amounts of influence activities. To mark a clear separation between the pre- and post-campaign period, we designate the three years before 2012 (i.e., 2009, 2010, and 2011) as the "pre" window and the three years after (2013, 2014, and 2015) as the "post" window.

Anecdotes, as well as academic research, indicate that the anti-corruption campaign's has had a real effect on the Chinese business culture. Apart from the reported significant drops in restaurant bookings, domestic sales in Luis Vuitton stores, and the prices of Mao Tai, Cao, Wang, and Zhou (2018) describe that between 2013 and 2014 alone, over 20,000 government officials and nearly 5,000 other Chinese Communist Party members were punished for violating the new guidelines, and that 59 provincial level officials were put into prison for the same reasons. According to Xin Hua News Agency, the Chinese government's official news outlet, there were 80,516 corruption-related cases in 2015, and the average time from the start of the disciplinary

[9] We searched for the key word "anti-corruption" in the titles of all newspaper articles published in all official provincial government newspapers between 2007 and 2014. In China, media is strictly controlled by the government. Each provincial-level government has an official publication, called the "Daily": for example, the Henan Daily and the Shangdong Daily are the official newspapers published by the Henan and Shangdong provincial governments respectively. Beijing, Shanghai, Tianjin, and Chongqing are four municipalities that enjoy the same administrative status as a province. Publications by these municipal governments (e.g., Beijing Daily) are also in our sample.

inspection to punishment shortened from 253 days in 2014 to 78 days in 2015. A survey conducted by the Anti-corruption Research Center of the Chinese Academy of Social Sciences, China's leading think tank, indicated that 93.7% of Communist Party leaders at various levels perceived the government's resolute to catch and punish corruption as "very strong" or "strong."[10] Zhang (2018) shows that the anti-corruption campaign reduced the likelihood of other types of corporate fraud by nearly 50%.

The second type of exogenous event that we rely on are personnel changes among the local government officials responsible for innovation, due to job reassignments by the central government. In China, government postings are frequently reshuffled among the Chinese Communist Party cadres (for a discussion, see Huang, 2002). Strict rules govern the maximum number of years an official can remain at a post. According to the "Party and Government Leading Cadres Selection and Appointment Regulations" put in place in 2002,[11] technology bureau heads (along with other officials at the same administrative level in the Chinese Community Party's cadre system) are required to step down after a five-year term. Exceptionally this can be extended for another term to ten years. Sometimes, special promotions and rotations also occur, leading to sudden, unannounced official departures.[12]

For our purposes, these personnel changes in the local governments offer an ideal context to infer the causal relationship between corruption and subsidies. First, these changes are staggered in different provinces over time, making the identification sharper than the one-off event of the nation-wide anti-corruption campaign. Second, these departures are mandated by Party rules, and

[10] http://www.xinhuanet.com/politics/2016-01/15/c_128630563.htm.
[11] http://renshi.people.com.cn/n/2014/0116/c139617-24132478.html.
[12] The personnel rotation is typically conducted by the secretive Organization Department of the Chinese Communist Party. For instance, Fan, et al. (2011) cite an example whereby in April 2011 the leaders of Sinopec, CNOON, and CNPC, China's three largest state-owned oil companies, were simultaneously rotated, to the surprise of the market and even the insiders of these firms.

thus they are exogenous to official performance, local economic conditions, and are not under the control of local firms, thus providing an exogenous shock to the relationships between the firms and individual government officials. Last but not least, personal relationships are at the heart of potential corruption: individual government officials both wield the power of the subsidy allocation decisions and stand to gain from corruption. Firms thus have a logical reason to cultivate cozy relationships with local officials. But when a local government official is reassigned and a new official appointed, the relationships between firms and individual officials are severed, which is likely to translate to a reduction in subsidies to firms that have previously engaged heavily in influence activities.

2. Data and Descriptive Statistics

Our sample consists of firms that are publicly listed in China's two major exchanges, the Shanghai and Shenzhen A-share markets. Following the spirit of Jaffe and Trajtenberg (2005), we focus on firms in the following sectors, which appear to be the most technology-driven and R&D-intensive: petro-chemicals (Chinese Security Regulation Commission industry code C4), electronics (C5), metals and materials (C6), machinery and equipment (C7), pharmaceuticals and biotechnology (C8), and information technology (G). Our sample of firms represent 60% of China's domestically listed firms, and 73% and 80% respectively of the total R&D expenses and patent output by China's domestically listed companies.

In 2006, the CSRC implemented a new set of reporting and accounting rules (*The Accounting Rules of China's Enterprises (2006)*), which required listed firms to disclose their annual R&D expenditures, as well as the amount and the details of government subsidies received. We thus focus on the period from 2007 to 2015. We collect firms' R&D expenditures as well as other financial and ownership data from their annual reports compiled by WIND, a database similar to the Compustat in the U.S.

We now turn to describing the key empirical measures in this paper, including corruption, R&D subsidies, and innovation, as well as our identification approach.

A. *Measuring corruption: Entertainment and Travel Costs*

To measure firm level corruption, we follow Cai, Fang, and Xu (2011) and use the Entertainment and Travel Costs reported by Chinese firms in the footnotes of their annual statements. As argued in Cai, Fang, and Xu (2011), while such expenses contain legitimate business expenses, in practice, there is significant latitude in how executives and employees claim such expenses. For example, Chinese business people regularly bribe government officials with gifts, alcohol, cigarettes, banquets, and Karaoke entertainment. If these products and services are procured at a business hotel, all these expenses can be billed into the room and reported as Entertainment and Travel Costs. The hotel invoices will satisfy the accounting and auditing checks. A more flagrant form of corruption is to issue fake invoices for hóngbāo (cash payments, colloquially known as "red envelopes") to officials and pass off these illegal payments as legitimate expenses.

While all reported expenses need to be invoiced to satisfy accounting and auditing requirements, it is difficult to tell legitimate business expenses from corrupt payments. Therefore, the raw ETC costs are a useful but imperfect measure of corruption. To control for legitimate systematic variations in legitimate business costs, we borrow from Cai, Fang, and Xu (2011), as well as the accounting literature on the treatment of discretionary accruals (Kothari, Leone, and Wasley, 2005; Gul, Cheng, and Leung, 2011), and estimate the following cross-sectional regression for each industry-year sub-sample:

$$ETC_{i,t} = \gamma_0 + \gamma_1 Size_{i,t} + \gamma_2 Business\ In\ Other\ Regions_{i,t} + \gamma_3 PerCapGDP_{i,t} + \varepsilon_{i,t} \quad (1)$$

where Size is the firm's total assets, Business In Other Regions is the number of geographical regions where a firm's revenue come from other than the region where the firm is based,[13] and PerCapGDP is the (log of one plus) per-capita GDP of the firm's domicile province. We use these three control variables to estimate firms' predicted ETC expenses, which are likely to vary systematically.[14] We then take the residual from this regression as the abnormal ETC (AETC) incurred by the firm, which we use as the primary proxy for corruption in subsequent analyses.

B. R&D subsidies

Information on direct monetary R&D subsidies that firms receive from the government is hand collected from the footnotes of firms' annual reports. According to the 2007 Chinese "Company Accounting Principles Rule 16 – Government Subsidies", firms are required to disclose in the notes of the annual reports the type and amount of such subsidies received from government sources. We manually read these notes for all firm-years in our sample, and included as R&D subsidy for each firm-year as the sum of the following seven types of funding: 1) subsidies for product development, intermediate testing, and major R&D projects; 2) funding from the national and provincial Small and Medium Technology Enterprises Innovation Funds; 3) subsidies for small and medium enterprises' technological adaptation and upgrading; 4) subsidies for technological modification; 5) subsidies for technology commercialization; 6) R&D grants; and 7) subsidies for patent applications. Throughout the paper, we standardize the subsidy amounts by

[13] Firms report the regional distribution of their revenues in the annual reports. Chinese provinces are grouped into eight geographic regions in China: North China (华北), South China (华南), Middle China (华中), East China (华东), North-East (东北), North-West （西北, South-West （西南, and Hong Kong/Macau/Taiwan （港，澳，台. Foreign countries are coded as one separate region.

[14] Our results are robust to including additional control variables, such as firm leverage and operating performance (return on assets). They are also robust to using panel regressions, rather than industry-year sub-sample cross-sectional regressions, to estimate the abnormal ETF. These additional results are available on request.

scaling it by firm revenue. (We repeated our analysis using unscaled subsidies; those results are reported in our internet appendix in Tables IA4 through IA7.)

C. Firms' historical innovative efficiency

We take into account both firms' R&D inputs and their outputs to construct a historical R&D efficiency measure, which we use in Tables 1 through 7. We use firms' R&D expenditures (collected from their annual financial statements) as the measure of R&D inputs. We use patents to measure firms' innovation output. Following Hirshleifer, Hsu and Li (2013), we define firms' innovation efficiency as the following ratio between innovation output and input:

$$\text{R\&D Efficiency}_{i,t} = \text{Patent}_{i,t} / (\text{R\&D}_{i,t} + 0.8 * \text{R\&D}_{i,t-1} + 0.6 * \text{R\&D}_{i,t-2}) \qquad (2)$$

where $\text{Patent}_{i,t}$ is firm *i*'s new patent applications filed in year *t* that were approved by the end of 2016; and the $\text{R\&D}_{i,t}$, $\text{R\&D}_{i,t-1}$, and $\text{R\&D}_{i,t-2}$ are the R&D expenditure in millions of RMB during year t, t-1, and t-2.

Our primary patent data come from the Chinese State Intellectual Property Office (CSIPO), China's counterpart to the United States Patent and Trademark Office (USPTO).[15] CSIPO provides annual information from 1985 to 2016 on each granted patent's application year, grant year, technological class, number of citations subsequently received, etc. We manually collect this information from the CSIPO website. U.S. patents are often considered higher quality than Chinese patents. However, it is still relatively rare for the firms in our sample to have U.S. patents: while 84% of our firms have been granted Chinese patents as of the end of 2016, only 15% of them have granted U.S. patents. Therefore, we use the Chinese patent data to construct R&D efficiency, one of our main independent (or sorting) variables. In our later analyses that focus specifically on patent quality, we supplement our Chinese data by using U.S. patent and citation data. For data on

[15] http://epub.sipo.gov.cn/gjcx.jsp.

Chinese firms' U.S. patents and U.S. patent citation counts, we downloaded all granted patents filed by a Chinese entity for our sample period; then manually matched the name and address of the patent assignee to the firms in our sample.

One concern about this measure may be the imprecision with which Chinese firms measure and report their R&D expenditures. (This concern extends well beyond China: see, for instance, National Research Council, 2005). In order to address this concern, we repeated the analysis using the ratio of ultimately successful patents applied for in any year to sales as an alternative innovation efficiency measure. These results are reported in Tables IA8 through IA12 of the internet appendix.

D. Firm's future innovation output

We construct three variables to measure a firm's innovative output, Patents/Sales, Relative Citation Strength, and Foreign Sales/Sales, which we use in Tables 8 and 9.

Patents/Sales is the number of patent applications filed by a firm in year t that are ultimately granted by the end of 2016, divided by its revenue in year t. Our second measure of innovation output is Relative Citation Strength, which we calculate as follows: for each patent applied for in year t (that is ultimately granted by the end of 2016), its Relative Citation Strength is the number of citations it received up to the end of 2016, divided by the number of citations per patent received over the same period by all patents applied for in year t (that are also ultimately granted by the end of 2016) in the same four-digit technological class.[16] This is a relative citation strength measure; the scaling controls for the application year and technological class. A Relative Citation Strength higher than one means that a particular patent is cited more than the average patent successfully filed for in the same year in the same technology class.

[16] China uses the International Patent Classification (IPC) codes for classifying domestic patents. The U.S. data uses the closely related Cooperative Patent Classification scheme. Thus, the subject and scope of the four-digit technology classes in each case are very similar.

