How Does Political Connection Affect Resource Allocation in China

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Abstract

This paper explores the impact of political connections on resource allocation in China. I examine the role of connection in securing subsidies, reducing capital costs, and lowering tax burdens. Firms with politically connected managers are shown to receive significantly higher direct subsidies and benefit from more favorable financial conditions. National-level connections primarily drive access to direct subsidies, while local connections are associated with reduced capital costs and tax paid. Using a difference-in-difference model, I show that newly connected firms experience an average 38% annual increase in subsidies during the following four years. The paper also highlights time and industry heterogeneity. The anti-corruption campaign, launched in 2012, has been found to disrupt established networks and limit the formation of relations with officials in position.

Keywords : Political Connection, Subsidy, Tax Avoidance, Misallocation.

JEL Codes : D24, D72, L38, L52, H2, O25

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1 Introduction

In China, the government controls a significant portion of the economy's resources, and private firms frequently encounter discrimination. This situation lets them operate in an unfavorable economic environment (Li et al. 2008). Given these constraints, private firms circumvent these barriers by cultivating close relationships with bureaucrats. Political connections play a central role in shaping the allocation of resources in China. These connections are particularly important in countries where formal institutions offer limited protection for private businesses. Firms with ties to government officials often gain access to subsidies, tax benefits, and cheaper financing. Since China directs hundreds of billions of dollars in subsidies to favored domestic companies every year, attracting resources becomes a crucial issue (DiPippo et al. 2022). However, the lack of transparency complicates understanding the selection process. Authorities provide little evidence on resource allocation determinants—whether the most productive, strategic, or party-connected firms are favored. In China, nearly all listed companies received subsidies in 2015 (Lardy 2019), and the allocation appears to follow criteria beyond mere economic rationality to curb market failure. Also, divergences persist between local and national leaders on which firms should receive funding. Local governments are tempted to favor their local champions against Beijing's will, fueling overproduction issues.

A comprehensive understanding of the selection process is crucial, especially amid rising tensions regarding Chinese subsidies. This paper aims to shed light on the determinants of subsidy awards in China, where political connections are a common channel for firms to access public resources. The analysis builds on the simple observation that former officials are a good channel to access power. They can use their address book in the service of the firm or bring their knowledge on the processes of obtaining subsidies or preferential treatments (Fan, Wong, and Zhang 2007; Wu et al. 2012; Hao et al. 2020). Connections can be local (municipality and province), or national. Separating both levels enables to disentangle the effects and to highlight potential divergences in the selection process. Each type of connection may affect different resources, with particular attention to the banking system, as most banks are locally state-owned enterprises (Naughton 2021; Mavroidis and Sapir 2021). My econometric strategy exploits the staggered timing of firm switching from not connected to connected and measures the evolution of resources (direct subsidies or capital cost) received by firms. Using a difference-in-difference model (DID), I investigate the causal effect of connection on direct subsidies.

To conduct the research, I rely on two kinds of data made available for listed firms: textual and financial. First, I use the biography of each firm's members made available in their annual reports to dig any previous official position. In this paper, a firm is flagged as *connected* if it has at least one former or current government or People's Congress member as a manager. Officials of these two institutions are the most capable of favoring their new employer as they are usually Party members, politicians, or bureaucrats[1]. Second, I gather subsidy flows received by each firm. Since 2007, listed firms in the Shanghai and Shenzhen stock exchanges have been required to show all direct government subsidies received. Since independent auditors review these financial statements before they are released to the public, these subsidy data should be more reliable than other self-reported data sources used so far in the literature, such as the National Bureau of Statistics (NBS). To compute interest rates and tax avoidance, I complete the data with regular information made available on the balance sheet and financial statement. My measure of tax avoidance follows the methodology of Henry and Sansing (2018) to keep non-profitable firms and avoid selection bias. The timeline of the paper stretches from 2007 to 2022. A benefit of focusing on listed firms is that data is available until 2022, while other surveys (such as NBS) are only available until 2013. In addition, listed firms cover all sectors of the economy rather than just manufacturing. While the sample covers 4,187 firms, it is a large and growing share of the Chinese economy, accounting for 6% of GDP and 10% of industrial value-added in 2019 (Jurzyk 2021).

Connection plays a significant role in the allocation of subsidies. A specific type of connection impacts each resource. Focusing first on direct subsidies, being connected at the national level increases the total amount received. Firms experience a growth of about 38% for five years

[1] I exclude the Chinese People's Political Consultative Conference (CPPCC) from the analysis because it is a very symbolic assembly. Unlike CPPCC, the People's Congress is the highest organ of State power (see `http://www.china.org.cn/english/27743.htm` or `https://english.www.gov.cn/archive/china_abc/2016/02/23/content_281475295038070.htm` for more details). Furthermore, CPPCC is not a State organ; its members are from the private sector and are not bureaucrats.

after their first connection at the national level. The impact is not homogeneous and capital-intensive industries experience a stronger effet. Conversely, direct subsidies are not impacted by connection at the local level. The paper takes into account potential disruptive policies that might affect my results, such as the anti-corruption campaign launched by Xi Jinping in 2013. This campaign targeted both high-ranking (”tigers”) and local officials (”flies”), with a significant focus on scrutinizing the ties between politicians and private businesses. By 2018, over 2 million officials had been investigated for corruption. The 2013 anti-corruption campaign disrupted these relationships, limiting the formation of new connections.

In opposition to direct subsidies, the banking and tax systems respond differently to a connection since only local connections have a significant effect. Firms with a manager connected in the same jurisdiction as the firm headquarters are associated with a lower cost of capital (-0.025) and lower profit tax. Whether national connections favor direct subsidies, local ones increase financing. This difference may reflect the fact that direct subsidies are more likely to be official grants approved by Beijing. The central government has tried to curb subsidies given by local authorities to prevent overproduction and resource waste. However, most local banks are state-owned enterprises (SOEs), and local governments can use this lever to support their local champions.

I also explore potential gains for managers who are connected. Evidence shows that managers switching status can extract a higher rent than non-connected managers (about +6.5% on compensation). Finally, the anti-corruption campaign heavily impacted connected managers in the short term by decreasing their wages by 8% during 5 years.

The paper relies on the theoretical model of Bai, Hsieh, and Song (2020) on *Special Deals* in China. Those *deals* are special treatments only available to some firms, the connected ones. China has poor formal institutional protection for the private sector, and it faces hurdles hampering its development[2]. However, a business person may still break the glass ceiling using a connected manager. The frequency of special deals is high in countries with poor formal institutions, and China is no different. Soliciting connected managers is the most direct

[2]Robinson and Acemoglu 2012; Bai, Hsieh, and Song 2020 relate the case of Dai Guofang, a businessman put to jail without trial for competing with a SOE

channel for a firm to access political leaders and special deals. As local leaders' promotion depends on local prosperity, they benefit from special deals by attracting and supporting new private businesses. They also obtain personal earnings since they may extract part of the wealth created by the firm (through compensation). Consistent with Bai, Hsieh, and Song (2020)'s theoretical findings, the present paper finds empirical evidence of the importance of political connections on the size of resources allocated to firms. Second, I show that larger firms with higher wages are more likely to be connected and that connected managers have higher compensation than non-connected ones.

The paper contributes to the old literature exploring the effect of PC on resource allocation. Political connections allow firms to access public resources, including subsidies, favorable tax rates, and cheaper financing (Faccio, Masulis, and McConnell 2006; Adhikari, Derashid, and Zhang 2006; Claessens, Feijen, and Laeven 2008; Cooper, Gulen, and Ovtchinnikov 2010; Houston et al. 2014; Kim and Zhang 2016). Those studies use sector and year-fixed effects, which complicates causal inference at the firm level and they also do not have access to direct subsidies received by the firm.

In the Chinese context, connections are particularly important due to weak legal protections for private firms. The paper is therefore related to the finance and accounting literature dedicated to connection effects in China (Fan, Wong, and Zhang 2007; Wu et al. 2012; Liu, Tang, and Tian 2013). These studies typically focus on specific positions, such as CEOs, and do not consider the broader set of firm managers or type of connection (national or local). I use a similar approach to measure connection; apart from that, I do not restrict it to the CEO but extend it to all significant firm members. A connected CFO is valuable for the firm, just like a connected CEO. As previously mentioned, those papers use industry and year-fixed effects on IPO approval, post-IPO performance, and tax aggressiveness. Finally, I disentangle the effect of national and local connection.

Subsidies are a key channel through which political connections operate in China. Previous research has explored the determinants and effects of subsidies. For example, Jiang et al. (2018) analyze the impact of subsidies at the industry level, while Hao et al. (2020) focus on the 2013 anti-corruption campaign. However, these studies do not examine firm-level dynamics or distinguish between national and local connections. This paper fills this gap by providing firm-level evidence on how different types of connections influence subsidies.[3] Institutional reforms can disrupt the benefits of political connections. The 2013 anti-corruption campaign in China provides a natural experiment to study these effects. Hao et al. (2020) document the impact of the campaign on resource allocation, but they do not give any clue on the effects on connection.

The paper proceeds as follows. I begin by discussing the Chinese institutional context of political connection and subsidies in Section 2. I describe the data and establish a few descriptive facts in Section 3. Section 4 introduces the DID approach and various sensitive analyses to show the sense of causality. I extend my analysis to other public resources in Section 5. Section 6 gives conclusions.

2 Chinese Institutional Backgrounds

This section provides an overview of the benefits that firms derive from becoming politically connected in China, where legal protections often do not prevent government intervention. It also explores potential motivations for former political officials to transition into the private sector. Lastly, the discussion addresses the prevalence of subsidies in China, shedding light on the institutional factors that shape the value of political connections for firms.

Political Connection In China, the regulatory framework governing private enterprises is often opaque, and official rules are not always applied uniformly. Given that the government controls a significant portion of resources, private firms frequently encounter discrimination and operate in an unfavorable economic environment (Li et al. 2008). For example, non-state-owned enterprises pay substantially higher interest rates than SOEs (Harrison et al. 2019). Various cases illustrate the private sector's insecurity for competing within the state domain. McGregor (2013) and Robinson and Acemoglu (2012) tell the case of an entrepreneur who

[3] I note the existence of the political science paper Li (2023). I do not use the same subsidy data; it focuses on local subsidy programs, whereas I take all of them. He also works at the contract level, which is not the case here. Finally, I also take into account the national connection.

was arrested for competing with an SOE and detained for five years without trial. Similarly, high-profile business figures like Alibaba's founder, Jack Ma, have faced repercussions after challenging the central government. Foreign firms also face challenges, finding their access to the Chinese market obstructed (Mavroidis and Sapir 2021). These challenges are reflected in China's ranking on the World Bank's Ease of Doing Business indicator, which placed China between Kyrgyzstan and Panama in 2018[4].

Given these constraints, China's rapid economic growth may seem surprising. However, Bai, Hsieh, and Song (2020) theorize that private firms circumvent these obstacles by cultivating close relationships with bureaucrats, allowing them to bypass regulatory barriers. Political connections offer several advantages to firms. First, they enable lobbying efforts to influence government policies in favor of the firm. For instance, local governments may block competitors from entering markets to protect politically connected firms (Barwick, Cao, and Li 2021). Second, such connections may shield firms from prosecution for regulatory violations (Kim and Zhang 2016; Bourveau, Coulomb, and Sangnier 2021). Third, politically connected managers can leverage their relationships to secure critical economic resources (Li et al. 2008). These advantages make political connections essential for firms operating in China's regulatory environment.

While firms have strong incentives to form political connections, the motivations for politicians to join the private sector are also noteworthy. One key factor is the substantial wage gap between the public and private sectors. On average, private-sector salaries are four times higher than those in the public sector, incentivizing bureaucrats to enter the private sphere to capitalize on their political connections (Démurger, Li, and Yang 2012). Additionally, at high administrative levels, such as the provincial level, personal connections, rather than performance, play a decisive role in the promotions of officials (Landry, Lü, and Duan 2018). Consequently, many competent officials who lack influential networks are passed over for promotion but retain valuable political capital that private firms find useful (Li 2023). The process is made easier as members of People's Congresses are allowed to pair their terms with a private

[4] https://www.doingbusiness.org/content/dam/doingBusiness/media/Annual-Reports/English/DB2018-Full-Report.pdf

job.