For these two patent-based measures of firm's future innovation, we construct two versions, one using the Chinese patent and citation data and a second using U.S. patent and citation data. Our results are qualitatively the same using either version. However for brevity, in the section that examines firms' future innovation, we report only the results pertaining to future U.S. patents and their citations. (Results pertaining to firms' subsequent Chinese patent output and citations, which focuses only on the stronger invention patents, are reported in our internet appendix in Table IA15 and IA16.) An issue with these measures is truncation: a relative small fraction of patents filed in 2015 are likely to be issued by the end of 2016. To address these concerns, we add year fixed effects to each of these regressions. It should also be noted that Hall, Griliches, and Hausman (1986) highlight the very short lag between R&D spending and patent filing.

As a third measure of innovation outcome, we use a firm's foreign sales[17] as a share of total sales. The revenue data is from the WIND database. While this proxy is clearly imperfect, we use the fraction of foreign sales as an alternative measure of innovation on the assumption that innovative firms are likely to achieve greater traction in the global market.

We again explore the robustness of the results to alternative patent measures—in particular, unscaled patents and those scaled by assets--in Tables IA13 and IA14 of the internet appendix.

E. *Other variables*

Another variable relevant to our analysis is the firm's ownership type: we distinguish between State Owned Enterprises (SOEs) versus private sector firms. SOEs in China enjoy significant advantages in terms of access to bank financing and stock market listings (e.g., Dollar and Wei, 2007). Therefore, SOEs may not need to rely as much on government subsidy programs nor engage

[17] Foreign sales do not include sales to Hong Kong, Taiwan, or Macau, which are included as part of Chinese domestic sales.

in corruption in order to obtain subsidies. Private sector firms, lacking these financing channels, may have more incentives to compete aggressively for subsidies.

We classify firms' ownership type by tracing their ultimate ownership identified through annual statements. Since 2001, Chinese listed firms are required to report their ownership (equity) structure. Following prior literature (e.g., Wang, Wong, and Xia, 2008), we define a company as state owned if its largest ultimate shareholder is a government entity, which can be a central (e.g., the Ministry of Finance), provincial, or local entity. Otherwise, we define the company as a private enterprise (i.e., if the largest ultimate owner of these firms is either an individual—we aggregate individual investors who are family members—or a private institutional investor). On average, the government ownership stake in the SOEs in our sample is 37.3%.

We are also interested in how firms' political connections affect the subsidies that they receive.[18] For our sample firms, we manually collected data on the CEOs' and chairmen's political connections from these individuals' profiles in the "Profile of Directors and Senior Managers" section of the firms' IPO prospectuses and annual reports. These profiles typically contain information on the individual's age, gender, education, professional background, and employment history. We coded a firm as politically connected in a given year if the CEO or chairman is currently or formerly was an officer in the central government, a local government, or the military. This definition of political connection is the same as Fan, Wang, and Zhang (2007). Definitions of the variables used in this paper are summarized in Appendix 1.

F. Descriptive statistics

Figure 4 depicts the time trend of firms' average ETC spending in our sample. This time trend suggests that ETC is a valid measure of corruption. Average ETC spending increased by about

[18] Khwaja and Mian (2005) and Bao et al. (2015) examine whether political connections affect capital market access in China. The general conclusion is that the market appear able to undo any biases associated with political connections.

20%, from 0.52% of revenue in 2007 to 0.62% of revenue in 2012, but decreased precipitously in 2013 and 2014, before increasing slightly in 2015. Overall, ETC spending exhibits a downward trend after 2012, the inception of the anti-corruption campaign.

Table 1 provides summary statistics for our sample, which consists of annual firm-level observations between 2007 and 2015. Panel A reveals a number of interesting statistics regarding Chinese firms' R&D spending and innovation. First, subsidies are an important source of overall R&D funding, representing 22.3% of these firms' total R&D spending. This magnitude matches almost exactly to the aggregate figures in the *2016 Statistical Year Book* presented in the introduction and suggests that our samples are representative of Chinese firms as a whole in terms of subsidies. Second, these Chinese firms spend a similar amount in R&D (relative to firm size) as their U.S. counterparts: in our sample, firms spent 3.7% of sales on R&D each year. (Domestic R&D by U.S. firms in 2013 was 3.5% of domestic net sales, including basic industries not in the Chinese sample.[19]) Third, firms also spent significant resources on ETC, averaging 0.6% of annual sales. Since firms received 0.5% of annual sales as R&D subsidies on average, assuming that 50% of the ETC spending was for briberies and corruption, then roughly for each dollar of ETC spending, firms received 1.7 dollars of innovative subsidies. The average R&D efficiency measure is 0.62, meaning that on average, firms obtained 0.62 Chinese patents for each million RMB of (capitalized) R&D, which is in range of the estimates (0.49 – 2.57) from Hirshleifer, Hsu, and Li (2013). The average relative citation strength for domestic patents is 0.44. This figure is low (below 1) because the table reports unconditional averages, which includes firm-years with zero patents as having zero citation counts. In unreported calculations, we find that the conditional relative citation strength for the patents in our sample is 1.001, meaning that the patents in our sample on

[19] U.S. National Science Foundation, *Business Research and Development and Innovation: 2013 Detailed Statistical Tables*, Report no. NSF 16-313, https://www.nsf.gov/statistics/2016/nsf16313/pdf/nsf16313.pdf, Table 19.

average receive the same amount of citations as comparables (patents successfully filed in the same year and technology class), which makes sense and indicates that our sample is representative of the Chinese patent universe. The unconditional relative citation strength for the firms' U.S. patents is only 0.02, reflecting that many firms that simply do not have U.S. patents. The conditional U.S. patent relative citation strength for our sample (unreported in the table) is 0.66, meaning that our sample firms' U.S. patents on average receive two-thirds of the citations compared to their U.S. counterparts.[20]

Panel B focuses on the relationship between our two main sorting variables – R&D efficiency and AETC. We are interested in this relationship for both econometric and economic reasons. Since our subsequent analysis focuses on how these two variables separately and jointly affect subsidies, it is important to understand the correlation between them from an econometric point of view. Economically, the relationship between these two variables should also shed light on whether merit (R&D efficiency) and corruption (AETC) are complements or substitutes. If they are complements, they would be positively correlated (highly efficient firms spend large amounts on corruption). This would suggest a "greasing the wheel" setting whereby efficient firms engage in corrupt behavior as a means to obtain resources. In such a world, corruption is a transaction cost that could enhance overall efficiency by enabling the funding of efficient firms. If they are substitutes, the two would be negatively correlated (highly efficient firms spend little on corruption and inefficiency firms spend large amounts). This would suggest an environment in which corruption leads to misallocation and is a cost to society. If the two covariates are uncorrelated,

[20] The lower relative citation strength of Chinese firms' U.S. patents relative to other comparable U.S. patents could reflect a number of factors: (a) the delays associated with the issuance of foreign patent applications (since the applications are typically filed first at home, and only later in the United States), (b) the likelihood that even after issue, U.S. patents may cite the original Chinese patent, rather than its U.S. counterpart, and (c) the genuine technological impact is lower.

then they are neither complements nor substitutes, and are simply different firm attributes that can separately influence subsidies.

In Panel B, we first report the frequency distribution when we sort firms by R&D efficiency and by AETC. Specifically, for each firm, we calculate the average R&D efficiency and AETC for the three pre-campaign years (2009, 2010, and 2011). We then use the median of each measure and separately divide the sample into high and low R&D efficiency firms, and high and low AETC firms. The table reports the number of unique firms that falls into each quadrant of the double sort (high efficiency/high AETC, high efficiency/low AETC, etc.). We find that the number of firms in each quadrant is remarkably close: roughly 270 unique firms in each. Thus, the two key variables appear to have little correlation. The Spearman rank correlation is -0.039 with a p-value of 0.197, not significantly different from zero.

Therefore empirically we find that firms' R&D efficiency and their abnormal ETC spending are uncorrelated, indicating that they are independent firm attributes that separately influence subsidy grant decisions, which we examine next.

3. Innovation efficiency, corruption, and government subsidies

A. Difference-in-differences around the anti-corruption campaign

We begin by using the anti-corruption campaign to conduct our difference-in-differences analysis. We compare the before-and-after changes in government subsidies received by firms with high or low innovation efficiency, and by firms with high or low AETC. For each firm in our sample, we calculate its average R&D efficiency during 2009, 2010, and 2011, the three years in the pre-campaign window. We use the median of this average efficiency to divide the sample firms into high- and low-efficiency groups. We likewise divide the sample into high and low AETC groups using data from the pre-campaign period. After the sample formation, we calculate the average amount of subsidies received (scaled by sales) by the high and low efficiency (or AETC) groups both before and after the anti-corruption campaign, and compare the increase from before to after across the two groups.

Panel A examines the parallel trends assumption before the anti-corruption campaign by comparing the annual percentage increases in R&D subsidies received (scaled by sales) in the high and low efficiency groups, and separately by the high and low AETC groups (each calculated during the three pre-campaign years). We do not detect any significant differences in the growth pattern of subsidies received for firms with high and low R&D efficiency. Likewise, we find no significant differences between firms with high and low AETC spending. Figure IA1 in our internet appendix contain a series of plots that examine the parallel trends assumption for key firm-level variables such as leverage, return on assets (ROA), and Tobin's Q, and suggest a similar absence of patterns.

Panel B presents the main difference-in-differences analysis for firms with high and low R&D efficiency. We find that subsidies received by high-efficiency firms increased by over 40% after the anti-corruption campaign, from 0.43% of revenue to 0.62% of revenue. Meanwhile, subsidies received by low-efficiency firms showed no significant increase after the anti-corruption campaign, going from 0.51% of revenue to 0.54% of revenue. The DiD comparison between the two sets of firms is significant at the ten-percent confidence level.

Panel C undertakes a difference-in-difference test for firms with high and low AETC spending prior to the anti-corruption campaign.[21] We find that while there was no significant change in the amount of subsidies received by high AETC firms after the campaign, the amount

[21] Our results are qualitatively similar if we use the raw ETC measure to sort firms.

of subsidies received by low AETC firms increased by over 50%, from 0.45% of revenue to 0.70% of revenue. The difference-in-difference between the two groups is significant at the one-percent level.

Figure 1 visually depicts the difference-in-differences results by showing the evolution of subsidies received by the different sets of firms over time. Panel A shows the result for firms with high and low R&D efficiency and reveals a noticeable increase in the subsidies (scaled by sales) received by high-efficiency firms but little change in the subsidies received by low-efficiency firms. The divergence of the two groups became more obvious after 2012. Panel B shows the result for firms with high and low AETC spending. It shows that prior to 2012, high AETC firms received larger subsidies than low AETC ones, but the pattern reversed after 2012: subsidies to high AETC firms dropped while subsidies to low AETC firms increased. By the end of our sample, low AETC firms were receiving larger amounts of subsidies than high AETC firms.

Overall, results in Table 2 and Figure 1 indicate that the anti-corruption campaign is associated with a significant re-weighting of merit (R&D efficiency) and corruption (AETC) in the subsidy-granting decisions. Post campaign, subsidy grants are significantly more sensitive to merit and less sensitive to corruption.

Table 3 examines these effects in a panel regression setting. Panel A presents the full sample result. The dependent variable is the amount of R&D subsidies received by a firm in a given year (scaled by the firm's revenue in that year). The key independent variables are R&D efficiency, AETC, a post-campaign indicator variable, and interaction terms between R&D efficiency and the post-campaign indicator and between AETC and the post-campaign indicator. Other control variables include whether a firm is an SOE, whether it is politically connected (as defined above), its return on assets, Tobin's Q, and leverage (defined as the book value of total liabilities divided by the book value of total assets). All independent variables except the post-campaign indicator variable are lagged by one year.

In models (1) and (2), the interaction terms do not enter the regression; these models evaluate the baseline impact of R&D efficiency and corruption on subsidies. The results indicate that R&D efficiency and corruption both have a positive and significant effect on subsidies. The coefficients suggest that a one standard deviation increase in R&D efficiency is associated with a 10% increase in R&D subsidies.[22] Likewise, a one standard deviation increase in AETC is associated with 9.4% increase in R&D subsidies.[23] Thus, the two variables have roughly equal impact on subsidies.

Models (3)-(6) include the interaction terms between R&D efficiency and the post-campaign variable, and between AETC and the post-campaign variable. Consistently across the four specifications, we find that the interaction term between R&D efficiency and the post-campaign indicator is positive and significant, indicating that the effect of efficiency on subsidies is stronger after the campaign. By way of contrast, the interaction term between AETC and the post-campaign indicator is significantly negative across all four models, meaning that the effect of AETC on subsidies weakened after the anti-corruption campaign. These results are consistent with the difference-in-differences results shown earlier. Based on the coefficient estimates of model (6), which includes firm fixed effects, a one standard deviation increase in R&D efficiency in the post-campaign years is associated with a 10% increase in R&D subsidies relative to the mean. The R&D efficiency variable alone is insignificant, indicating that pre-campaign, it has insignificant impact on subsidies. In other words, almost all of R&D's impact comes from the post-campaign

[22] The standard deviation of R&D efficiency is 0.169 (Table 1). Given the coefficient on R&D efficiency is 0.003, the associated impact on subsidies is 0.0005 (0.169*0.003). Since the average subsidies are 0.005 (Table 1), this means the increase is about 10% of the average subsidies received.
[23] The calculation parallels that in footnote 20: 0.008*0.059/0.005=9.4%.

period. On the other hand, a one standard deviation increase in AETC in *pre*-campaign years is associated with a 10% increase in subsidies from the average,[24] but this effect largely disappears after the campaign as the sum of the coefficients on the AETC and on its interaction term with the post-campaign variable is essentially zero (0.065 – 0.067). Thus, while overall R&D efficiency and AETC have roughly the same impact on subsidies, there is a reversal in their impact on subsidies post campaign, when R&D efficiency gained significance and AETC lost significance. These results are consistent with our findings in the difference-in-differences analysis, and indicate that the anti-corruption campaign had the effect of significantly sharpening the relationship between R&D efficiency and subsidies and dampening the relation between AETC spending and subsidies.

Other control variables generally have expected signs. For instance, we note that SOEs generally receive fewer subsidies, perhaps reflecting the fact that SOEs are generally better funded and have other channels for accessing state resources. Firms with higher Tobin's Q tend to receive more subsidies and firms with higher leverage tend to receive fewer subsidies. Political connections, on the other hand, do not influence subsidies.

If the changes in subsidy allocations are related to anti-corruption efforts, we expect them to be more pronounced in regions that were ex ante more corrupt. To examine this regional variation, we use the corruption index calculated by China's National Economic Research Institute (NERI). The NERI index is a widely used measure of corruption in China, which is constructed from two questions gathered in surveys of Chinese companies: 1) the time spent by businesses in dealing with bureaucracy and 2) the non-tax expenses levied on enterprises, including informal

[24] Performing similar calculations as in footnote 16, the associated increase in R&D/Sales is 0.065*0.008, or 5 basis points, which is 10% of the average R&D/sales of 50 basis points.

charges and illegal fines from the local government, as a percentage of sales.[25] We use the province-level corruption indices in Fan, Wang and Zhu (2010) and (2011) to calculate each province's average corruption index over the years prior to the campaign. We then use the median of this variable to split China's provinces into "high corruption" and "low corruption" regions. Panel B reports regression analysis pertaining to these sub-samples. For brevity, only key coefficients are reported.

Consistent with our expectations, the main results that subsidies become more (less) sensitive to R&D efficiency (AETC) are more pronounced in ex-ante high corruption regions. In fact, prior to the campaign, R&D efficiency has no significant impact on subsidy allocation in high-corruption regressions (the coefficient is an insignificant -0.0002). But after the campaign, efficiency has a positive impact on subsidies, as the interaction terms between efficiency and the post-campaign dummy are positive and significant. The coefficient estimate of 0.01 means that a one standard increase in R&D efficiency is associated with roughly a one-third increase in subsidies.[26] In contrast, in the regression for low-corruption areas, we see that R&D efficiency itself positively predicts subsidies, but the interaction term is positive although insignificant, The results indicate that in less-corrupt regions, R&D efficiency was always a significant determinant of subsides, but there was no significant change in this relation after the campaign.

Overall the results in this section indicate that firms' R&D efficiency and corruption both had a positive influence on the amount of subsidies they received; one standard deviation increase in each variable led to about 10% increase in subsidies. But the anti-corruption campaign resulted

[25] The NERI indices are constructed roughly every three years since 2001, but there are gaps. The available reports to date were published in 2001, 2004, 2007, 2010, 2011, and 2017. We use the reports from 2007, 2010, and 2011, as they cover the years prior to the anti-corruption campaign that is relevant for this paper.

[26] Similar to the calculations in footnotes 16 and 17, the associated increase in R&D/Sales here is 0.169*0.01, or about 17 basis points, which is about 1/3 of the average R&D/Sales of 50 basis points.

in a reversal in importance of the two variables: post campaign, R&D efficiency became significant while corruption (AETC) lost much of its significance. Thus the campaign simultaneously sharpened the relationship between merit (R&D efficiency) and subsidies, and reduced the influence of corruption (AETC) on subsidies.

B. Difference-in-differences around official departures

In this section, we conduct a parallel sets of analyses as the previous section, but focus on our second identification strategy based on the departures of provincial technology bureau heads. As discussed in Section 1, the advantage of this identification strategy is that official departures are staggered across time in different provinces and are exogenous to individual firm performance and regional economic conditions. Since official departures lead to a depreciation of the built-up relationship between firms and the individual bureaucrat, we expect a reduction in the influence of corruption on subsidies after these departures. Moreover, as long as the officials' decisions are at least partially merit-based, we should see the impact of R&D efficiency on subsidies become sharper after the official departures.

We manually compiled information on the departure of provincial technology bureau heads from various online and offline sources, including the official websites of each provincial government and the central government, newspaper reports, and postings and announcements about personnel movements from the Chinese Communist Party's Organization Department.[27] Over our sample period, we identified 53 cases of official departures[28] representing changes in 30

[27] The Organization Department is the equivalent to the human resources department of the Chinese Communist Party. Our specific search procedure is as follows. We search for the key words "technology bureau," and "technology head" from the mentioned sources and general web portals. From this we construct a database of the names of the technology bureau heads for each province during our sample period. We then identify departures dates.

[28] Of the 53 departures, there are 14 (26%) that are due to promotions or lateral moves within the technology administration field. The remaining 39 (74%) are due to retirements, demotions, corruption-related charges, or moves that cause the official to move to another field. In an unreported analysis, we found that our results reported

provinces (i.e., all Chinese provinces except for Yunan). In all, these events affected 3694 firm-year observations for the firms located in the each of the affected provinces between three years before and three years after each departure, or roughly 40% of the total sample firm-years. Figure 5 plots the number of official departures by year over our sample period, and indicates that these events are staggered across time. We also estimated regressions of these departures on the provinces' GDP growth in the year before (reported in Table IA1 of the internet appendix) and found that the latter has no explanatory power. This analysis confirms that these departures are not driven by local economic performance, as would be expected since the departures are typically part of the Chinese government's routine personnel management procedures.

Table 4 shows the results of the difference-in-differences analysis of R&D subsidies around the departures of provincial technology bureau heads.[29] For each departure event in year *t*, we define the three years before (i.e., t-1, t-2, and t-3) as the pre-event window, and up to three years, t+1, t+2, and t+3 as the post-event (some events may not have three post-event years, as our sample ends in 2015). For each firm affected by an official departure, we calculate its average R&D efficiency during the three pre-event years, and use the median value of this average efficiency to divide the sample into high and low efficiency groups. We similarly create the high and low AETC groups.

Panel A checks the parallel trends assumption. We tabulate, by event year, the average annual percentage changes in subsidies (scaled by sales) received by the high and low R&D efficiency groups, and separately by the high and low AETC groups. We do not find any significant differences in the pre-event trends between the high and low sub-groups defined by

below are primarily driven by the latter types of departures, which are more likely to sever the out-going officials' influence.

[29] Ideally we would also like to include movements of the municipal level officials. However we are unable to obtain comprehensive personnel data at the municipal level.

either sorting variable. Figure IA2 in our internet appendix examine the parallel trends assumption for other key variables, and indicate a similar absence of patterns.

Panel B shows the results of the main DiD analysis for firms with high and low R&D efficiency prior to official departures. For this analysis, we calculate the average levels of subsidies (scaled by sales) received by the high and low sub-groups before and after the event and compare the increase from before to after across the two groups. From this panel, we see that the amount of subsidies received by high-efficiency firms more than doubled in the three years after official departures, from 0.19% of revenue to 0.50%, significant at the 5% level. Meanwhile, there is no notable difference in the amount of subsidies received by low-efficiency firms before and after official departures.

Panel C of Table 4 shows the DiD analysis for firms with high and low levels of AETC expenditures prior to official departures. The empirical approach is identical to Panel B, except that the sorting variable is AETC. The results show that while there is no change in subsidies to high AETC firms after official departures, subsidies to low AETC firms nearly doubled from 0.24% before to 0.47% after these departures. Thus, official departures significantly reduced the influence of corruption on government subsidies. Combining the results of Panels B and C, we conclude that official departures resulted in subsidies becoming more sensitive to R&D efficiency and less sensitive to AETC spending, similar to the results after the anti-corruption campaign.

Figure 2 illustrates these results graphically. In Panel A, we can discern a notable increase in the subsidies to high-efficiency firms and a less prominent increase for low-efficiency firms. Panel B shows a clear increase in subsidies to low AETC firms and a simultaneous decrease in subsidies to high-AETC firms.

Table 5 examines R&D subsidies before and after official departures in a regression setting. The dependent variable is the R&D subsidy scaled by sales. The key independent variables are the firm's lagged R&D efficiency, lagged AETC, a "Post Departure" indicator that equals one for up to three years after the departure year of a government official for each firm that is affected (i.e., located in that province), and the interaction terms between the Post Departure dummy and R&D efficiency and AETC respectively. Lagged dependent variables are included to control for persistence. The table's organization parallels Table 3, the analysis around the inception of the anti-corruption campaign.

In all regressions, we find that the coefficient on the interaction term between AETC and the post-departure dummy is significant and negative, indicating that corruption had a weaker effect on subsidies after official departures. In terms of magnitude, the coefficients indicate that the effect of corruption on subsidies is essentially negated by departures. For instance, in model (6) with firm fixed effects, the coefficient on AETC is 0.079. This coefficient indicates that a one-standard deviation increase in AETC is associated with a 13% increase in subsidies (0.074*0.008/0.005) prior to an official departure. But the interaction term between AETC and the post-departure dummy is -0.078, suggesting that the net effect of AETC on subsidies in the aftermath of departures was close to zero. We note that the coefficients on the interaction term between R&D efficiency and the post departure indicator are insignificant, indicating that official departures do not increase the sensitivity of grant decisions towards R&D efficiency; the salient change is mainly a reduced sensitivity to corruption.

Overall, results in this section consistently indicate that events that result in lower likelihood of corruption—the anti-corruption campaign or government official departures—have the effect of sharpening the impact of merit (R&D efficiency) on subsidies and reducing the influence of corruption (AETC) on subsidies. In the next section, we examine robustness of these findings as well as alternative interpretations.

4. Alternative Hypotheses and Robustness Checks

4.1. Placebo Test

One natural concern relates to our first identification strategy based on the anti-corruption campaign. The campaign might be contemporaneous with other changes that also affected innovation in China. For example, while we find that high-efficiency firms receive larger increases in subsidies than low-efficiency firms, it is possible that this reflects a general improvement in China's resource allocation over time.