Political connections can be either explicit or implicit. Carboni (2017) categorizes explicit political connections as those where firms employ former politicians or bureaucrats through "revolving-door" recruitment (Fan, Wong, and Zhang 2007; Wu et al. 2012; Liu, Tang, and Tian 2013; Lu and Wang 2023). Implicit connections involve indirect forms of influence, such as donations or lobbying (Claessens, Feijen, and Laeven 2008; Cooper, Gulen, and Ovtchinnikov 2010). In this paper, I focus on explicit political connections at the national, provincial, and municipal levels, with a combined focus on the latter two (*local*) due to the difficulty in distinguishing between them. Politicians with national experience often carry more weight and are more valuable to firms seeking to enhance their reputation and access to national-level resources.

The tight relationship between the private sector and officials left room for abuse. Thus, the newly elected President Xi Jinping carried out in 2013 a massive anti-corruption campaign targeting political-business relationships, aiming to reduce corruption among both high-ranking ("tigers") and local officials ("flies"). Given that over two million officials were investigated by 2018, this campaign may had substantial implications for political connections and is considered in the methodology.

Subsidy As described in Schwartz and Clements (1999), State aid may take various forms[5]. A substantial body of research has documented the widespread use of subsidies in China, where governmental support has long been a vital source of external finance for firms (Allen, Qian, and Qian 2005; Kalouptsidi 2018; OECD 2019; Naughton 2021; Mavroidis and Sapir 2021). These subsidies serve a variety of purposes and are closely aligned with the state's industrial policy objectives. Since 2006, industrial policy has played an increasingly central role in the Chinese economic system, with the Medium and Long-Term Program for Science and Tech-

[5]Direct government payments to producers or consumers (cash subsidies or cash grants); Reductions of specific tax liabilities (tax subsidies); Government equity participation (equity subsidies); Government credit guarantees, interest subsidies to enterprises, or soft loans (credit subsidies); Government provision of goods and services at below-market prices (in-kind subsidies); Government purchases of goods and services at above-market prices (procurement subsidies); Implicit payments through government regulatory actions that alter market prices or access (regulatory subsidies).

nology adopted by the central government in 2006 marking a significant milestone (Naughton 2021). This program inaugurated a "top-down" approach where the government set broad innovation goals and financed key projects aimed at reducing foreign dependency, fostering research and development (R&D), and enhancing productivity. The overarching goal of these interventions was to "shape the market," establishing favorable conditions for firms to grow through a combination of state-owned financial institutions, tax exemptions, and regulatory support.

At the local level, economic growth is a political priority, as officials' promotions are tied to economic performance. Vice-Mayors are often tasked with attracting new businesses, and they play a pivotal role in facilitating local economic development. Vice-Mayors in Chinese cities typically manage relationships with around 30 private firms, offering preferential treatment such as subsidies and exclusive market access to spur economic growth (Bai, Hsieh, and Song 2020). A notable example is the Shanghai-Volkswagen joint venture, which enjoyed a monopoly on taxi services in Shanghai from the early 1980s until around 2010, a position supported by local government intervention. This monopoly was eventually challenged when Chery, a car manufacturer based in Wuhu, secured political support from the local Vice-Mayor.

The focus of this paper is not to provide an exhaustive overview of China's subsidy programs but to explore the determinants of public resource allocation at the firm level. As previously discussed, allocation often follows political rather than purely economic considerations. Politically connected firms have greater access to public resources through three primary channels: direct subsidies, reduced capital costs, and tax avoidance strategies. Since China's banking system is largely state-controlled, politically connected firms may receive more favorable financing terms. Additionally, connections offer institutional protections that facilitate tax minimization strategies (Kim and Zhang 2016; Bourveau, Coulomb, and Sangnier 2021). Through these channels, I aim to offer insights into how political connections influence firm-level economic outcomes within the Chinese context.

3 Data and Facts

This section describes the primary sources of administrative data used in the analysis. First, it details the economic firm-level data collected from financial statements and balance sheets. Then, it explains the process of constructing the political connection variable. Finally, it presents summary statistics and some key descriptive facts about the dataset.

3.1 Data

The analysis uses firm-level data from 2007 to 2022 for listed companies on the Shanghai and Shenzhen stock exchanges. The primary data sources are Refinitiv and the China Securities Markets and Accounting Research (CSMAR) database. Refinitiv provides financial data, including firm size, assets, and employment. CSMAR contains information on government subsidies, the biographies of the firm's managers, and ownership-specifying if the firm is state-owned (SOEs).

The political connection (PC) variables are constructed using the biographies of firm managers available in the CSMAR database. Textual analysis is applied to each biography to identify whether a manager has previously or is currently serving as a government official or a member of the People's Congress at either the national or local (provincial or municipal) level. These two institutions are chosen because their members typically possess the authority and networks to facilitate special deals, as they are often Party members, politicians, or bureaucrats (Wu et al. 2012)[6]. The full set of *PC* variables built is shown in Table 1. *All Connection* takes the value one if the firm is connected, whatever the level of connection. *Local* and *National Connections* distinguish the level. I also create *Same Location Co.*, which is equal to one if the firm is connected in the same jurisdiction as the location of the headquarters.

Direct subsidies are available in firms' financial statements. Since 2007, Chinese law has required listed firms to disclose government subsidy information in the notes to their financial

[6]The Chinese People's Political Consultative Conference (CPPCC) is excluded from the analysis, as it is primarily a symbolic assembly with no substantive decision-making authority. The National People's Congress (NPC), by contrast, is the highest organ of state power, whereas the CPPCC primarily holds an honorific status for private sector figures.

reports (Branstetter, Li, and Ren 2022). As many firms do not disclose details about the reason for receiving subsidies, all subsidies are aggregated at the firm-year level without distinction.[7]

Control variables include firm size (total assets), employment, and productivity (TFP)[8]. We use the logarithm of each control variable except TFP and lagged values to address potential endogeneity.

3.2 Sample Selection and Descriptive Analysis

Since 2007, the amount of subsidies received by listed firms has exponentially increased. Figure 1 reports the total and the mean of direct subsidies received by listed firms over time.[9] On average, Chinese listed firms received approximately $16 million[10] in direct subsidies, with the total reaching $22 billion in 2022. Relative to firm size, these subsidies represent roughly $1,700 per employee. The total amount of direct subsidy allocated increases by year as long as the number of targeted firms grows.[11].

Tables 2, 3 & 4 provide summary statistics for the primary data sample, categorizing firms based on their political connection status. Firms classified as *Always* Connected receive significantly higher levels of direct subsidies. On average, these firms receive about $14 million in subsidies, compared to $4.5 million for *Never* Connected firms. *Switchers*, or firms that change their connection status over time, show a notable difference in subsidy amounts depending on their connection status. Connected firms within this group receive around $10 million in subsidies, while *not* connected firms (made up of not-yet and not-anymore connected) receive approximately $6.5 million. Although the mean subsidy for *not* connected firms exceeds that of *Never* Connected firms, the median value is lower, indicating greater variability in subsidy distribution within this group. While these findings do not establish a causal link, they suggest

[7] See Appendix A.1 for details.

[8] I follow the methodology of Wooldridge (2009). See Appendix A.1 for details.

[9] To ensure comparability, the sample is restricted to firms that were active from 2007 to 2022, maintaining a consistent sample size throughout time.

[10] All monetary values are in RMB unless specified otherwise. When expressed in USD, the exchange rate of 7.12 is used. Values on the Figure are deflated using the Consumer Price Index (CPI).

[11] Figure A.1 shows the distribution of direct subsidy data for three different years. Due to the skewed nature of the data, the logarithm of the direct subsidy is used. Outliers, mostly state-owned enterprises (SOEs) in the mining industry, such as Sinopec and PetroChina, are identified separately.

a positive correlation between political connections and the level of subsidies received. The absence of a positive difference between connected and non-connected firms would have cast doubt on the potential benefits of political connections.

Table 5 presents descriptive statistics for firms based on their ownership structure. As expected, SOEs receive significantly higher subsidies than non-SOEs, a finding consistent with prior research by Lardy (2019). On average, SOEs receive around \$12 million in subsidies, compared to approximately \$6.5 million for non-SOEs. This large disparity highlights the preferential treatment that SOEs receive in terms of subsidy allocation, underscoring the important role that state ownership plays in securing government support.

A Industry and Spatial Heterogeneity

The allocation of subsidies substantially varies between industries. Figure 2 presents the ratio of the mean of subsidies received to total revenue, broken down by industry and political connection status. Capital-intensive industries, particularly those with potential rent-seeking opportunities, tend to receive significantly more subsidies. Leading sectors include transportation, public service, electronics, and information technology. While connected firms generally receive more subsidies across all industries, the largest gaps between connected and non-connected firms are found in these capital-intensive sectors. The next section investigates potential heterogeneity betw

The data also reveals significant spatial heterogeneity in subsidy allocation. Figure 3 shows the average amount of subsidies provided by each province. The differences between provinces are striking, with Beijing, Anhui, Shanghai, and Inner Mongolia standing out as the leading providers of subsidies on a per-firm basis. Figure 4 further breaks this down by political connection status, showing that in most provinces, connected firms receive more subsidies than their unconnected counterparts. It is important to note that provinces do not subsidize the same industries, with significant sectoral differences at the regional level. Table A.2 gives the two main interests of each province with the value in million \$US and their position in the global distribution. For instance, Inner Mongolia mainly allocates resources to food and metal products, whereas Anhui is dedicated to mineral and transportation equipment.

B Determinants of Political Connections

Before investigating the relationship between political connections and subsidies, it is essential to understand the factors that influence a firm's likelihood of having political connections. To explore the determinants of political connections, I run a logit model where the dependent variable is a dummy variable indicating whether a firm is politically connected (PC) and covariates that may influence the connection status:

$$\begin{aligned} PC_{i,t} = &\beta_1 Compensation_{i,t-1} + \beta_2 Assets_{i,t-1} \\ &+ \beta_3 Employement_{i,t-1} + \beta_4 TFP_{i,t-1} + \beta_5 HHI_{s,t} \\ &+ \beta_6 Market\ Index_{p,t} + \beta_7 Age_{i,t} + \beta_8 Strategic \alpha_i + \gamma_t + \omega_s + \Omega_p + \epsilon_{i,t} \end{aligned} \tag{1}$$

The key variables included are the average compensation given to managers in year t, total assets, the number of employees, and the age of the firm. These variables are logarithmic to control for scale. I suspect that larger and more established firms offering higher compensation are more likely to attract political connections (Bai, Hsieh, and Song 2020 show the theoretical mechanism pushing former bureaucrats to join private firms). Additionally, I include the firm's total factor productivity (TFP), computed using the methodology of Wooldridge (2009), the Herfindahl–Hirschman Index (HHI) to capture industry (s) concentration, and the *Market Index* (MI) from Fan (2011) to capture the degree of marketization heterogeneity across provinces (p). A dummy variable, *Strategic*, is also included, equaling one if the firm operates in a strategic industry. This variable is based on a database developed by CNRDS, which classifies industries identified as strategic by the central government for the current five-year plan. HHI and MI are included in the model because higher industry concentration and lower marketization levels might push firms to seek political connections to protect against competitors or navigate less market-oriented environments. Finally, TFP is included to examine whether more productive firms are more inclined to pursue political connections. I add firm (i), year (t), province (p), and industry (s) fixed effects to control for unobserved heterogeneity across these dimensions.