Our second identification strategy based on departures of provincial innovation office leaders alleviates this concern as those events are staggered over time. Nevertheless, to directly address this concern, we conduct a number of analyses. Our first analysis is a placebo test, in which we repeat the DiD analysis but pretend that the anti-corruption campaign happened in a different year. Specifically, we examine three placebo years: 2009, 2010, and 2011. For each of the placebos, we conduct the same DiD analysis as with the actual campaign; namely, we compare the outcomes using the three years before and three years after the placebo year.

Table 6 presents the key regression coefficients for the placebo analysis. The specification is identical to model (5) in Table 3, the panel regression analysis around the anti-corruption campaign. For ease of comparison, the first column repeats the coefficients from Table 3, Panel A, model (5). Recall that the key finding from Table 3 was that the interaction term between R&D efficiency and the post-campaign dummy was positive and significant, while the interaction term between AETC and Post Campaign was negative and significant, indicating that subsidies are more sensitive to R&D efficiency and less to AETC after the campaign. These key results are largely absent from Table 6: the key interaction terms are not significant in the placebo years of 2009 and 2010; it is significant at the 5% level in 2011 which is very close to the actual year of the campaign. The post-campaign coefficient itself is generally positive and significant for all placebo years used, indicating that overall subsidies have increased over time. But the absence of significant interaction effects in the placebo tests suggests that the change in sensitivities of R&D subsidies to R&D efficiency and AETC is associated with 2012, the year of the anti-corruption campaign.

Other checks we conducted include adding year fixed effects or a linear time trend to pick up the overall improvement in resource allocation over time. None of these analyses alter our results qualitatively. These results can be found in Tables IA2 and IA3 of our internet appendix. Overall, we conclude that the findings around the anti-corruption campaign was not merely picking up an improvement of resource allocation over time.

4.2 Do Subsidies Alleviate Financial Constraints?

Even though we find that both the anti-corruption campaign and local official departures resulted in more subsidies granted to efficient firms, these results do not necessarily imply more effective resource allocation. One alternative interpretation is that officials simply became "lazy" and allocate resources to obvious winners. Such a strategy would not only make them look good but also help them escape the scrutiny from the anti-corruption watchdogs as it is often hard to determine the marginal impact of research grants. But these "good" firms may already had plenty of resources, while at the same time truly deserving yet financially constrained firms remained under-funded.

If changes in subsidy allocation helped relax financial constraints, we should observe that constrained and yet efficient firms enjoy the greatest benefits. To examine whether the changes in subsidy allocation resulted in relaxing of financial constraints for these firms, we augment our analysis by introducing two financial constraint measures. Our first measure is firm size, with small firms considered to more likely be constrained. This is clearly a crude measure. Our second measure is a measure of firms' dependence on external financing, based on Rajan and Zingales (RZ, 1998). In the spirit of the RZ analysis, we calculate an industry level dependence on external financing as follows. First, for each firm in our sample, we calculate its average external financing dependence using data from 2009, 2010, and 2011, the three pre-anti-corruption campaign years. A firm's dependence on external financing in a given year is the firm's capital expenditure in a given year minus its cash flow from operations, divided by capital expenditure. We then calculate an industry-level dependence measure for each of the two-digit Chinese industry codes[30] by averaging the financing dependence measure across all firms in that industry. Finally, we use the median financial dependence in our sample to divide all industries into those that have "high" and "low" external-finance dependence. Sample firms' external finance dependence are then defined by their industry membership.[31]

Table 7 reports regression analysis of the change in subsidies before and after the anti-corruption campaign (analogous to the analysis in Table 3) for small and large firms (models (1) and (2)) and for firms with high and low external financing needs (models (3) and (4)). We find that the changes in R&D subsidy allocations are more pronounced among small firms and firms with higher external financing needs. The coefficients suggest that among small firms, R&D subsidies became four times more sensitive to R&D efficiency after the anti-corruption campaign

[30] Chinese industry codes are defined by the China Security Regulations Commission (CSRC).

[31] While we follow the definitions in RZ (1998) as closely as possible, we do not emulate their approach of using the U.S. industry data to undertake the division of firms. We felt that the financial characteristics of Chinese industries would be sharply different, due both to strategic financial choices (e.g., differing reliance on outsourced components and use of trade credit), as well as differing profitability rates.

than before: the overall coefficient on efficiency is 0.002 and its interaction with the post-campaign indicator is 0.008. These coefficients indicate that for small firms, a one standard increase in R&D efficiency is associated with a one-third increase in R&D subsidies after the anti-corruption campaign.[32] Meanwhile, the sensitivity of R&D subsidy to AETC is reduced by over 80% (the coefficient on AETC is 0.096 and its interaction term -0.078). Results based on external financing needs are similar qualitatively and in magnitude. Meanwhile, neither effect is significant among large firms or firms with low external financial needs. There results support an interpretation that the changes in the way R&D subsidies are allocated following anti-corruption efforts particularly addressed financially constrained firms.

5. Subsidies and Future Innovation

The previous sections have shown that both firms' innovation efficiency and corruption positively influence the amount of government subsidies received. In this section, we investigate the association between subsidies and future innovative outcomes. If subsidy grants become more merit-based after the anti-corruption campaign and official departures, particularly for financially constrained firms, we might expect subsidies to be more strongly associated with future innovation after these events. We should note our analysis here focuses on association, and cannot show whether the subsidies *cause* subsequent innovations.[33]

To study the association between subsidies and future innovation, we estimate panel regressions of future innovation outcomes. The dependent variables are the three innovation

[32] The sum of the coefficients on the R&D efficiency variable and its interaction term with the post-departure indicator is 0.002+0.008=0.01. The standard deviation of R&D efficiency is 0.169. So the associated change in the dependent variable Subsidies/Sales is 0.169*0.01=0.0017, which is about one-third of the mean Subsidies/Sales (0.005, Table 1).
[33] Using internal administrative data—in particular, regression discontinuity analyses of company evaluations—Wang, Li, and Furman (2017) argue that state innovation funds do not cause higher firm-level innovation.

outcome measures defined in Section 2D, namely, Patents/Sales, Relative Citation Strength, and Foreign Sales/Sales. (Reported results use U.S. patent and citations data. Results using Chinese patent and citations data are similar and are reported in Tables IA15 and IA16 our internet appendix.) The key independent variables are the R&D subsidy in the prior year (scaled by sales), the post anti-corruption campaign indicator (or indicators for local government official departures), and the interactions between the two. Lagged dependent variables are again included to control for persistence. Because of the relatively short time series since the anti-corruption campaign, the lengthy patent application and approval process and the time lag between patent grants and citations, our patent and citations data have a truncation bias, especially for the post campaign years. To partially correct for this bias, we include year fixed effects in our regressions. To avoid co-linearity, the post-campaign indicator is omitted, but its interaction term with the subsidy variable is the key variable of interest for inferences. Since the anti-corruption campaign and the official departures appeared to reduce the distortions of corruption, we expect that the association of subsidies and innovation to be stronger thereafter.

Results pertaining to this analysis are shown in Table 8. In this panel regression, the unit of analysis is each firm in the sample, with annual observations between 2007 and 2015. Panel A examines firms' subsequent U.S. patenting. First, we find that the coefficient on subsidies is always positive and highly significant, indicating that subsidies are correlated with more future patents. Importantly, the interaction term between subsidies and the post-campaign indicator also has a positive and significant coefficient, indicating that the positive relationship is stronger in post-campaign years. The economic magnitude is large. The coefficient of 0.006 on the interaction term is three times that on the subsidies variable alone (0.002), meaning that the overall association of subsidies and future patenting post-campaign is three times larger than pre-campaign. It also means that in post-campaign years, a one standard deviation increase in subsidies (as a percentage of sales) is associated with an extra 54% increase in the U.S. patenting rate.[34]

Results in Panel B pertaining to U.S. patent relative citation strength are qualitatively and quantitatively similar. The coefficients on the interaction term between subsidy and post campaign is 1.575, about five times as large as the coefficient on the subsidies variable alone (0.295). In terms of magnitudes, a one standard deviation increase in subsidies (as a percentage of sales) is associated with an extra 52% increase in relative citation strength post-campaign compared to pre-campaign.[35]

Finally, results in Panel C indicate that while subsidies in general did not have much association with foreign sales, they had a significantly positive relationship after the anti-corruption campaign. Overall, results in Table 8 provide strong evidence that subsidies are significantly more associated with future innovation post-campaign than pre-campaign.

Table 9 examines the association of subsidies and future innovation before and after government official departures in panel regressions. The analysis is at the firm-year level, as above. The analyses parallel those in Table 8. The dependent variables are the three innovation output measures. The key independent variables are again the R&D subsidies (scaled by sales) in the year before, the post departure indicator variable, and the interaction of the two. The variable "Post Departure" is set to one for up to three years after the departure year of a government official for each affected firm. Lagged dependent variables are again included to control for persistence.

The results in Table 9 are consistent with those in Table 8. The interaction term between subsidies and the post departure indicator is positive and significant in every model and for every

[34] The coefficient is 0.006. The standard deviation of Subsidies/Sales is 0.009 (Table 1). Thus, the magnitude of the increase is 0.006*0.009. Since the average value of the dependent variable Patents/Sales is 0.0001, in percentage terms the increase is 0.006*0.009/0.0001 = 54%.

[35] Following the same steps as footnote 28, this is calculated as 1.575*0.009/0.027 = 52%.

measure of future innovation, indicating that R&D subsidies are more strongly associated with future innovation after government official departures. The magnitude of the effect is large. For instance, Model (3) in Panel A shows that the coefficient on the interaction term between the post-departure dummy and the subsidy measure is 0.004, larger than the coefficient on the subsidy variable itself (0.003), indicating that the association between subsidies and future patenting doubles after official departures. It also means that a one standard deviation increase in subsidies (as a percentage of sales) is associated with an extra 36% in patenting after official departures.[36] Similarly, in regression (3) of Panel B, the coefficient of the interaction term between subsidies and the post-departure indicator (0.935) means that the effect of subsidies on patent citations increases by roughly 75% after departures. In terms of magnitudes, a one standard deviation increase in subsidies (as a percentage of sales) is also associated with an extra one-third increase in future patent citations after official departures.[37] Panel C shows that subsidies are also associated with higher foreign sales after official departures.

Overall, results in Table 9 indicate that official departures, which break the ties between firms and bureaucrats, have an effect similar to the anti-corruption campaign: subsidies are more strongly related to future innovation outcomes after local official departures.

In summary, the results in this section indicate that subsidies are associated with firms' innovative outcomes. This positive effect is further enhanced by anti-corruption efforts and by other events that disrupted the close relationship between firms and individual government officials, a key channel for corruption. The magnitudes of the effects are striking. The relation between subsidies and future innovation more than doubles post-campaign and after official departures. A one standard deviation increase in subsidies is associated with a 50% increase in

[36] The calculation is similar to footnote 25: 0.004*0.009/0.0001 = 36%.
[37] The calculation is similar to footnote 26: 0.935*0.009/0.027 = 31%

both U.S. patenting and citations after the anti-corruption campaign, and the associated gain is about one-third after official departures.

6. Conclusions

Using data from China, we investigate the relationship between corruption, government subsidies, and innovation. Governments all over the world subsidize innovation efforts, and corruption may be a problem facing many of these efforts. When individuals control the rights to allocate resources (R&D dollars), the presence of corruption can distort the allocation decisions (or the impact may be more benign). China is a fertile testing ground for these issues, given the pervasiveness of innovative subsidies and corruption.

Exploiting the recent anti-corruption campaign in China, and the rotations of government officials responsible for provincial innovation programs, we establish that firms' innovative abilities and corruption are both drivers of subsidies obtained from the government. The generally positive association of government subsidies and future innovative outcomes is significantly enhanced in the years after the anti-corruption campaign and after official movements. Anti-corruption efforts, and other mechanisms that broke up the ties between firms and officials, increased the sensitivity of subsidy allocation to innovative ability, as well as being associated with more efficacious subsidy programs.