Table 6 resents the results for three key connection variables: local, national, and all connections. The size of the firm and manager compensation emerge as the primary determinants of political connections. While TFP is positive and significant at the 10% level for national and overall connections, sector concentration (HHI), marketization (MI), and strategic industry status do not significantly influence the likelihood of a firm being politically connected. These results suggest that the firm's size and the level of compensation offered to its executives are the most important factors in establishing connections, with stronger effects observed for national connections. Interestingly, productivity and strategic status play a less prominent role, suggesting that political connections may be more driven by personal incentives—such as compensation—than by a deliberate strategy orchestrated by authorities to support high-productivity or strategically important firms. This finding aligns with literature pointing to the wage gap between private and public sectors in China, highlighting how compensation differences can incentivize political connections (Démurger, Li, and Yang 2012). Furthermore, officials tend to favor big firms as returns are easier to extract (Bai, Hsieh, and Song 2020).

In Appendix A, I further investigate the effect of being connected. This section analyzes the impact of political connections on managers' compensation. The data is structured at the individual-firm-year level, allowing us to test the effect of connection on total compensation. The estimation models reveal that politically connected managers earn 7.8% more in compensation compared to non-connected peers. When controlling for individual fixed effects, transitioning to a connected status increases compensation by 6.8%. These results are consistent across different levels of political connections, affirming a clear financial advantage for connected managers.

C Direct Subsidy

Extensive Margin I now turn to the relationship between political connections and subsidies, starting with the extensive margin. Equation 2 presents the logit model where the dependent variable is whether or not a firm receives a subsidy.

$$\begin{aligned} \textit{Dummy Subsidy}_{i,t} = & \beta_1 PC_{i,t} + \beta_2 Assets_{i,t-1} + \beta_3 Employement_{i,t-1} \\ & + \beta_4 TFP_{i,t-1} + \alpha_i + \gamma_t + \omega_s + \Omega_p + \epsilon_{i,t} \end{aligned} \tag{2}$$

With *Dummy Subsidy*$_{i,t}$ taking the value one if the firm i is subsidized in year t, and the province capital. Results are shown in Table 7. The probability of receiving a subsidy seems largely driven by the firm's size and its number of employees. This is consistent with the idea that larger firms, which provide more employment, attract special attention from the government, likely due to the social and economic importance of protecting jobs.

Intensive Margin After extensive margin, I now explore intensive one. As a naive first approach, the following specification is run to show the correlation between connection and subsidy amount received.

$$Direct\ Subsidy_{i,t} = \beta_1 PC_{i,t} + \beta_2 X_{i,t-1} + \alpha_i + \omega_{s_{(i)},t} + \Omega_{p_{(i)},t} + \epsilon_{i,t} \tag{3}$$

where *Direct Subsidy*$_{i,t}$ is the logarithm of the total amount received by firm i, located in province p, in industry s, at year t. The key independent variable, $PC_{i,t}$, is a dummy variable that takes the value one if the firm i is politically connected at the year t. $X_{i,t-1}$ stands for the control variables used for the extensive margin, the firm's total assets, the number of employees, and productivity. I take the logarithm of total assets and number of employees and apply a one-year lag. I believe big firms, with many jobs at stake, are more likely to be subsidized. Several fixed effects are added, such as α_i as firm fixed effect, $\omega_{s_{(i)},t}$ industry-year fixed effect, and $\Omega_{p_{(i)},t}$ for province-year fixed effect. I add province-year and industry-year FE to capture any difference in trends between provinces and industries. Clusters are set at the firm level.

The analysis is designed to (I) motivate further research into the connection-subsidy relationship and (II) highlight potential channels through which political connections may influence subsidies. Table 8 shows the results after regressing Equation 3. Models (1) and (2) consider all types of political connections to define $PC_{i,t}$. In both models, the coefficient for political connections is positive and significant, indicating that connected firms tend to receive higher subsidies. This finding holds even after including firm fixed effects, suggesting a robust correlation between being politically connected and receiving subsidies for the firm. The control variables behave as expected, with larger firms with higher jobs at stake receiving more subsidies and more productive firms being more subsidized. Models (3)-(4) further distinguish between local and national connections, while Model (5) focuses on connections within the same jurisdiction. In each specification, national connection is associated with higher subsidies, whereas local connection is not. From Model (4), after controlling for firm, province-year, and industry-year fixed effects, having a former or current national official as a member of the firm is associated with a 9% increase in the amount of subsidies received.

4 Investigating Causality

The preceding section outlines several critical aspects of resource allocation. However, it does not address causality. This section seeks to address this gap using a staggered difference-in-difference (DID) approach.

Two potential scenarios for causality are considered: (I) A firm may hire a politically connected manager to establish privileged relationships with authorities, resulting in increased subsidies following the connection. This scenario would support the hypothesis that political connections directly influence resource allocation. (II) Alternatively, a firm might cultivate connections with a sitting politician before the manager joins the firm. In this case, the politician may influence resource allocation directly before joining the firm. This scenario is tested by examining the anticipation up to two years in my DID setting.

The remainder of this section is organized as follows. First, the empirical strategy is detailed, including the construction of control and treatment groups. Subsequently, the results are presented and disaggregated to highlight heterogeneity across different cohorts and firms.

4.1 Methodology

Given the staggered nature of the DID setup, the impact of connection may vary across time and firms, potentially leading to negative-weight bias in the results (De Chaisemartin and D'Haultfœuille 2020; Callaway and Sant'Anna 2021; Borusyak, Jaravel, and Spiess 2024). To address this, I utilize the estimand proposed by Borusyak, Jaravel, and Spiess (2024) to mitigate concerns related to negative weights[12]. I also remove firms with fewer than two observations before the connection to include leads of the connection variable and ensure accurate causality assessment by controlling for parallel trends and anticipatory behavior.

I estimate the specifications of the following form:

$$Direct\ Subsidy_{i,t} = \sum_{\substack{k=-a \\ k\neq -1}}^{b} \delta^k PC_{i,t}^k + \beta_2 X_{i,t-1} + \alpha_i + \omega_{s_{(i)},t} + \Omega_{p_{(i)},t} + \epsilon_{i,t} \tag{4}$$

Equation 4 shows the DID strategy used with a the number of years before the connection and b after, $Direct\ Subsidy_{i,t}$ is the logarithm of total amount received by i in year t, $PC_{i,t}^k$ is the dummy variable equal to 1 if t is the k^{th} year after the national connection. I compare firms' resource grants before and after a firm became connected for the first time, controlling for firm, industry-year, and province-year fixed effects. $X_{i,t-1}$ stands for the lagged covariates, the logarithm of total assets, the logarithm of total number of employees, and TFP. Firm fixed effects (α_i) control for time-invariant heterogeneity, while sector-year ($\omega_{s_{(i)},t}$) and province-year ($\Omega_{p_{(i)},t}$) account for macroeconomic shocks at the industry and province levels.

For the control group, three sets are constructed. (a) The first group comprises firms that have never been connected (regardless of connection level) between 2004 and 2022. This group is advantageous due to its lack of any connection-related disturbances, though it may consist of smaller or less efficient firms. To address this, (b) firms connected at the local level at least (and never at the national level) once are used as the second control group. This group is expected to be more similar to firms connected at the national level but may still experience altered resource allocation due to their connection. Thus, I will first check the dynamic effect of being connected locally with a group (a) as the control group. Finally, (c) combines groups (a) and (b). The descriptive statistics of these groups are presented in Table A.3.

The DID estimand relies on several key assumptions for validity and unbiasedness. The first assumption is parallel trends, which states that the treatment and control groups should follow similar trends prior to the connection. The second assumption is the absence of anticipation

[12]The regression uses the logarithm of direct subsidies. Zeros account for fewer than 5% of the sample and are removed to avoid transformation.

effects. To account for potential anticipation, I adopt the methodology from Borusyak, Jaravel, and Spiess (2024), allowing for anticipation by assuming the treatment occurred two periods earlier for each treated unit[13].

4.2 Main Results

To check whether locally connected firms are a good control group, my initial focus is on evaluating the causal effect of local connections on the amount of direct subsidies received. Firms that have never been connected during the sample period are used as the control group. The dynamic effects are shown in Figure 5, where red squares control for the parallel trend, t-2 and t-1 black dots for the anticipation and t to t+4 denote lags relative to the first local connection. Anticipation effects are assessed by applying a two-year shift before the connection. Although the coefficient for the year immediately following a local connection is higher, none of the estimates are statistically significant at the 10% level. This indicates that using locally connected firms as a control group is valid when assessing national connections as the treatment.

Now that we have provided evidence that locally connected firms are a valid control group, we turn to analyze the dynamic effects of national connection on direct subsidy received. I first examine the validity of the two key assumptions for the DID methodology: parallel trends and no anticipation. Figure 6 gives the pre-trend analyses for the three control groups: (a) firms never connected, (b) firms connected locally at least once, and (c) the combined control group. The pre-trend graphs provide strong evidence against the violation of the parallel trend assumption, as indicated by the consistency of the pre-treatment trends (red squares). Although there is some indication of potential preferential treatment in the year preceding the connection (higher coefficients), it is not statistically significant. More detailed explanations are provided in the subsequent section 4.3.

Turning to the post-treatment effects, Figure 7 presents the direct causal impact of national connections on direct subsidies for the three control groups. The coefficients across the graphs are highly consistent, showing a positive effect of national connection starting from the year of

[13] This is implemented using the *shift* option in Borusyak, Jaravel, and Spiess (2024)'s Stata command.

connection and continuing for up to three years. After the fourth year, while the coefficients remain positive, they decrease, and they are not significant. These findings provide robust evidence of the positive impact of national connections on the amount of subsidies received.[14] Table 9 reports the average effect of connection. For national connection, first-time connected firms experience a 27% increase in subsidies compared to the control group (Model 2).

To summarize the first findings, the analysis has shown that only national connections lead to higher direct subsidies. Since my subsidy database is an official one, the measure is likely to catch direct and official subsidies, which should mainly be approved by Beijing (and are prone to be influenced by national connections). Therefore, national-level connections have a stronger influence on it. This could be one reason why local political connections play a smaller role in official subsidy allocation. Furthermore, these findings do not give any clue regarding potential heterogeneity in effects. The next subsection is dedicated to exploring variations in the effects of industry and the timing of the 2013 anti-corruption campaign.

4.3 Disaggregated Results

In this subsection, I further investigate potential heterogeneity in connection effects. I focus on two sources of heterogeneity: (I) the impact of connection may vary across industries depending on their capital structure. Second, the 2013 anti-corruption campaign likely introduces variation in the effects for firms connected for the first time before and after 2013. To address these concerns, I present estimations separately by subgroups based on industry capital intensity and temporal dimensions according to the chosen specification.

A Industrial Heterogeneity

I suspect some heterogeneity between industry types. More capital-intensive industries may have preferential treatment since rent-seeking positions are easier. Capital-intensive industries (e.g., defense, infrastructure, energy, pharmaceuticals) with high fixed costs and barriers to

[14] Table A.4 details the coefficients for all variables in the model. Among the control variables, both the number of employees and total assets exhibit a positive and statistically significant relationship with the amount of direct subsidies received. In contrast, productivity does not significantly influence subsidy levels.

entry rely more on government contracts, subsidies, and preferential policies. These firms have strong incentives to cultivate close relationships with policymakers to secure contracts or favorable funding.

To test this hypothesis, I reorganize and aggregate industries into three categories based on capital intensity, which is measured as the ratio of fixed assets to the number of employees. The three groups are created by applying two cutoffs to divide the distribution into three parts, effectively creating three percentiles[15]. I implement the same methodology as in the previous section but let the anticipation and post-connection effects be different between industries. Figure 8 reports the heterogeneous effect between the three groups[16]. Industries with higher capital intensity experience more anticipation and a longer effect post-connection. The results suggest that those firms maintain stronger relationships with the power and have already made contact with bureaucrats prior to official connection. It hints at a rent-seeking position since capital-intensive industries favor such behavior. Incumbent firms use political influence to create or maintain entry barriers, preventing new competitors or capturing subsidies.

B Temporal Heterogeneity

A notable political event that may influence my baseline results is President Xi Jinping's anti-corruption campaign launched in 2013. This campaign targeted both high-ranking ("tigers") and local officials ("flies"), with a significant focus on scrutinizing the ties between politicians and private businesses. By 2018, over 2 million officials had been investigated for corruption. I assume that this political disruption might have impacted the effectiveness of connections formed after 2013.

Figure 9 presents a comparative analysis of firms connected for the first time before and after 2013. I utilize firms that have never been connected as a control group, given that the anti-corruption campaign also targeted local officials.

[15]The three groups are composed as follows: High intensity includes Energy Supply, Gas & Chemistry, Metal Products, Mineral Products, Mining, Other Service, Printing, Public Services, Real Estate, and Transportation. Middle intensity: Agriculture, Food, Other Manufacturing, Pharmaceutical, Scientific Research, Transportation Equipment and Wholesale. Low intensity: Apparel, Construction, Electronic, Entertainment, Information Technology, and Machinery

[16]The control group is never connected firms.

The results indicate that the major difference lies in anticipation effects. Firms connected before 2013 exhibited higher anticipation behavior in the two years preceding the connection, suggesting prior relationships with politicians before the official connection. In contrast, firms connected post-2013 show no such anticipation. Furthermore, the post-connection outcomes are greater for connections made before 2013. The anti-corruption campaign seems to have partially narrowed links between the economic and the political spheres.[17]

To further investigate the impact of the campaign, I examine in Appendix B the effects on compensations received by politically connected individuals. The hypothesis is that the campaign changed the structure of power and alliance within the administration, reducing the ability of already established connected managers to contact their address book. It should lead to a decrease in their compensation since their value has narrowed. Using an event study framework, the results reveal that following the campaign, connected managers experienced a 7.9% decrease in compensation compared to 2013. This finding shows evidence of loss of power for connected managers.

As a final potential disruptive event, I investigate the role of the COVID-19 pandemic. To account for the disruptions caused by the pandemic and its associated lockdowns, I re-estimate the model, excluding data from 2019 onwards. Table A.5 shows that the coefficients remain qualitatively similar, albeit with larger magnitudes. This suggests that while the pandemic may have influenced the overall scale of subsidies, it does not fundamentally alter the observed relationship between political connections and subsidy allocation.

However, as discussed by Naughton (2021), local governments often act to protect and support their local industries, sometimes even contrary to central government policies. Consequently, the direct subsidy measure may not fully capture the influence of local connections. In Section 5, I focus on the role of the banking system and capital costs associated with local connections. Given that banks in China are predominantly locally owned, I anticipate that local connections may directly affect the terms and availability of bank financing. This analysis aims to explore how local connections influence capital costs.

[17] The larger size of confidence intervals is due to a smaller number of firms connected for the first time between 2009 and 2013.

5 Indirect Subsidies

While direct subsidies are a clear method of supporting firms, the government may leverage alternative channels. This section explores two other channels: the cost of capital and tax avoidance. Thus far, local connections have not shown a substantial impact on resource allocation. However, their influence might be more pronounced in the banking system, which local governments predominantly control. Additionally, political connections could aid firms in reducing their tax liabilities.

Cost of Capital: In China, the private sector may experience hurdles to access capital. As for direct subsidies, connection lifts these restrictions. Capital plays a crucial role as a tool for local governments to support their industries (Naughton 2021; Mavroidis and Sapir 2021).

To measure the cost of capital, I use the ratio of interest expense[18] to the total debt due to the year (Harrison et al. 2019). Because of extreme values, the data is winsored at the 1% and 99% levels, and the banking sector is excluded from the analysis. In the spirit of Equation 4, I run the following equation using Borusyak, Jaravel, and Spiess (2024) estimand:

$$K\ Cost_{i,t} = \sum_{\substack{k=-a \\ k\neq -1}}^{b} \delta^k PC^k_{i,t} + \beta_2 X_{i,t-1} + \alpha_i + \omega_{s_{(i)},t} + \Omega_{p_{(i)},t} + \epsilon_{i,t} \tag{5}$$

Since the dependent variable changed, Equation 5 includes a different set of control variables. X_{it} stands for the number of employees, productivity, revenue, return of assets, and share of tangible assets.

Following the same methodology as direct subsidy, I first check the effect of national connection on capital cost. Since banks are SOEs, I suspect that the effect will mainly come from local connections, leaving firms nationally connected as a potential control group. Figure 10 reports the dynamic effect of national connection on the interest rate. Due to the absence of effect, I include these firms as a second control group.[19]

Focusing now on local connection, Figure 11 presents the causal effect on the cost of capital.[20]

[18] I use the variable Interest Expense - Net of Capitalized interest.

[19] Due to the smaller number of firms having national connections, it is not possible to restrict the control group to them. I include them with never connected.

[20] See Figure A.2 for the validity of pretrend and anticipation.

Unlike direct subsidies, the cost of capital is significantly influenced by local connections. On average, after being locally connected, firms experienced a drop of 2.5% in the percentage paid.[21]. When restricting to connections within the same jurisdiction as the firm's headquarters, results are roughly similar, even if the significance is lower. Local banks, often locally state-owned, are more likely to offer lower rates to locally connected firms. This tendency is explained by the autonomy of local governments in assisting their local champions, which pushes firms to develop tight links with local bureaucrats. These findings suggest that capital is an important channel for supporting targeted firms. They also align with the literature, which shows that political connections correlate with lower interest rates in the US and Italy (Houston et al. 2014; Infante and Piazza 2014).

Tax Avoidance: As a final aspect of governmental intervention, I examine whether politically connected firms receive preferential tax treatment. Prior research indicates that political connections may enable firms to engage in more aggressive tax strategies due to their protection and access to potentially favorable tax rates (e.g., Kim and Zhang 2016; Bourveau, Coulomb, and Sangnier 2021).

To explore this, I compare the effective tax rates (ETR) between politically connected and non-connected firms. The ETR is defined as:

$$ETR_{ir} = \frac{TXPD_{ir}}{PI_{ir}}$$

with $TXPD_{ir}$ the cash tax paid by the firm over the period r and PI_{ir} the pre-tax income. As explained in Martin, Parenti, and Toubal (2021), given the volatility of cash ETR using annual data, and because the measure could include tax payments from previous periods, r corresponds to an arbitrary number of years. I sum the values of each variable annually over four years, defining a firm as connected if it is politically connected (PC) in the last year of the period. This measure captures the ability of firms to maintain a low effective tax rate over an extended period, which is more informative.

However, as noted by Henry and Sansing (2018), this ETR measure excludes firms with

[21] Table A.6 reports the average effect of connection. The dependent variable, capital cost, is expressed as a rate; hence, 2.5% reflects a direct reduction in the interest rate paid.

negative pre-tax income, leading to selection bias. To address this, I use an alternative indicator that retains these observations:

$$\Delta_{ir} = \frac{TXPD_{ir} - \tau \times PI_{ir}}{MV_{ir}}$$

with Δ_{ir} the indicator of tax avoidance from firm i over the period r, τ the statutory tax rate of China and MV_{ir} the market value[22]. If Δ_{ir} is equal to 0, it means that the firm i paid the expected amount over the period r, and if $\Delta_{ir} < 0$, the firm is tax-favored and tax-disfavoured if greater than 0. I may warn the reader that the indicator does not say anything about the legal status of this tax avoidance. I only compare firms on their PC status.

I estimate the following equation using OLS:

$$\Delta_{i,r} = \beta_1 PC_{i,r} + \beta_2 X_{i,r} + \alpha_i + \omega_{s,r} + \Omega_{p,r} + \epsilon_{i,r}$$

$PC_{i,r}$ equals one if firms i is connected to the last year of r period, $X_{i,r}$ includes a bunch of control variables known to be associated with tax avoidance. Following Dyreng, Hanlon, and Maydew 2010; Koester, Shevlin, and Wangerin 2017, I control for research and development expense ($R\&D$), productivity, total revenue, and the share of intangible assets[23]. I compute the mean of each covariate over the period r and take the logarithm. Finally, I add fixed effects at the period level rather than the year level.

The results in Table 10 show that politically connected firms pay significantly lower taxes. The effects are mostly driven by local connections with a coefficient significant at 5% in column (2). When restricting to connections in the same location, column (3), the coefficient size increases and becomes significant at 1%. It accounts for 17% of the sample mean of $\Delta_{i,r}$. In absolute value, over 4 years, politically connected firms pay $20 million less in taxes than non-connected ones, on average.[24]

[22]For computation, I use for $TXPD$ income taxes - paid/(reimbursed) - cash flow, and total assets for MV. The statutory tax rate in China is 33% until 2007 and 25% afterward.

[23]For intangible assets, I take the ratio of the total amount of intangible assets to total assets. $R\&D$ stands for the ratio of R&D expenses to total operating expenses. Total assets are removed from the covariates since it is used to build $\Delta_{i,r}$.

[24]To find this value, I multiply the coefficient of local connection in column (3) by the mean value of total assets in the sample.

My results are robust when changing the number of years to 3. Table A.7 reports the coefficients which remain constant. In all specifications, control variables behave as expected, except for *Intangible Assets*, which has a positive sign. These results show robust evidence that politically connected firms have a deeper tax-aggressive behavior. I highlight two potential reasons: (I) officials protect connected firms, and the detection risk by tax authorities can be lower, which leads to lower expected costs (Bourveau, Coulomb, and Sangnier 2021). (II) The firm can get access to confidential information regarding future changes in tax laws or resources allocated to tax fraud enforcement (Kim and Zhang 2016).

6 Conclusion

In China, political connections are a significant factor in a firm's access to public resources. My research highlights the critical role of having a former politician as member, which allows firms to navigate bureaucratic challenges and obtain preferential treatment. By analyzing firm-level data from Chinese listed companies between 2007 and 2022, I reveal that political connections trigger higher direct subsidies and are associated with lower capital costs and reduced tax burdens.

One key finding is the distinction between national and local connections. National connections are more influential in obtaining direct subsidies. Using a difference-in-difference model, I show that newly nationally connected firms experience growth of around 38% each year for five years. The results highlight important time heterogeneity between firms connected before and after the 2013 anti-corruption campaign. The high number of prosecutions prevented firms from establishing bonds before official recruitment for firms switching to connected for the first time after 2013. Finally, local connection is associated with lower taxes paid and lower capital costs. I explain my result by the nature of direct subsidy data. Direct subsidies are more likely to be official grants approved by Beijing. Recently, the central government has been curbing subsidies given by local authorities to prevent overproduction and resource waste. However, most local banks are local SOEs, and local governments can still use this lever to support their local champions.

This paper contributes to the literature by providing empirical evidence on the relationship between political connections and resource allocation in a developing economy with opaque legal systems. It also reinforces the notion that firm size and political ties, rather than productivity, play a central role in determining access to subsidies in China. Lastly, my findings align with the theoretical predictions of Bai, Hsieh, and Song (2020)'s model, showing that larger firms with more rent-seeking potential are more likely to receive governmental support, emphasizing the importance of political influence in shaping economic policy in China.

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7 Supplementary Documents

7.1 Tables

Table 1: Connection Variables

Variables	**N**	**Mean**	**Median**	**sd**
All Connection	48282	0.35	0	0.477
Local Connection	48282	0.298	0	0.458
National Connection	48282	0.105	0	0.306
Same Location Co.	48282	0.215	0	0.411

Notes: This Table includes the four connection variables used in this paper. *All Connection* does not differentiate between national or local levels. *Local* includes connections at the municipality and provincial level. Finally, *Same Location Co.* takes the value one if the connected person is in the same jurisdiction as the firm location. Each variable equals one if one of the managers is connected at the desired level.

Table 2: Summary Statistics for Always Connected

Variables	N	Mean	Median	sd	25%	75%
Employees (Thousand)	5003	12.122	2.683	47.205	1.117	6.066
Income before Taxes ($ Million)	5092	576.371	26.479	3641.346	8.7	96.215
Capital ($ Million)	4895	2493.57	91.81	21554.57	22.12	358.616
Subsidy ($ Million)	5093	13.922	2.072	90.096	0.722	5.843
Total Assets ($ Million)	5092	33374.64	604.711	258281	270.734	1819.416

Notes: This Table includes only firms that have always been connected in the sample period. N accounts for the number of firm-year observations. Capital stands for current liabilities; employees is the number of employees at the end of the period; and subsidy is the total amount received. All variables are expressed in $US.