References

Akcigit, Ufuk, Salome Baslandze, and Francesca Lott, 2017, Connecting to Power: Political Connections, Innovation, and Firm Dynamics, Unpublished working paper, University of Chicago.

Almus, Matthias, and Dirk Czarnitzki, 2003, The Effects of Public R&D Subsidies on Firms' Innovation Activities: The Case of Eastern Germany, Journal of Business and Economic Statistics 21, 226–36.

Atanassov, Julian, 2013, Do Hostile Takeovers Stifle Innovation?, Journal of Finance 68, 1097-1131.

Arrow, Kenneth. 1962, Economic Welfare and the Allocation of Resources for Invention. In Richard R. Nelson, editor, The Rate and Direction of Inventive Activity: Economic and Social Factors. Princeton: Princeton University Press, 609-625.

Bao, Xiaolu, Sofia Johan, and Kenji Kutsuna, 2015, Do Political Connections Matter in Accessing Capital Markets? Evidence from China, Emerging Markets Review 29, 24-41.

Bertrand, Marianne, Simeon Djankov, Rema Hanna and Sendhil Mullainathan, 2007, Obtaining a Driver's License in India: An Experimental Approach to Studying Corruption, Quarterly Journal of Economics 122, 1639-1676.

Bond, Stephen, Dietmar Harhoff, and John Van Reenen, 2005, Investment, R&D and Financial Constraints in Britain and Germany, Annales d'Economie et de Statistique 79–80, 433–60.

Cao, Xiaoping, Yuchen Wang, Sili Zhou, 2018, Anti-Corruption Campaigns and Corporate Information Release in China, Journal of Corporate Finance 49, 186-203.

Cohen, Linda R., and Roger G. Noll, 1991, The Technology Pork Barrel. Washington: Brookings Institution.

Bronzini, Raffaello, and Eleonora Iachini. 2014, Are Incentives for R&D Effective? Evidence from a Regression Discontinuity Approach, American Economic Journal: Economic Policy 6, 100–134.

Cai, Hongbin, Hanming Fang, and Lixin Colin Xu, 2011, Eat, Drink, Firms, Government: An Investigation of Corruption from the Entertainment and Travel Costs of Chinese Firms, Journal of Law and Economics 54, 55-78.

Dollar, David, and Shang-Jin Wei. 2007, Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China, Working Paper 13103, National Bureau of Economic Research.

Fan, Gang, Xiaolu Wang, and Hengpeng Zhu. 2010, NERI Index of Marketization of China's Provinces 2009 Report. Beijing, Economic Science Press.

Fan, Gang, Xiaolu Wang, and Hengpeng Zhu. 2011, NERI Index of Marketization of China's Provinces 2011 Report. Beijing, Economic Science Press.

Fan, Joseph P.H., T.J. Wong, and Tianyu Zhang. 2007, Politically Connected CEOs, Corporate Governance, and Post-IPO Performance of China's Newly Partially Privatized Firms, Journal of Financial Economics 84, 330-357.

Gul, Ferdinand A., Louis T.W Cheng, and T.Y. Leung, 2011, Perks and the Informativeness of Stock Prices in the Chinese Market, Journal of Corporate Finance 17, 1410-29.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative Efficiency and Stock Returns, Journal of Financial Economics 107, 632-654.

Hall, Bronwyn H., Zvi Griliches, and Jerry A. Hausman, 1986, Patents and R and D: Is There a Lag?, International Economic Review 27, 265-283.

Howell, Sabrina T. 2017. Financing Innovation: Evidence from R&D Grants, American Economic Review 107, 1136–1164.

Jacobs, Andrew, 2013, Elite in China Face Austerity under Xi's Rule, New York Times, March 27, 2013.

Jaffe, Adam B., and Trinh Le, 2015, The Impact of R&D Subsidy on Innovation: A Study of New Zealand Firms, Working Paper 21479, National Bureau of Economic Research.

Jaffe, Adam B., and Manuel Trajtenberg, 2002, *Patents, Citations, and Innovations: A Window on the Knowledge Economy*, Cambridge, MIT Press.

Khwaja, Asim Ijaz, and Atif Mian, 2005, Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market, Quarterly Journal of Economics 120, 1371—1411.

Kothari, S.P., Andrew Leone, and Charles E. Wasley, 2005, Performance Matched Discretionary Accrual Measures, Journal of Accounting and Economics 39, 163-197.

Lach, Saul, 2002, Do R&D Subsidies Stimulate or Displace Private R&D? Evidence from Israel, Journal of Industrial Economics 50, 369–90

Lerner, Josh, 1999. The Government as Venture Capitalist: The Long-Run Effects of the SBIR Program, Journal of Business 72, 285-318.

Li, Hongbin, and Li-An Zhou, 2005, Political Turnover and Economic Performance: The Incentive Role of Personnel Control in China, Journal of Public Economics 89, 1743-62.

Huang, Yasheng, 2002, Managing Chinese Bureaucrats: An Institutional Economics Perspective, Political Studies 50, 61-79.

Mazzucato, Mariana, 2013, The Entrepreneurial State: Debunking Public vs. Private Sector Myths. New York: Anthem Press.

National Research Council, 2005, Measuring Research and Development Expenditures in the U.S. Economy. Washington, The National Academies Press.

Nelson, Richard R., 1959, The Simple Economics of Basic Scientific Research, Journal of Political Economy 67, 297-306.

Pei, Minxin, 2016, China's Crony Capitalism: The Dynamics of Regime Decay. Cambridge: Harvard University Press.

Rajan, Raghuram, and Luigi Zingales, 1998, Financial Dependence and Growth, American Economic Review 88, 559–586.

Senor, Dan, and Saul Singer, 2009, Start-Up Nation: The Story of Israel's Economic Miracle. New York: Grand Central Publishing.

Shleifer, Andrei, and Robert W. Vishny, 1998, The Grabbing Hand: Government Pathologies and Their Cures, Cambridge: Harvard University Press.

Wallsten, Scott J., 2000, The Effects of Government-Industry R&D Programs on Private R&D: The Case of the Small Business Innovation Research Program, RAND Journal of Economics 31, 82–100.

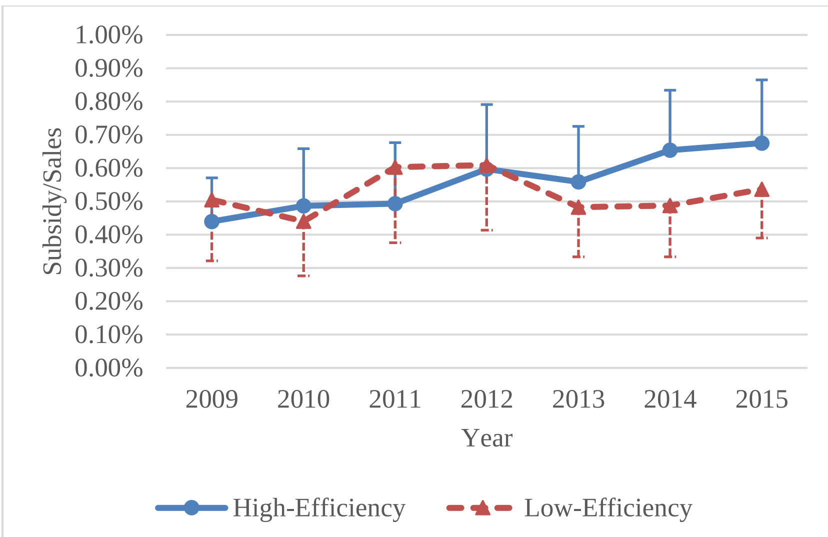
Wang, Yanbo, Jizhen Li, and Jeffrey L. Furman, 2017, Firm Performance and State Innovation Funding: Evidence from China's Innofund Program, Research Policy 46, 1142-1161.

Zhang, Jian, 2016, Public Governance and Corporate Fraud: Evidence from the Recent Anti-Corruption Campaign in China, Journal of Business Ethics 148, 275-296.

Figure 1: R&D Subsidies Before and After the Anti-Corruption Campaign

This figure plots the R&D subsidies (scaled by firm revenue) received by firms before and after the anti-corruption campaign. In Panel A, we sort firms by the average R&D efficiency (calculated as in Equation 2) during the pre-anti-corruption campaign years of 2009, 2010, and 2011. Firms with above (below) median efficiency are classified as high- (low-) efficiency firms. In Panel B, we sort firms by the average abnormal ETC (AETC; calculated from Equation 1) spending during the pre-anti-corruption campaign years of 2009, 2010, and 2011. Firms with above (below) median spending are classified as high- (low-) ETC firms. The vertical bars represent 95% confidence intervals.

A. Sorting firms by R&D Efficiency



B. Sorting firms by AETC Spending

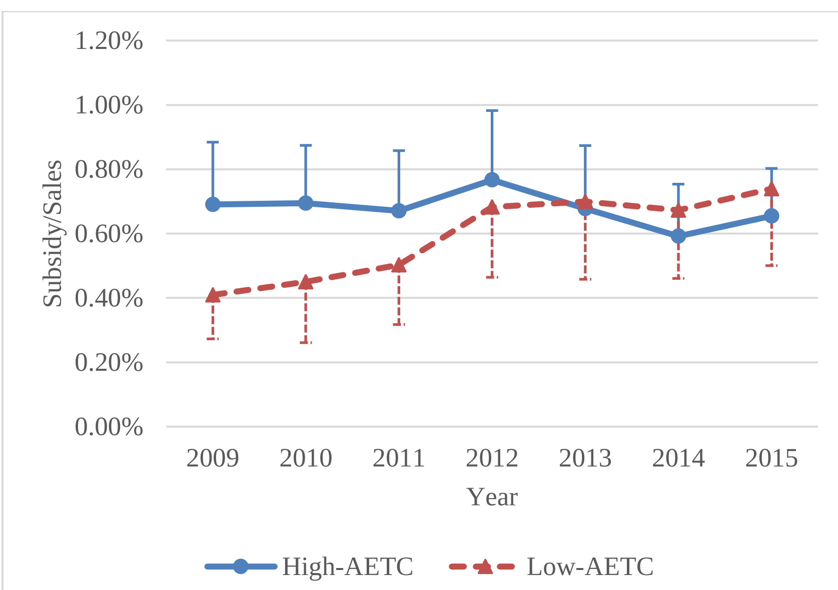
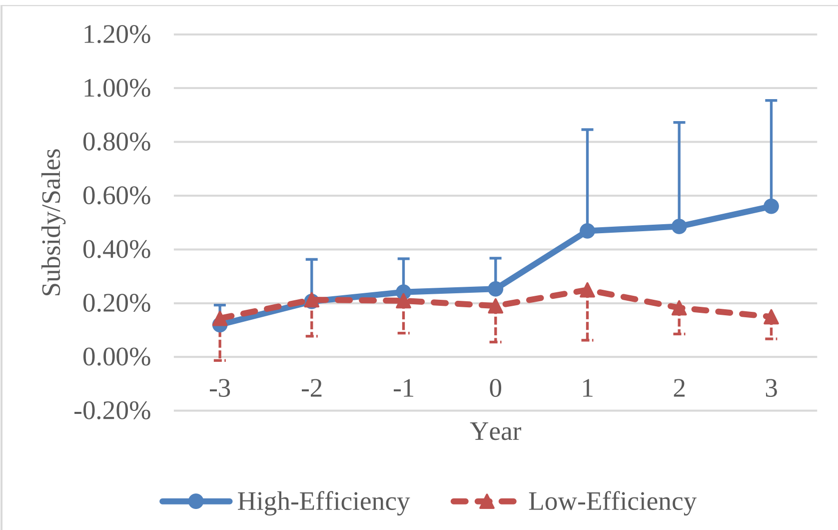


Figure 2: R&D Subsidies Before and After Official Departures

This figure plots the R&D subsidies (scaled by firm revenue) received by firms before and after the departure of provincial technology bureau heads. In Panel A, we sort firms by the average R&D efficiency (calculated as in Equation 2) during the three event years prior to the official departures. Firms with above (below) median efficiency are classified as high- (low-) efficiency firms. In Panel B, we sort firms by the average AETC spending during the three event years before the officials' departures. Firms with above (below) median spending are classified as high- (low-) ETC firms. The vertical bars represent 95% confidence intervals.