Table 3: Summary Statistics for Never Connected

Variables	N	Mean	Median	sd	25%	75%
Employees (Thousand)	18689	3.386	1.379	10.945	0.666	3.022
Income before Taxes ($ Million)	18947	49.199	15.849	321.128	5.762	40.74
Capital ($ Million)	18091	200.407	37.713	863.465	8.614	123.292
Subsidy ($ Million)	18947	4.464	1.456	15.428	0.507	3.62
Total Assets ($ Million)	18944	1159.581	347.482	5245	181.2	751.995

Notes: This Table only includes firms that have never been connected. N accounts for the number of firm-year observations. Capital stands for current liabilities; employees is the number of employees at the end of the period; and subsidy is the total amount received. All variables are expressed in $US.

Table 4: Summary Statistics for Switchers

Variables	**N**	**Mean**	**Median**	**sd**	**25%**	**75%**
Not Connect.						
Employees (Thousand)	12599	5.836	1.972	18.064	0.859	4.806
Income before Taxes ($ Million)	12902	116.41	17.406	1149.769	3.907	61.897
Capital ($ Million)	12282	488.176	75.313	3288.456	19.308	255.733
Subsidy ($ Million)	12904	6.555	1.339	25.387	0.298	4.278
Total Assets ($ Million)	12895	4319.2	512.528	70978.11	209.847	1414.376
Connect.						
Employees (Thousand)	11733	7.93	2.188	27.409	1.008	5.494
Income before Taxes ($ Million)	12026	245.036	21.878	1918.285	5.68	79.018
Capital ($ Million)	11551	953.549	91.329	6340.919	25.833	329.055
Subsidy ($ Million)	12027	9.778	1.672	77.281	0.442	5.423
Total Assets ($ Million)	12024	12044.72	610.529	129253.9	261.802	1758.708

Notes: This Table only includes firms that switched at least once from one State to another. N accounts for the number of firm-year observations. Capital stands for current liabilities; *Assets* are total assets; *employees* is the number of employees at the end of the period, and subsidy is the total amount received. All variables are expressed in $US.

Table 5: Summary Statistics for SOEs

Variables	**N**	**Mean**	**Median**	**sd**	**25%**	**75%**
SOEs						
Employees (Thousand)	5429	10.75	3.048	38.125	1.358	7.51
Income before Taxes ($ Million)	5622	446.683	26.357	3270.517	6.523	89.544
Capital ($ Million)	5386	1151.153	112.542	6713.551	30.069	412.394
Subsidy ($ Million)	5623	12.305	1.817	108.44	0.345	6.579
Total Assets ($ Million)	5619	21248.02	800.63	176509	320.648	2339.329
Others						
Employees (Thousand)	41945	5.493	1.7	21.068	0.776	3.999
Income before Taxes ($ Million)	42656	135.371	17.561	1293.411	5.357	54.08
Capital ($ Million)	40829	650.944	57.52	8074.406	14.045	197.799
Subsidy ($ Million)	42659	6.726	1.52	37.547	0.466	4.199
Total Assets ($ Million)	42647	6390.618	429.982	100918.1	204.164	1100.984

Notes: This table classifies firms by ownership type. N accounts for the number of firm-year observations. Capital stands for current liabilities; *Assets* are total assets; *employees* is the number of employees at the end of the period, and subsidy is the total amount received. All variables are expressed in $US.

Table 6: Connection Determinants

VARIABLES	(1) All	(2) National	(3) Local
Log of Compensation$_{t-1}$	0.219***	0.466***	0.193***
	(0.061)	(0.137)	(0.068)
Log of Assets$_{t-1}$	0.241***	0.478***	0.198***
	(0.061)	(0.147)	(0.068)
Log of Employment$_{t-1}$	0.006	0.021	0.007
	(0.050)	(0.138)	(0.057)
TFP$_{t-1}$	0.013	0.044	0.017
	(0.014)	(0.037)	(0.017)
HHI	-0.037	0.710	-0.521
	(0.666)	(1.612)	(0.804)
Market Index	0.040	-0.022	0.005
	(0.052)	(0.123)	(0.059)
Log of Age	0.569*	0.336	0.654*
	(0.294)	(0.600)	(0.345)
National Strategic	0.030	0.027	0.021
	(0.090)	(0.213)	(0.099)
Observations	14,184	5,607	13,105
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Province FE	YES	YES	YES
Cluster	Firm-level	Firm-level	Firm-level

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. All columns use logit regressions with fixed effects. The dependent variable is equal to one if the firm is connected. Reported coefficients are average (semi) elasticities. HHI is the Herfindahl–Hirschman index. TFP is computed using Wooldridge (2009). The logarithm is used for sales, total assets, number of employees, and intermediate inputs purchased to compute the TFP. *Compensation* is the average compensation given to managers by year by the firm. *Market Index* measures market development at the province level (Fan 2011). Because *Market Index* is only available until 2020, the regression stretches from 2007 to 2020. Industry fixed effects aggregate the CSRC Industry Code.

Table 7: Political Connection & Subsidy Extensive Margin

VARIABLES	(1)	(2)	(3)
All Connection	-0.001		
	(0.005)		
National Connection		-0.009	-0.010
		(0.009)	(0.009)
Local Connection		-0.005	
		(0.006)	
Same Location Co.			0.002
			(0.006)
Log of Assets$_{t-1}$	0.018***	0.018***	0.018***
	(0.005)	(0.005)	(0.005)
Log of Employment$_{t-1}$	0.011**	0.011**	0.011**
	(0.004)	(0.004)	(0.004)
TFP$_{t-1}$	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Observations	7,939	7,939	7,939
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Province FE	YES	YES	YES
Cluster	Firm-level	Firm-level	Firm-level

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. All columns use logit regressions with fixed effects. The dependent variable is equal to one if the firm is subsidized. Reported coefficients are average (semi) elasticities. TFP is computed using Wooldridge (2009). Industry fixed effects aggregate the CSRC Industry Code.

Table 8: Political Connection & Subsidy Intensive Margin

VARIABLES	(1)	(2)	(3)	(4)	(5)
All Connection	0.051*	0.059**			
	(0.026)	(0.024)			
National Connection			0.138***	0.083**	0.085**
			(0.045)	(0.042)	(0.042)
Local Connection			0.009	0.041	
			(0.027)	(0.026)	
Same Location Co.					0.030
					(0.028)
Log of Assets$_{t-1}$	0.590***	0.648***	0.586***	0.647***	0.648***
	(0.021)	(0.031)	(0.021)	(0.031)	(0.031)
Log of Employment$_{t-1}$	0.354***	0.303***	0.354***	0.303***	0.303***
	(0.020)	(0.027)	(0.020)	(0.027)	(0.027)
TFP$_{t-1}$	0.009	0.011	0.009	0.010	0.010
	(0.009)	(0.007)	(0.009)	(0.007)	(0.007)
Observations	36,766	36,280	36,766	36,280	36,280
R-squared	0.468	0.718	0.469	0.718	0.718
Firm FE	NO	YES	NO	YES	YES
Province X Year FE	YES	YES	YES	YES	YES
Industry X Year FE	YES	YES	YES	YES	YES
Cluster	Firm-level	Firm-level	Firm-level	Firm-level	Firm-level
F-test	0	0	0	0	0
Pseudo R-squared	0.456	0.675	0.456	0.675	0.675

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. All columns are Ordinary Least Square (OLS) regressions with fixed effects. The dependent variable is the logarithm of the total amount of subsidies received by the firm. TFP is computed using Wooldridge (2009). Industry fixed effects aggregate the CSRC Industry Code.

Table 9: Average Effect of Connection on Subsidy

VARIABLES	(1) Treated: Local Control: Never	(2) Control: Never	(3) Treated: National Control: Local	(4) Control: All
PostXConnection	0.0739	0.274**	0.203**	0.251**
	(0.0761)	(0.120)	(0.103)	(0.108)
Log of Assets$_{t-1}$	0.630***	0.604***	0.681***	0.646***
	(0.0493)	(0.0512)	(0.0458)	(0.0346)
Log of Employment$_{t-1}$	0.314***	0.338***	0.264***	0.310***
	(0.0415)	(0.0425)	(0.0391)	(0.0298)
TFP$_{t-1}$	0.0110	0.0139	0.00807	0.0123
	(0.0123)	(0.0129)	(0.0105)	(0.00806)
Observations	20,468	17,088	17,424	31,560
Firm FE	YES	YES	YES	YES
Province X Year FE	YES	YES	YES	YES
Industry X Year FE	YES	YES	YES	YES
Cluster	Firm-level	Firm-level	Firm-level	Firm-level

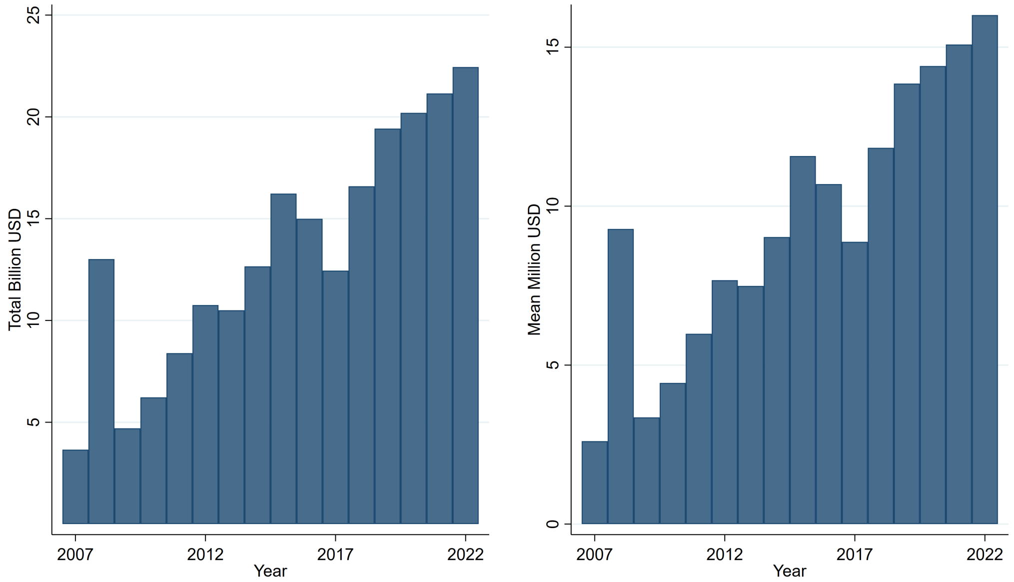
Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. I use OLS model with Borusyak, Jaravel, and Spiess (2024) package. The dependent variable is the logarithm of the subsidy. *PostXConnection* gives the average causal effect of connection. Column 1 uses locally connected firms as treated and never connected as control. Columns 2-4 use nationally connected firms as treated.