A. Sorting firms by R&D Efficiency



B. Sorting firms by AETC Spending

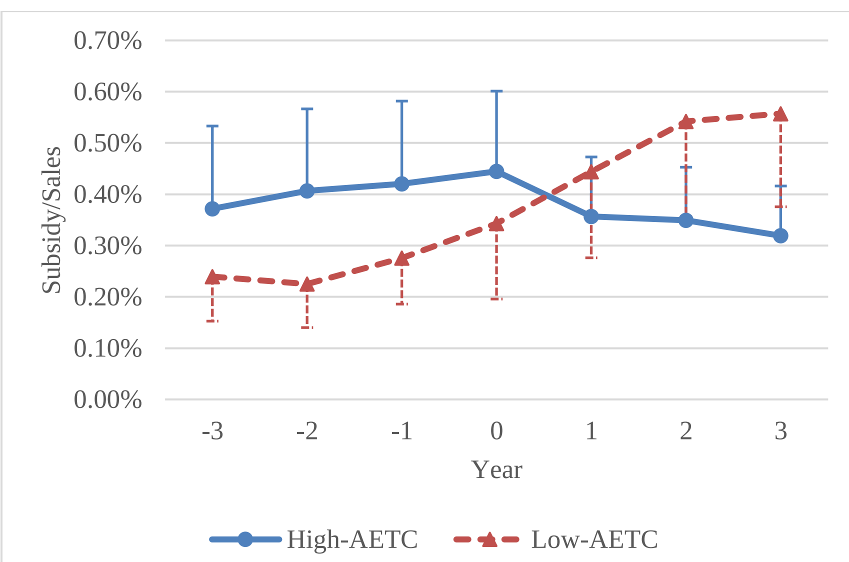


Figure 3: Anti-Corruption Media Coverage

This graph shows the time trend of the percentage of articles in all official provincial newspapers (the "Daily" newspapers published by provincial governments) with the words "anti-corruption" in their titles. For details on Chinese newspapers, see footnote 7.

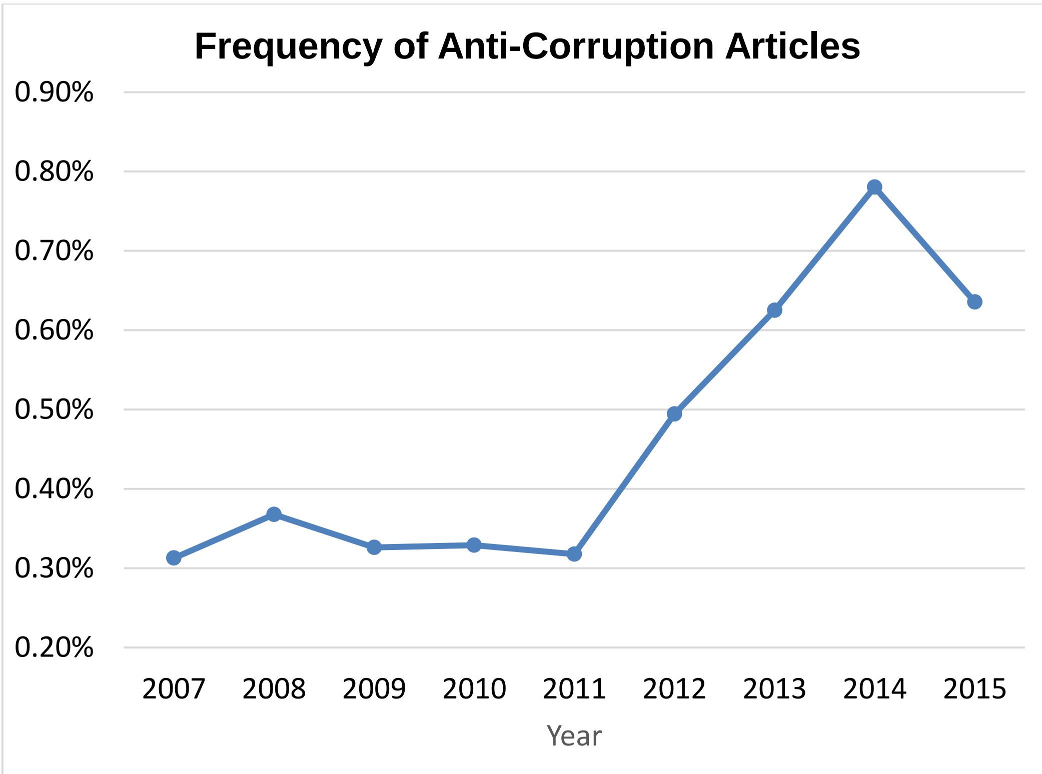


Figure 4: ETC Spending

This figure shows the trend of the average ETC as a percentage of revenue. ETC is firms' entertainment and travel costs, AS reported in their annual statements.

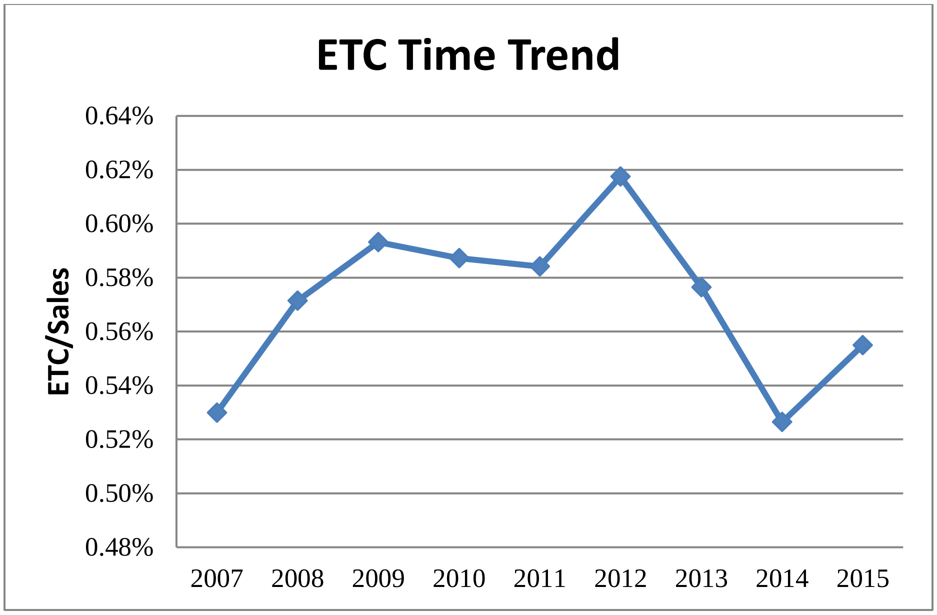


Figure 5: Official Departures over Time

This figure plots the number of departures of provincial technology bureau heads over time.

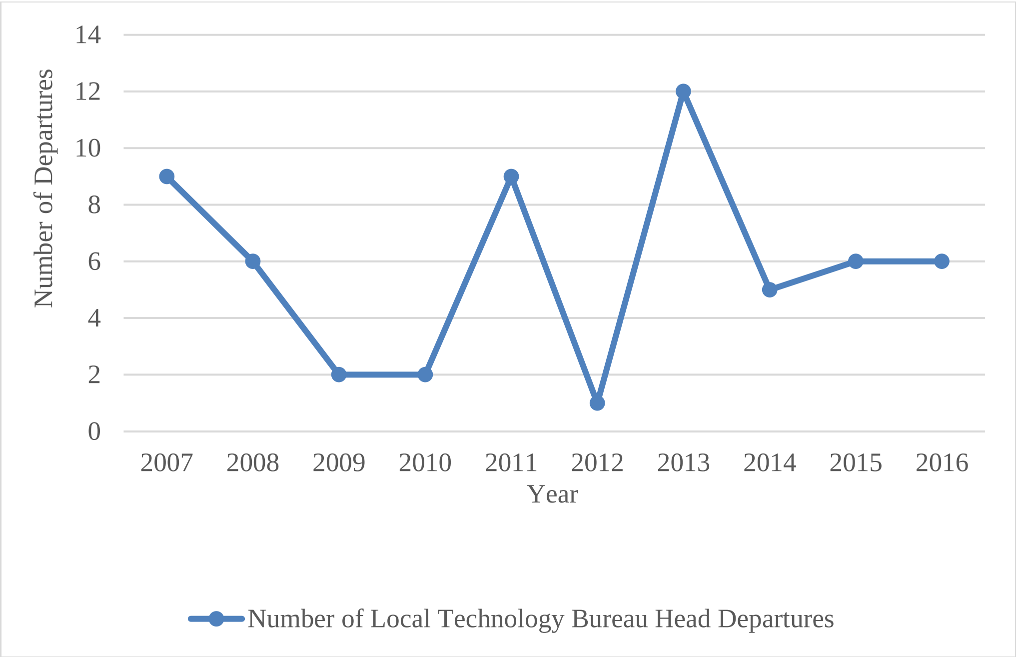


Table 1 – Descriptive Statistics

This table provides descriptive statistics of our sample, which consists of annual firm-level observations between 2007 and 2015. Detailed variable definitions are found in the Appendix 1. All financial amounts are measured in millions of RMB. All financial ratios are calculated annually using annual statements. Panel A presents summary statistics and Panel B investigates the relationship between the two key independent variables, R&D efficiency, and AETC.

Panel A: Sample statistics

Variable	Mean	Standard Deviation	Min.	Median	Max.	Observations
			Main Variables			
Subsidy/Sales	0.005	0.009	0	0.002	0.064	8628
ETC/Sales	0.006	0.009	0	0.004	0.086	8628
AETC/Sales	0	0.008	-0.018	-0.001	0.080	8628
R&D/Sales	0.037	0.044	0	0.030	0.311	8628
Subsidy/ R&D	0.223	0.618	0	0.071	6.401	7293
Patent/Sales (China)	0.004	0.009	0	0	0.070	8628
Relative Citation Strength (China)	0.444	0.861	0	0	5.641	8628
Patent/Sales (U.S.)	0.0001	0.0007	0	0	0.007	8628
Relative Citation Strength (U.S.)	0.027	0.206	0	0	2.975	8628
R&D Efficiency	0.062	0.169	0	0.007	1.607	8381
Foreign Sales/Sales	0.144	0.210	0	0.043	0.925	8628
			Control Variables			
Size (Mil. RMB)	4638	9147	140.4	1961	78000	8628
Age (Year)	15.47	4.843	2	15	37	8628
Leverage	0.415	0.235	0.030	0.400	1.567	8628
ROA	0.039	0.066	-0.335	0.039	0.270	8628
Tobin' Q	3.037	2.357	0.903	2.338	18.98	8628
Intangible Asset	0.045	0.042	0	0.036	0.310	8628
SOE	0.365	0.481	0	0	1	8628
Political Connection	0.296	0.456	0	0	1	8628
Business in other regions	2.631	1.217	0	2	8	8628

Panel B: Relationship between R&D efficiency and AETC

Number of firms	High efficiency	Low efficiency
High AETC	278	265
Low AETC	265	278
Spearman rank correlation coefficient between efficiency and AETC:		-0.039
p-value for rank correlation coefficient:		0.197

Table 2. Difference-in-Differences Analysis: Subsidies before and after the Anti-Corruption Campaign

This table conducts a difference-in-difference analysis and examines the change in R&D subsidies received by firms with high and low R&D efficiency (or high and low AETC) before and after the anti-corruption campaign. Subsidies are measured as the amount of R&D subsidies a firm receives in a given year, divided by its annual revenue in that year. 2009, 2010, and 2011 are pre-campaign years, and 2013, 2014, and 2105 are post-campaign years. We sort firms by the average R&D efficiency during 2009, 2010, and 2011. Firms with above (below) median efficiency are classified as high- (low-) efficiency firms. Panel A investigates the parallel trends assumption in the pre-campaign years by comparing the year-on-year growth in R&D subsidies (scaled by sales) received by the high and low efficiency groups. Panel B (C) reports the difference-in-differences in the levels of R&D subsidies (scaled by sales) received by firms with high and low R&D efficiency (AETC) groups. Detailed variable definitions are found in the Appendix 1. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels in a two-tailed test, respectively.