Table 10: Tax Avoidance & Political Connections

VARIABLES	(1) 4-YEARS	(2) 4-YEARS	(3) 4-YEARS
All Connection	-0.002**		
	(0.001)		
National Connection		0.000	0.000
		(0.001)	(0.001)
Local Connection		-0.002**	
		(0.001)	
Same Location Co.			-0.003***
			(0.001)
Log of Revenue	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
TFP	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Intangible Assets	0.039***	0.039***	0.039***
	(0.008)	(0.008)	(0.008)
Ratio R&D Expense	-0.075***	-0.075***	-0.074***
	(0.013)	(0.013)	(0.013)
Observations	6,004	6,004	6,004
Firm FE	YES	YES	YES
Province X Period FE	YES	YES	YES
Industry X Period FE	YES	YES	YES
Cluster	Firm-level	Firm-level	Firm-level
F test	0	0	0
Adjusted R-squared	0.724	0.724	0.725

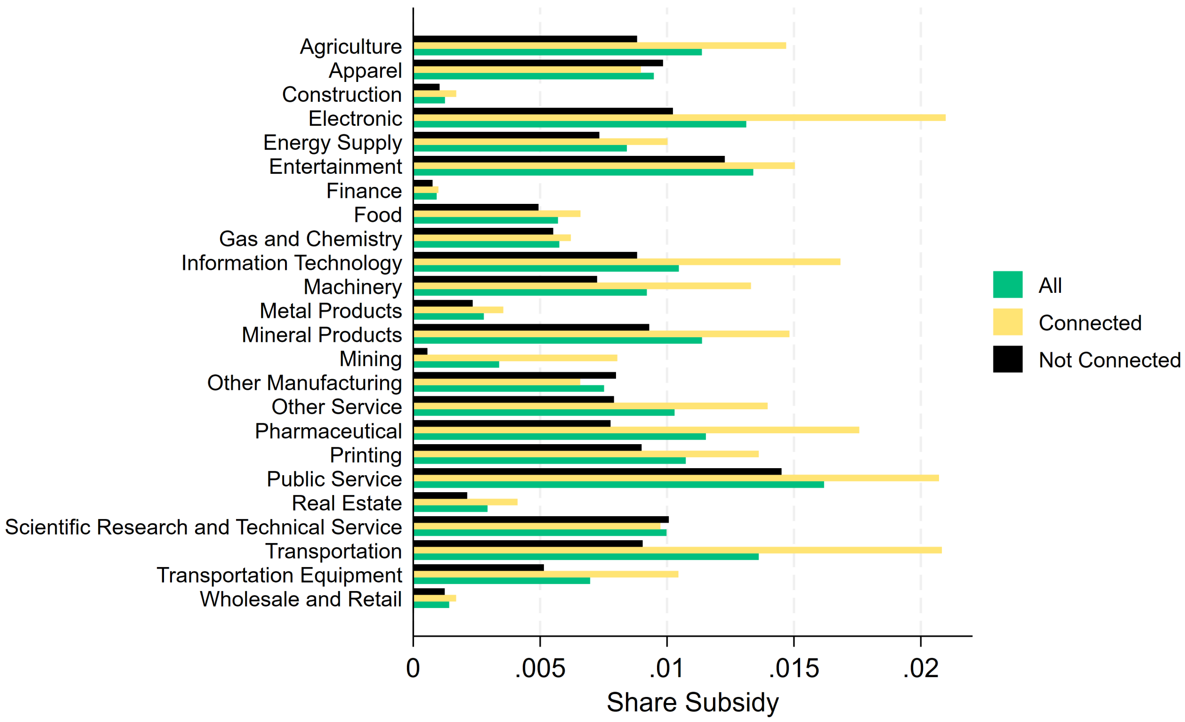
Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. All columns are OLS regressions with fixed effects. The dependent variable is the tax avoidance measure $\Delta_{i,r}$. It follows the methodology of Henry and Sansing (2018) (see the text for more details). The period r used in the Table is four years, from 2007 to 2022. A firm is defined as connected if it is connected in the last year of the period. For the control variables, I take the mean over the period r and take the logarithm.

7.2 Figures



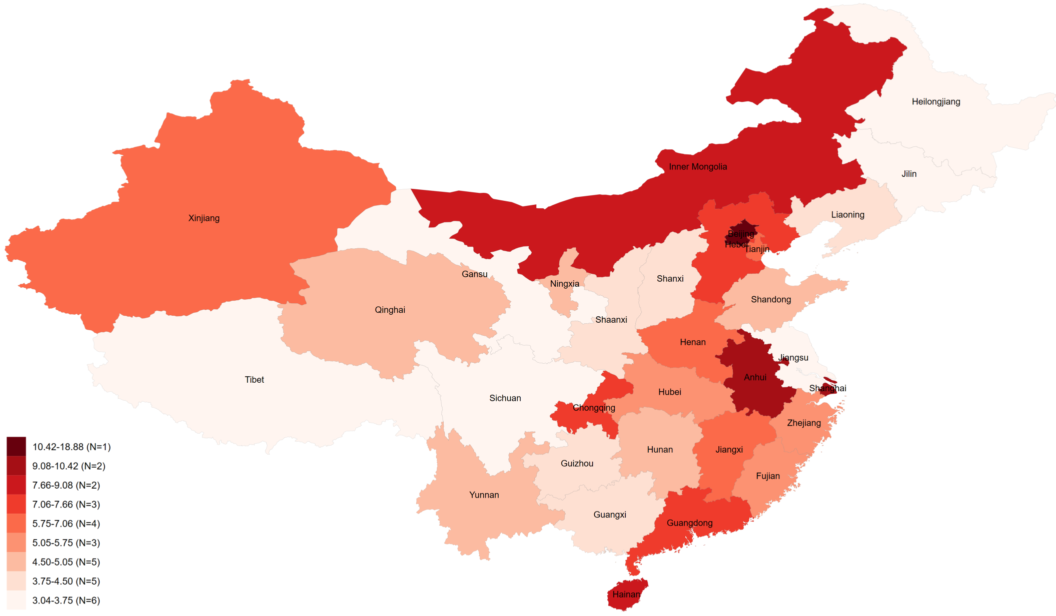
Notes: I only include active firms from 2007 to 2022 to keep the same sample. Values are expressed in deflated $US using the Chinese Consumer Price Index.

Figure 1: Total & Mean Direct Subsidies Received by Chinese-Listed Firms



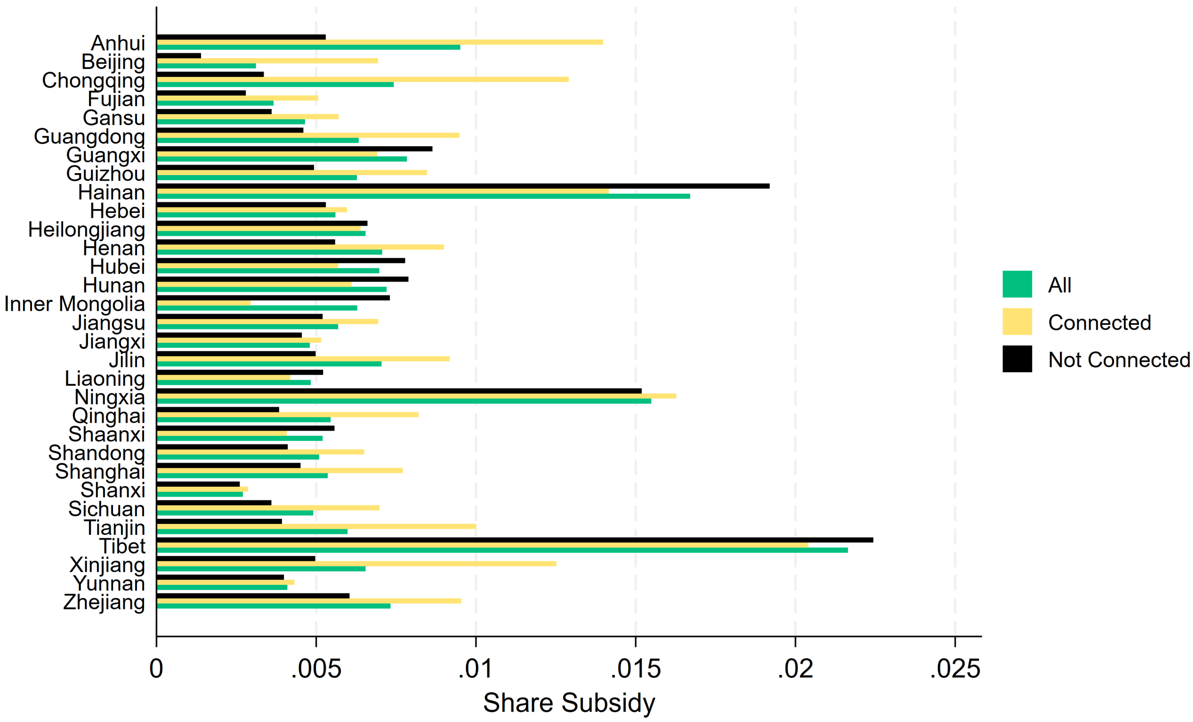
Notes: This Figure reports the distribution of subsidies by industry groups. Values reflect the ratio between the average amount of subsidies received and the average revenue by industry.

Figure 2: Distribution of Subsidies by Industries and Connection Status



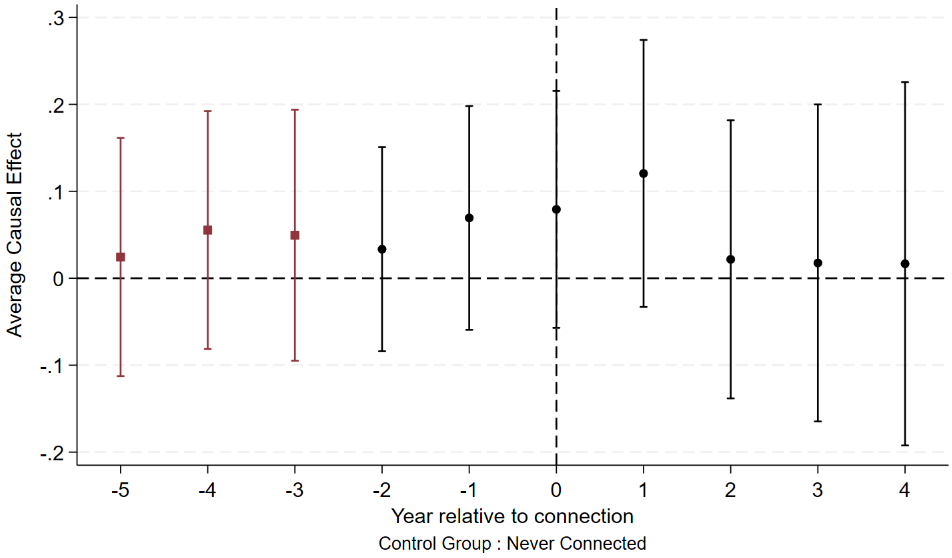
Notes: Mean subsidies given to the firm by the province in millions of $US. Values are expressed in deflated $US using the Chinese Consumer Price Index.

Figure 3: Mean Subsidy by Province



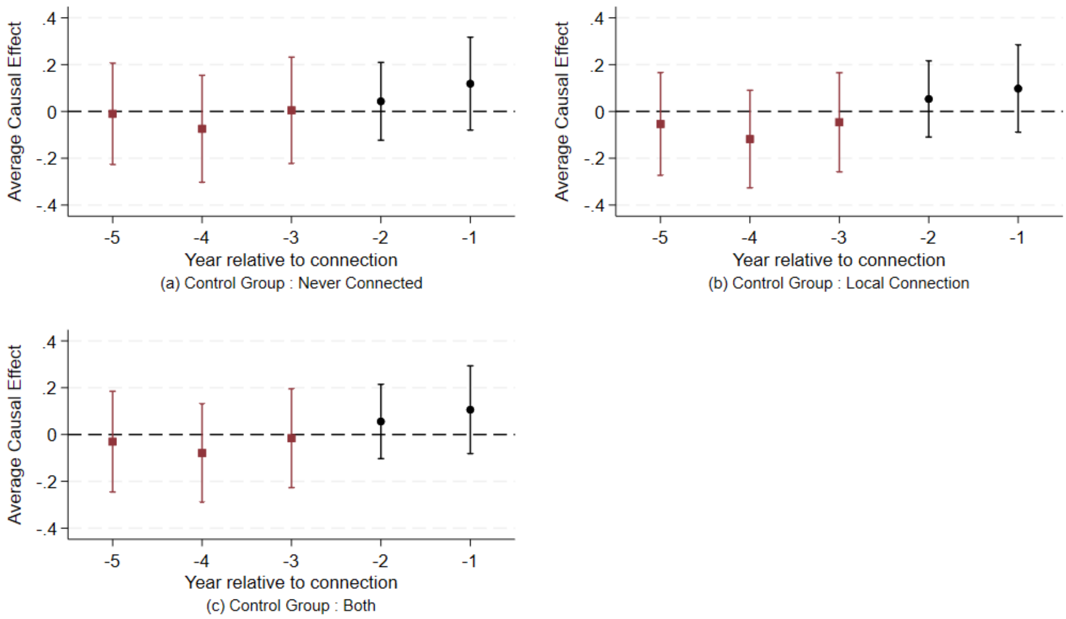
Notes: This Figure reports the distribution of subsidies by industry groups. Values reflect the ratio between the average amount of subsidies received and the average revenue by province.

Figure 4: Distribution of Subsidies by Province and Connection Status



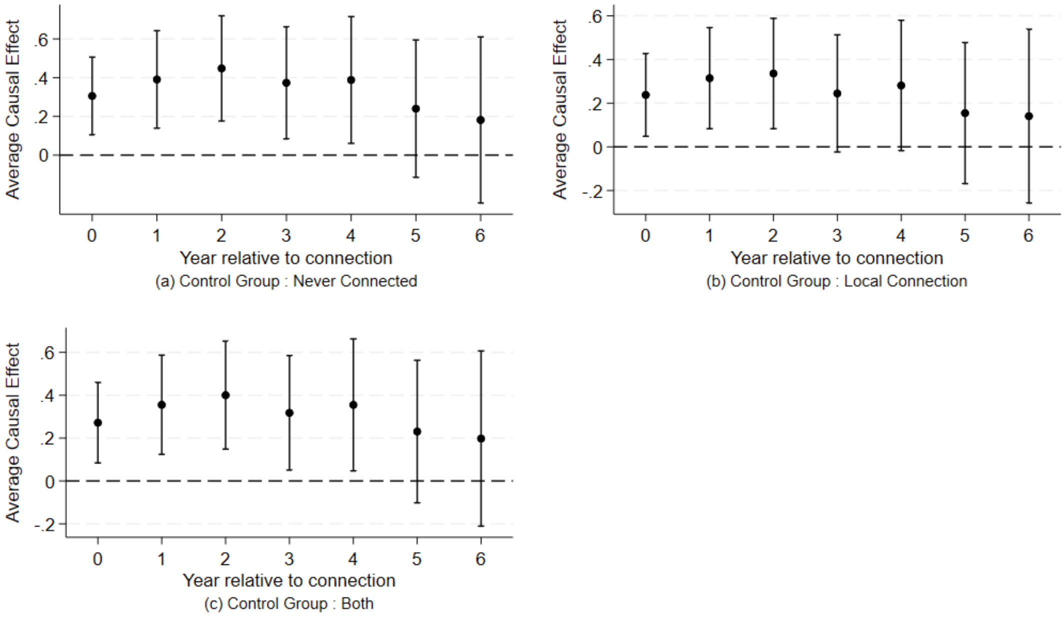
Notes: The Figure reports the dynamic effect of local connection on subsidy received. The dependent variable is the logarithm of the total subsidy received by the firm. The treated group includes firms connected at the local level. The control group includes never-connected firms. Red squares stand for the pretrend test, and black dots for post-treatment effects. Coefficients in $t-1$ and $t-2$ control for anticipation. 95% confidence intervals are shown using standard errors clustered by firm.

Figure 5: Dynamic Effect of Local Connection on Subsidy



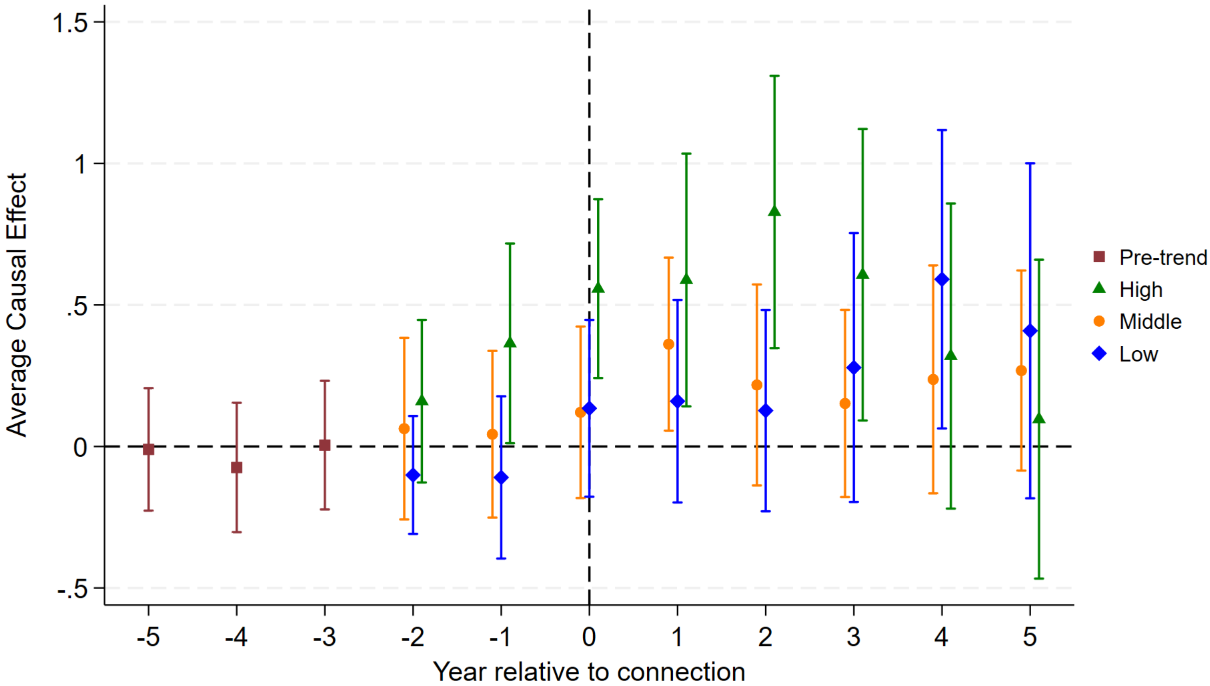
Notes: The Figure reports pre-trend estimates using Borusyak, Jaravel, and Spiess (2024)'s methodology. The dependent variable is the logarithm of the total subsidy received by the firm. The treated group includes firms connected at the national level. The coefficients prior to connection are estimated with untreated observations only. Red squares stand for the pretrend test, and the black dotes test for anticipation. 95% confidence intervals are shown using standard errors clustered by firm.

Figure 6: Pre-treatment Effects of National Connection on Subsidy



Notes: The Figure reports post-connection estimates using Borusyak, Jaravel, and Spiess (2024)'s methodology. The dependent variable is the logarithm of the total subsidy received by the firm. The treated group includes firms connected at the national level. 95% confidence intervals are shown using standard errors clustered by firm.

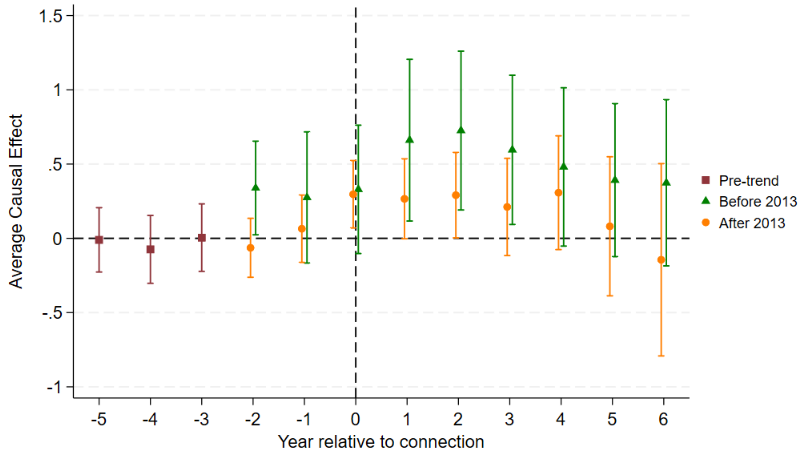
Figure 7: Dynamic Effect of National Connection



(a) Control Group : Never Connected

Notes: The Figure reports connection estimates using Borusyak, Jaravel, and Spiess (2024)'s methodology. The dependent variable is the logarithm of the total subsidy received by the firm. Red squares represent the pretrend test, and coefficients at $t-1$ and $t-2$ account for anticipation effects. The control group consists of firms that are never connected. Industries are grouped into three categories based on capital intensity, which is measured as the ratio of fixed assets to the number of employees. The three groups are created by applying two cutoffs on capital intensity to divide the sample into three size-similar groups. High intensity includes Construction, Energy Supply, Entertainment, Information Technology, Mining, Other Services, Public Services, Real Estate, Transportation, and Wholesale. Middle intensity: Gas & Chemistry, Machinery, Metal Products, Mineral Products, Scientific Research. Low intensity: Agriculture, Apparel, Electronic, Food, Other Manufacturing, Pharmaceutical, Printing, Transportation Equipment. Green arrows illustrate the causal effect of being connected for the first time in the *High* capital intensity sector, orange dots for the *Middle* intensity sector, and blue diamonds for the *Low* intensity sector. The 95% confidence intervals are calculated using standard errors clustered by firm.

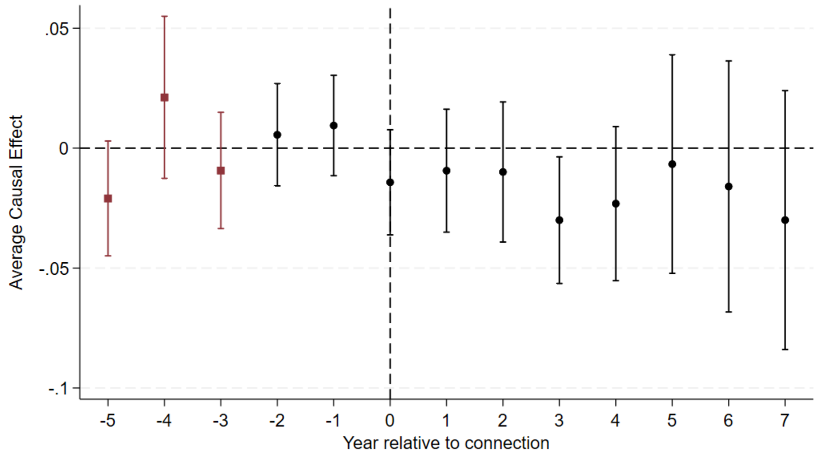
Figure 8: Heterogeneous Effects of Connection on Subsidy by Capital Intensity



(a) Control Group : Never Connected

Notes:The Figure reports connection estimates using Borusyak, Jaravel, and Spiess (2024)'s methodology. The dependent variable is the logarithm of the total subsidy received by the firm. Red squares represent the pretrend test, and coefficients at $t-1$ and $t-2$ account for anticipation effects. The control group consists of firms that are never connected. Green arrows show the causal effect of being connected for the first time before the corruption campaign launched in 2012, and orange dots after. 95% confidence intervals are shown using standard errors clustered by firm.