Panel A: Pre-Trend Test: Annual growth in subsidies/sales

	2009	2010	2011
High Efficiency	0.323	0.037	0.160
Low Efficiency	0.528	-0.101	0.247
t-stat (High – Low)	-0.109	1.465	-0.867

	2009	2010	2011
High AETC	0.297	0.111	0.134
Low AETC	0.258	0.057	0.252
t-stat (High – Low)	0.246	0.536	-1.146

Panel B: Subsidies/sales for firms with high and low R&D efficiency

	Before	After	After - Before	t-stat
High efficiency	0.0043	0.0062	0.0019	3.570***
Low efficiency	0.0051	0.0054	0.0003	0.673
High - Low	-0.0008	0.0008	0.0016	2.200**

Panel C: Subsidies/sales for firms with high and low AETC spending

	Before	After	After - Before	t-stat
High AETC	0.0068	0.0064	-0.0004	-0.684
Low AETC	0.0045	0.0070	0.0025	3.089***
High - Low	0.0023	-0.0006	-0.0029	-2.845***

Table 3. R&D Subsidies Before and After Anti-Corruption Campaign: Panel regressions

This table reports panel regression analysis of R&D subsidies before and after the anti-corruption campaign. Subsidies are measured as the amount of R&D subsidies a firm receives in a given year, divided by its annual revenue in that year. Panel A presents the results pertaining to the full sample; Panel B presents results when splitting the sample into high and low corruption regions. In Panel B, for brevity, only key coefficients are reported. Detailed variable definitions are found in the Appendix 1. Huber-White heteroskedasticity-consistent standard errors clustered by firm are used for all regressions. *p*-values are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Full sample

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var =	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales
R&D Efficiency$_{t-1}$	0.003***	0.003***	0.002***	0.002***	0.002**	0.0004
	(0.004)	(0.001)	(0.004)	(0.002)	(0.033)	(0.420)
AETC $_{t-1}$		0.059**	0.080***	0.078***	0.086**	0.064***
		(0.025)	(0.000)	(0.000)	(0.014)	(0.001)
Post Campaign		0.001***	0.001***	0.001**	0.001**	0.0001
		(0.000)	(0.001)	(0.011)	(0.023)	(0.522)
Efficiency $_{t-1}$×Post Campaign			0.005***	0.005***	0.006**	0.003**
			(0.000)	(0.000)	(0.019)	(0.010)
AETC $_{t-1}$×Post Campaign			-0.043*	-0.046*	-0.062*	-0.069***
			(0.082)	(0.064)	(0.057)	(0.000)
SOE $_{t-1}$				-0.001***	-0.0002	-0.002***
				(0.000)	(0.673)	(0.009)
Political Connection $_{t-1}$				-0.0001	-0.0001	-0.0001
				(0.563)	(0.769)	(0.777)
ROA $_{t-1}$					-0.006**	-0.005***
					(0.019)	(0.001)
Tobin's Q $_{t-1}$					0.0003***	-0.0001
					(0.003)	(0.436)
Leverage $_{t-1}$					-0.007***	-0.002**
					(0.000)	(0.026)
Constant	0.003***	0.002**	0.002***	0.003***	0.005***	0.008***
	(0.006)	(0.022)	(0.000)	(0.000)	(0.000)	(0.000)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	No
Province fixed effects	Yes	Yes	Yes	Yes	Yes	No
Firm fixed effects	No	No	No	No	No	Yes
N	7052	7052	7052	7052	7052	7052
R^2	0.073	0.079	0.081	0.086	0.117	0.642

Panel B: High versus low corruption regions

	(1)	(2)	(3)	(4)
	High Corruption	High Corruption	Low Corruption	Low Corruption
	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales
R&D Efficiency$_{t-1}$	0.002	-0.0002	0.003***	0.002**
	(0.382)	(0.806)	(0.004)	(0.018)
AETC $_{t-1}$		0.066		0.094**
		(0.238)		(0.022)
Post Campaign		0.001**		0.0004*
		(0.014)		(0.088)
Efficiency $_{t-1}$×Post Campaign		0.010*		0.003
		(0.053)		(0.111)
AETC $_{t-1}$×Post Campaign		-0.125**		-0.020
		(0.037)		(0.564)
Constant	0.002	0.004**	0.003***	0.005***
	(0.142)	(0.049)	(0.005)	(0.000)
Lagged firm controls	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
N	1408	1408	5644	5644
R^2	0.047	0.121	0.077	0.120

Table 4. Difference-in-Differences Analysis: Subsidies before and after government official moves

This table conducts a difference-in-difference analysis and examines the change in R&D subsidies received by firms with high and low R&D efficiency (or high and low AETC) before and after the departures of the local technology bureau head. Subsidies are measured as the amount of R&D subsidies a firm receives in a given year, divided by its annual revenue in that year. For each official departure event in year t, we use the three years before the departure year (t-1, t-2, and t-3) as the "before" window, and the three years after the departure year (t+1, t+2, and t+3) as the "after" window. We sort firms by the average R&D efficiency (or average AETC) during the three event years prior to the official departures. Firms with above (below) median efficiency (AETC) are classified as high- (low-) efficiency (AETC) firms. Panel A investigates the parallel trends assumption in the "before" window by comparing the year-one-year growth in R&D subsidies (scaled by sales) received by the high and low R&D efficiency (AETC) groups. Panel B (C) reports the difference-in-differences analysis for firms with high and low R&D efficiency (AETC) prior to the official departure. Detailed variable definitions are found in the Appendix 1. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels in a two-tailed test, respectively.

Panel A: Pre-trend annual growth in subsidies/sales

	Event Year -3	Event Year -2	Event Year -1
High R&D Efficiency	0.032	0.285	0.074
Low R&D Efficiency	0.270	0.530	-0.135
t-stat (High – Low)	-0.692	-0.584	0.107
	Event Year -3	Event Year -2	Event Year -1
High AETC	0.440	0.309	-0.034
Low AETC	0.391	0.226	0.018
t-stat (High – Low)	0.157	0.279	-0.366

Panel B: Difference-in-differences test for firms with high and low R&D efficiency

	Before	After	After - Before	t-stat
High R&D Efficiency	0.0019	0.0050	0.0031	2.119**
Low R&D Efficiency	0.0018	0.0019	0.0001	0.157
High - Low	0.0001	0.0031	0.0030	2.030**

Panel C: Difference-in-differences test for firms with high and low AETC spending

	Before	After	After - Before	t-stat
High AETC	0.0043	0.0035	0.0008	0.046
Low AETC	0.0024	0.0047	0.0023	2.831***
High - Low	0.0019	-0.0012	-0.0031	-1.823*

Table 5. R&D Subsidies around Government Official Departures: Panel regressions

This table reports panel regression results of R&D subsidies around the departure of local technology bureau heads. Subsidies are measured as the amount of R&D subsidies a firm receives in a given year, divided by its annual revenue in that year. All departures include both routine departures due to retirements and job transfers as well as corruption. Corruption-related departures refer to departures of provincial officials due to corruption charges, identified from provincial newspaper reports. The R&D efficiency of firms is calculated as Equation (2). AETC is firms' abnormal ETC spending, calculated as Equation (1). Post departure is an indicator variable that equals 1 for years after the official departure and 0 otherwise. Detailed definitions of other control variables are found in the Appendix 1. Huber-White heteroskedasticity-consistent standard errors clustered by firm are used for all regressions. *p*-values are in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Dep Var =	(1) Subsidy /Sales	(2) Subsidy /Sales	(3) Subsidy /Sales	(4) Subsidy /Sales	(5) Subsidy /Sales	(6) Subsidy /Sales
R&D Efficiency $_{t-1}$	0.003***	0.003***	0.002**	0.003**	0.002**	0.001
	(0.004)	(0.003)	(0.035)	(0.031)	(0.045)	(0.249)
AETC/Sales $_{t-1}$		0.059**	0.094***	0.090***	0.084**	0.079**
		(0.025)	(0.005)	(0.007)	(0.016)	(0.044)
Post Departure		-0.00004	-0.0001	-0.0001	-0.0001	0.0004
		(0.866)	(0.696)	(0.696)	(0.715)	(0.110)
R&D Efficiency $_{t-1}$×Post Departure			0.001	0.001	0.001	-0.002
			(0.554)	(0.504)	(0.577)	(0.217)
AETC/Sales $_{t-1}$×Post Departure			-0.070**	-0.069**	-0.055*	-0.078***
			(0.019)	(0.021)	(0.088)	(0.007)
SOE $_{t-1}$				-0.002***	-0.000	-0.002
				(0.001)	(0.507)	(0.136)
Political Connection $_{t-1}$				-0.000	-0.000	-0.000
				(0.902)	(0.952)	(0.953)
ROA $_{t-1}$					-0.006**	-0.005**
					(0.014)	(0.025)
Tobin's Q $_{t-1}$					0.000***	-0.000
					(0.006)	(0.317)
Leverage $_{t-1}$					-0.007***	-0.001
					(0.000)	(0.424)
Constant	0.003***	0.003***	0.003***	0.003***	0.005***	0.001**
	(0.006)	(0.005)	(0.005)	(0.000)	(0.000)	(0.032)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	No
Province fixed effects	Yes	Yes	Yes	Yes	Yes	No
Firm fixed effects	No	No	No	No	No	Yes
N	7052	7052	7052	7052	7052	7052
R^2	0.073	0.076	0.077	0.083	0.113	0.648

Table 6. Placebo Tests

This table reports the results of our placebo tests, whereby we repeat the same regression analysis in Table 3, but pretend that the anti-corruption campaign occurred in 2009, or 2010, or 2011 instead of the actual year which was 2012. The empirical specification is identical to model (5) in Table 3. For each placebo year, we use three years before as the "before" window and three years after as the "after window". For instance, for the placebo year of 2009, 2006, 2007, and 2008 are used as the "before" window, and 2010, 2011, and 2012 as the "after" window. Detailed variable definitions are found in the Appendix 1. Huber-White heteroskedasticity-consistent standard errors clustered by firm are used for all regressions. *p*-values are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Actual cutoff year=2012	Placebo cutoff year=2009	Placebo cutoff year=2010	Placebo cutoff year=2011
Dep Var =	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales
R&D Efficiency$_{t-1}$	0.002**	0.001	0.001	0.001*
	(0.033)	(0.433)	(0.209)	(0.066)
AETC $_{t-1}$	0.086**	0.114*	0.088**	0.088**
	(0.014)	(0.076)	(0.027)	(0.036)
Post Campaign	0.001**	0.001***	0.001***	0.001***
	(0.023)	(0.000)	(0.002)	(0.000)
Efficiency $_{t-1}$×Post Campaign	0.006**	0.002	0.003	0.004**
	(0.019)	(0.239)	(0.253)	(0.015)
AETC $_{t-1}$×Post Campaign	-0.062*	-0.067	-0.015	-0.055
	(0.057)	(0.253)	(0.779)	(0.200)
Constant	0.005***	0.004***	0.005***	0.004***
	(0.000)	(0.000)	(0.002)	(0.000)
Lagged firm controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes

Table 7. R&D Subsidies and Financial Constraints

This table presents regression analysis of R&D subsidies before and after the anti-corruption campaign, for firms with high or low financial constraints. Subsidies are measured as the amount of R&D subsidies a firm receives in a given year, divided by its annual revenue in that year. The empirical specification is identical to model (5) in Table 3. We use two measures for financial constraint: Firm size, and the Rajan-Zingales (RZ) measure of external financing needs. Each year, we use the median firm enterprise value (market capitalization of equity plus the book value of total debt) to divide the sample into "Small firms" and "Large firms". We sort firms into those in industries with high and low external financing needs as described in the text. Detailed independent variable definitions are found in the Appendix 1. Huber-White heteroskedasticity-consistent standard errors clustered by firm are used for all regressions. *p*-values are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Small Firms	Large Firms	High external financing needs	Low external financing need
Dep Var =	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales	Subsidy/Sales
R&D Efficiency$_{t-1}$	0.002*	0.001	0.001	0.002
	(0.074)	(0.382)	(0.102)	(0.105)
AETC $_{t-1}$	0.096**	0.077*	0.078**	0.100*
	(0.023)	(0.077)	(0.037)	(0.065)
Post Campaign	0.0004	0.001**	0.001**	0.0003
	(0.365)	(0.010)	(0.022)	(0.264)
Efficiency $_{t-1}$×Post Campaign	0.008**	0.003	0.008**	0.003
	(0.043)	(0.204)	(0.031)	(0.246)
AETC $_{t-1}$×Post Campaign	-0.078*	0.001	-0.078**	-0.038
	(0.051)	(0.983)	(0.020)	(0.532)
Constant	0.006***	0.003***	0.005***	0.005***
	(0.000)	(0.006)	(0.000)	(0.000)
Lagged firm controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
N	3409	3643	3528	3524
R^2	0.109	0.141	0.113	0.134

Table 8. Subsidies and Future Innovation: The effect of anti-corruption campaign

This table investigates the relation between R&D subsidies and future innovation before and after the anti-corruption campaign. Panel A, B, and C presents results using three different measures of future innovation as the dependent variable. In Panel A, the dependent variable is Patent/Sales using U.S. patens data. In Panel B, the dependent variable is Relative Citation Strength using U.S. patent data. In Panel C, the dependent variable is Foreign Sales/Sales. In each regression, we include the lagged dependent variable to control for persistence. Detailed definitions of other variables are found in the Appendix 1. Huber-White heteroskedasticity-consistent standard errors clustered by firm are used for all regressions. *p*-values are in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Future U.S. patents

	(1)	(2)	(3)	(4)
	Patents/ Sales (U.S.)	Patents/ Sales (U.S.)	Patents/ Sales (U.S.)	Patents/ Sales (U.S.)
Patents/Sales (U.S.)$_{t-1}$	0.500***	0.499***	0.496***	0.485***
	(0.000)	(0.000)	(0.000)	(0.000)
Subsidy/Sales $_{t-1}$	0.005***	0.003*	0.002	0.002
	(0.001)	(0.075)	(0.180)	(0.208)
Subsidy/Sales $_{t-1}$×Post Campaign		0.007**	0.006**	0.007**
		(0.023)	(0.026)	(0.023)
Constant	0.00001	0.00002	-0.0001	-0.0002
	(0.465)	(0.251)	(0.570)	(0.310)
Lagged firm controls	No	No	Yes	Yes
Industry fixed effects	No	No	No	Yes
Province fixed effects	No	No	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	7295	7295	7295	7295
R^2	0.275	0.276	0.277	0.284

Panel B: Future U.S. patent citations

	(1) Relative Citation Strength (U.S.)	(2) Relative Citation Strength (U.S.)	(3) Relative Citation Strength (U.S.)	(4) Relative Citation Strength (U.S.)
Relative Citation Strength (U.S.)$_{t-1}$	0.225***	0.224***	0.220***	0.209***
	(0.000)	(0.000)	(0.000)	(0.000)
Subsidy/Sales $_{t-1}$	1.676***	1.194***	1.132***	1.016***
	(0.004)	(0.001)	(0.002)	(0.007)
Subsidy/Sales $_{t-1}$×Post Campaign		1.548*	1.620**	1.645**
		(0.052)	(0.042)	(0.039)
Constant	0.006	0.008	-0.242***	-0.301***
	(0.269)	(0.365)	(0.000)	(0.000)
Lagged firm controls	No	No	Yes	Yes
Industry fixed effects	No	No	No	Yes
Province fixed effects	No	No	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	7295	7295	7295	7295
R^2	0.063	0.064	0.067	0.077

Panel C: Subsidies and future foreign sales

	(1) Foreign sales/ Sales	(2) Foreign sales/ Sales	(3) Foreign sales/ Sales	(4) Foreign sales/ Sales
Foreign sales/ Sales $_{t-1}$	0.905***	0.905***	0.904***	0.893***
	(0.000)	(0.000)	(0.000)	(0.000)
Subsidy/Sales $_{t-1}$	0.059	-0.178	-0.191	-0.207
	(0.676)	(0.174)	(0.152)	(0.129)
Subsidy/Sales $_{t-1}$ ×Post Campaign		0.760**	0.771**	0.798**
		(0.025)	(0.023)	(0.020)
Constant	-0.001	-0.001	-0.037*	-0.058**
	(0.742)	(0.863)	(0.098)	(0.012)
Lagged firm controls	No	No	Yes	Yes
Industry fixed effects	No	No	No	Yes
Province fixed effects	No	No	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	7295	7295	7295	7295
R^2	0.834	0.834	0.835	0.836

Table 9. Subsidies and Future Innovation: Analysis around government official departures

This table investigates the relation between R&D subsidies and future innovation, around the departures of local officials. Panel A, B, and C presents results using three different measures of future innovation as the dependent variable. In Panel A, the dependent variable is Patent/Sales using U.S. patents data. In Panel B, the dependent variable is Relative Citation Strength using U.S. patent citation data. In Panel C, the dependent variable is Foreign Sales/Sales. In each regression, we include the lagged dependent variable to control for persistence. Detailed definitions of other variables are found in the Appendix 1. Huber-White heteroskedasticity-consistent standard errors clustered by firm are used for all regressions. *p*-values are in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Future U.S. patents

	(1)	(2)	(3)
	Patent/ Sales (U.S.)	Patent/ Sales (U.S.)	Patent/ Sales (U.S.)
Patent/ Sales (U.S.)$_{t-1}$	0.499***	0.496***	0.486***
	(0.000)	(0.000)	(0.000)
Subsidy/Sales $_{t-1}$	0.004***	0.003***	0.003***
	(0.000)	(0.001)	(0.002)
Post Departure	-0.0001***	-0.0001***	-0.00004**
	(0.001)	(0.002)	(0.026)
Subsidy/Sales $_{t-1}$×Post Departure	0.004*	0.004*	0.004*
	(0.070)	(0.090)	(0.086)
Constant	0.00003	-0.0001	-0.0002
	(0.170)	(0.577)	(0.263)
Lagged firm controls	No	Yes	Yes
Industry fixed effects	No	No	Yes
Province fixed effects	No	No	Yes
Year fixed effects	Yes	Yes	Yes
N	7295	7295	7295
R^2	0.276	0.278	0.284

Panel B. Future U.S. patent citations

	(1) Relative Citation Strength (U.S.)	(2) Relative Citation Strength (U.S.)	(3) Relative Citation Strength (U.S.)
Relative Citation Strength (U.S.)$_{t-1}$	0.224***	0.220***	0.209***
	(0.000)	(0.000)	(0.000)
Subsidy/Sales $_{t-1}$	1.366***	1.335***	1.267***
	(0.000)	(0.000)	(0.000)
Post Departure	-0.013***	-0.012***	-0.011***
	(0.000)	(0.000)	(0.000)
Subsidy/Sales $_{t-1}$×Post Departure	1.215***	1.190***	1.019***
	(0.000)	(0.000)	(0.003)
Constant	0.012***	-0.240***	-0.302***
	(0.000)	(0.002)	(0.000)
Lagged firm controls	No	Yes	Yes
Industry fixed effects	No	No	Yes
Province fixed effects	No	No	Yes
Year fixed effects	Yes	Yes	Yes
N	7295	7295	7295
R^2	0.064	0.068	0.077

Panel C. Foreign sales

	(1) Foreign sales/ Sales	(2) Foreign sales/ Sales	(3) Foreign sales/ Sales
Foreign Sales/ Sales$_{t-1}$	0.905***	0.904***	0.893***
	(0.000)	(0.000)	(0.000)
Subsidy/Sales $_{t-1}$	-0.079	-0.101	-0.120
	(0.581)	(0.489)	(0.418)
Post Departure	0.002	0.002	0.003
	(0.349)	(0.342)	(0.254)
Subsidy/Sales $_{t-1}$×Post Departure	0.599*	0.633*	0.660*
	(0.082)	(0.067)	(0.058)
Constant	-0.003	-0.038	-0.057**
	(0.455)	(0.142)	(0.038)
Lagged firm controls	No	Yes	Yes
Industry fixed effects	No	No	Yes
Province fixed effects	No	No	Yes
Year fixed effects	Yes	Yes	Yes
N	7295	7295	7295
R^2	0.834	0.835	0.836

Appendix 1 – Variable Definitions

Age: The number of years since a company's establishment.

Business in Other Regions: The number of geographical regions within a firm derives revenue from.

ETC/Sales (AETC/Sales): ETC stands for firms' Entertainment and Travel Costs, reported in firm's annual statements. ETC/Sales (AETC/Sales) is a firm's amount of ETC (Abnormal ETC) spending, divided by its annual revenue. AETC is the Abnormal Entertainment and Travel Costs, calculated as the residual of Equation (1).

Foreign Sales/Sales: A firms' overseas revenue divided by total revenue in a given year.

Intangible Asset: The book value of a firm's intangible assets divided by the book value of its total assets.

Small firms: Each year, firms whose enterprise value (market capitalization of equity plus the book value of total debt) is above the median enterprise value are classified as large firms.

Leverage: A firms' book value of total liabilities divided by its book value of total assets.

Patents/Sales: The number of Chinese invention patent applications filed by a firm in a given year that are ultimately granted through the end of 2016, divided by its revenue in that year.

Patents/Sales (U.S.): Similarly defined as Patent/Sales, using a firm's U.S. patents.

Political Connections: An indicator variable if a company's CEO or chairman of the board has been a government official in the past. CEO and chairman profiles are obtained from company annual statements.

Post Campaign: An indicator variable that equals 1 for the years 2013, 2014, and 2015, the three years after the beginning of the anti-corruption campaign that began in 2012.

Post Departure: An indicator variable that equals 1 for the three years after a provincial technology bureau official's departure from his/her post.

Relative Citation Strength: The number of Chinese patent citations through the end of 2016 per Chinese patent applied for in year *t* by firm *i* (that are ultimately granted by the end of 2016), divided by the number of citations per patent received over the same period by all patents applied for in year *t* (that are also ultimately granted by the end of 2016) in the same 4-digit technological class according to the International Patent Classification (IPC) code.

Relative Citation Strength (U.S.): Similarly defined as Citation Strength, using a firm's U.S. patents and the Cooperative Patent Classification scheme.

ROA (return on assets): A firm's net income divided by its book value of total assets.

R&D Efficiency: A firm's R&D efficiency, calculated as Equation (2) in the paper as the ratio between the number of patents applied by a firm in a given year that were ultimately approved, divided by a capitalized measure of R&D expenditure.

R&D/Sales: A firm's R&D expenditure in a year divided by its revenues in the same year.

RZ (Rajan-Zingales) measure of external financing needs: The average capital expenditure in firm's industry in a given year minus its cash flow from operations in the same year, divided by capital expenditure.

Size: The book value of a firm's total assets, in millions of RMB.

Small firms: Each year, firms whose enterprise value (market capitalization of equity plus the book value of total debt) is blow the median enterprise value are classified as small firms.

Subsidy/Sales: The amount of R&D subsidies a firm receives in a given year, divided by its annual revenue in that year.

SOE: An indicator variable if a company's largest ultimate shareholder, as disclosed in its annual statements, is a government entity.

Tobin's Q: A firm's market value of equity (average share price in a given year multiplied by its average number of shares outstanding) plus its book value of debt, divided by the book value of its total assets.