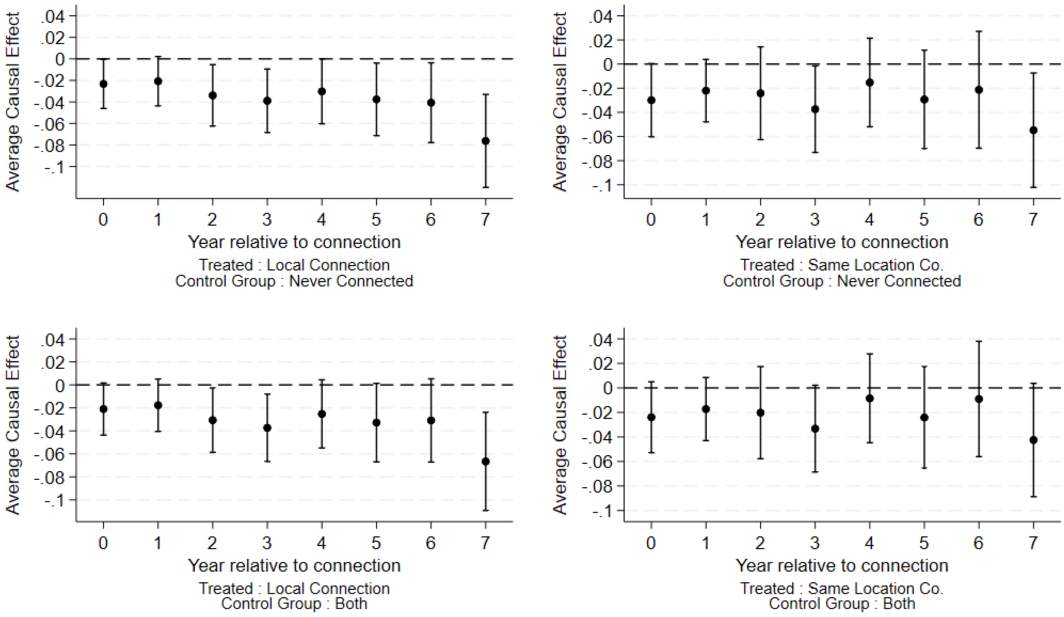
Figure 9: Effect of 2013 Anti-Corruption Campaign



Control Group : Never Connected

Notes: The Figure reports connection estimates using Borusyak, Jaravel, and Spiess (2024)'s methodology. The dependent variable is the capital cost paid by the firm. The cost is computed using the ratio of total interest expenses to total debt due to the year. Red squares represent the pretrend test, and coefficients at $t-1$ and $t-2$ account for anticipation effects. The control group consists of firms that are never connected. 95% confidence intervals are shown using standard errors clustered by firm.

Figure 10: Dynamic Effect of National Connection on Interest Rate



The Figure reports post-connection estimates using Borusyak, Jaravel, and Spiess (2024)'s methodology. The dependent variable is the capital cost of the firm. The treated group includes firms connected at the local level. *Same Location Co.* restricts the connection to the same locality as the headquarters of the firm. 95% confidence intervals are shown using standard errors clustered by firm.

Figure 11: Dynamic Effect of Local Connection on Interest Rate

Appendix A Supplementary Documents

A.1 Data Description

Direct Subsidies Listed firms' disclosures include the amount of subsidies received and sometimes the reasons provided for them. Concerns have been raised about the quality of Chinese data; however, as independent auditors review the financial statements before being publicly released, subsidy data are considered more reliable than other self-reported data sources. The risk of mismeasurement or misreporting, which often affects larger datasets such as those provided by the Chinese National Bureau of Statistics (NBS), is mitigated here. Nevertheless, the disclosed amounts may not capture all direct subsidies received by firms. To account for this potential gap, I broaden the scope of the analysis beyond direct subsidies to include capital costs and tax avoidance, reducing the risk of bias. Direct subsidies, while granted for a range of reasons, such as promoting nascent industries or environmental protection, are fungible and can be used for other purposes. Classifying subsidies by types is beyond the scope of the paper as many do not disclose details and apparently pay no penalty for these omissions. In this paper, I keep all flows and aggregate them at the firm-year level[25].

Total Factor Productivity To investigate the relationship between government subsidies and firm productivity, I compute total factor productivity (TFP) following the methodology of Wooldridge (2009). The production function is estimated separately by industry[26]. TFP is then calculated as the residual from the following firm-level regression:

$$y_{it} = \alpha + \beta l_{it} + \gamma k_{it} + \delta m_{it} + \epsilon_{it}$$

Where y_{it} represents the revenue of firm i in year t, l_{it} is the logarithm of the number of workers, k_{it} is the logarithm of total assets, and m_{it} is the logarithm of material and input expenses[27].

[25] Using AI classification with human validation, Branstetter, Li, and Ren (2022) explore and classify subsidies into several groups. See their paper for more details.

[26] Following Branstetter, Li, and Ren (2022), the China Securities Regulatory Commission's (CSRC) industry codes are aggregated into broader categories to ensure adequate observations for industry-level productivity estimations. The concordance between CSRC codes and industry groups is provided in Table A.1.

[27] Revenue ($y_i t$) is deflated by the producer price index, capital value (k_{it}) is deflated by the consumer price index, and intermediate material input (m_{it}) is deflated by the industrial producer input price index in each year. To deal with extreme values, I trim the top 1 and 99% of each variable.

A.2 Supplemental Descriptive Statistics

Table A.1: CSRC Industry Concordance

CSRC Industry Code	CSRC Industry Category Name	CSRC Industry Name	Collapsed Industry Name
A01	Agriculture, forestry, animal husbandry and fishery	Agriculture	Agriculture
A02	Agriculture, forestry, animal husbandry and fishery	Forestry	Agriculture
A03	Agriculture, forestry, animal husbandry and fishery	Animal husbandry	Agriculture
A04	Agriculture, forestry, animal husbandry and fishery	Fishery	Agriculture
A05	Agriculture, forestry, animal husbandry and fishery	Agriculture, forestry, animal husbandry and fishery Service	Agriculture
B06	Mining industry	Coal mining and washing industry	Mining
B07	Mining industry	Oil and gas extraction	Mining
B08	Mining industry	Mining and dressing of ferrous metals	Mining
B09	Mining industry	Mining and dressing of nonferrous metals	Mining
B10	Mining industry	Mining and dressing of non-metallic materials	Mining
B11	Mining industry	Mining support activities	Mining
B12	Mining industry	Other mining	Mining
C13	Manufacturing	Agricultural and sideline food processing industry	Food
C14	Manufacturing	Food manufacturing	Food
C15	Manufacturing	Liquor, beverage and refined tea manufacturing	Food

Table A.1: CSRC Industry Concordance

CSRC Industry Code	CSRC Industry Category Name	CSRC Industry Name	Collapsed Industry Name
C16	Manufacturing	Tobacco products industry	Food
C17	Manufacturing	Textile industry	Apparel
C18	Manufacturing	Textile, clothing, and apparel industry	Apparel
C19	Manufacturing	Leather, fur, feathers and articles thereof and footwear	Apparel
C20	Manufacturing	Timber processing and wood, bamboo, rattan, palm and straw products	Other manufacturing
C21	Manufacturing	Furniture manufacturing	Other manufacturing
C22	Manufacturing	Paper and paper products	Printing
C23	Manufacturing	Printing and recording media reproduction	Printing
C24	Manufacturing	Culture, education, beauty, sports and entertainment products manufacturing	Printing
C25	Manufacturing	Petroleum processing, coking and nuclear fuel processing industries	Gas and chemistry
C26	Manufacturing	Chemical raw materials and chemical products manufacturing	Gas and chemistry
C27	Manufacturing	Pharmaceutical manufacturing	Pharmaceutical
C28	Manufacturing	Chemical fiber manufacturing	Gas and chemistry
C29	Manufacturing	Rubber and plastic products	Gas and chemistry
C30	Manufacturing	Non-metallic mineral products industry	Mineral products
C31	Manufacturing	Ferrous metal smelting and rolling processing industry	Metal products
C32	Manufacturing	Non-ferrous metal smelting and rolling processing industry	Metal products

Table A.1: CSRC Industry Concordance

CSRC Industry Code	**CSRC Industry Category Name**	**CSRC Industry Name**	**Collapsed Industry Name**
C33	Manufacturing	Metal products industry	Metal products
C34	Manufacturing	General equipment manufacturing	Machinery
C35	Manufacturing	Special equipment manufacturing	Machinery
C36	Manufacturing	Automotive Manufacturing	Transportation equipment
C37	Manufacturing	Railway, ship, aerospace and other transportation equipment manufacturing	Transportation equipment
C38	Manufacturing	Electrical machinery and equipment manufacturing	Machinery
C39	Manufacturing	Computer, communications and other electronic equipment manufacturing	Electronic
C40	Manufacturing	Instrument manufacturing	Electronic
C41	Manufacturing	Other manufacturing	Other manufacturing
C42	Manufacturing	Comprehensive utilization of waste resources	Other manufacturing
C43	Manufacturing	Repair of metal products, machinery and equipment	Other manufacturing
D44	Electricity, heat, gas and water production and supply	Electricity, heat production and supply	Energy supply
D45	Electricity, heat, gas and water production and supply	Gas production and supply	Energy supply
D46	Electricity, heat, gas and water production and supply	Water production and supply	Public service
E47	Construction industry	Building industry	Construction
E48	Construction industry	Civil Engineering and Construction	Construction
E49	Construction industry	Construction and installation industry	Construction

Table A.1: CSRC Industry Concordance

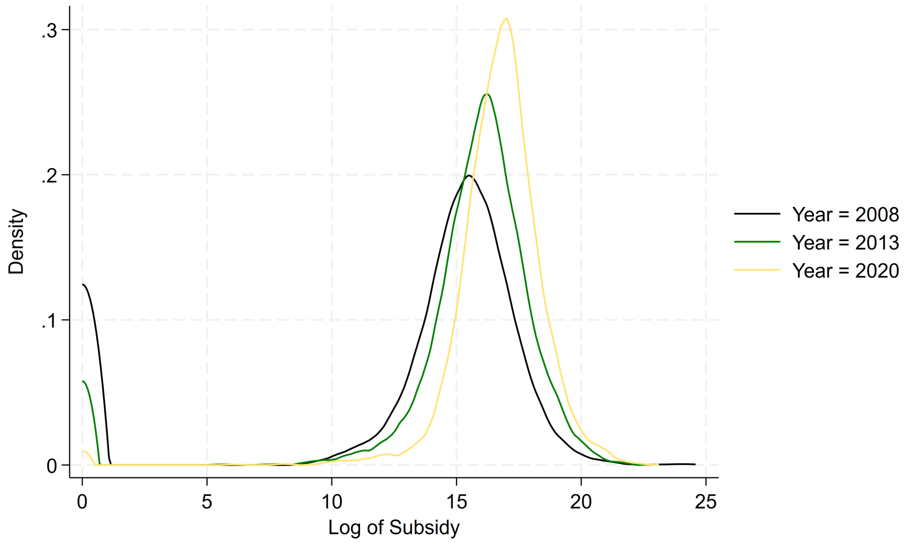
CSRC Industry Code	CSRC Industry Category Name	CSRC Industry Name	Collapsed Industry Name
E50	Construction industry	Building decoration and other construction industry	Construction
F51	Wholesale and retail industry	Wholesale industry	Wholesale and retail
F52	Wholesale and retail industry	Retail industry	Wholesale and retail
G53	Transportation, warehousing and postal services	Rail transport industry	Transportation
G54	Transportation, warehousing and postal services	Road transport industry	Transportation
G55	Transportation, warehousing and postal services	Water transport industry	Transportation
G56	Transportation, warehousing and postal services	Air transport industry	Transportation
G57	Transportation, warehousing and postal services	Pipeline transport industry	Transportation
G58	Transportation, warehousing and postal services	Handling and Transportation Agency	Transportation
G59	Transportation, warehousing and postal services	Warehousing industry	Transportation
G60	Transportation, warehousing and postal services	Postal industry	Transportation
H61	Accommodation and Catering	Accommodation	Other service
H62	Accommodation and Catering	Catering	Other service
I63	Information Transmission, Software and Information Technology Services	Telecommunications, radio and television and satellite transmission services	Information Technology

Table A.1: CSRC Industry Concordance

CSRC Industry Code	CSRC Industry Category Name	CSRC Industry Name	Collapsed Industry Name
I64	Information Transmission, Software and Information Technology Services	Internet and related services	Information Technology
I65	Information Transmission, Software and Information Technology Services	Software and Information Technology Services	Information Technology
J66	Financial industry	Monetary and financial services	Finance
J67	Financial industry	Capital market services	Finance
J68	Financial industry	Insurance	Finance
J69	Financial industry	Other financial industries	Finance
K70	Real estate	Real estate	Real estate
L71	Leasing and business services	Leasing industry	Real estate
L72	Leasing and business services	Business services	Real estate
M73	Scientific research and technical services	Research and experimental development	Scientific research and technical service
M74	Scientific research and technical services	Professional Technical Services	Scientific research and technical service
M75	Scientific research and technical services	Technology promotion and application service industry	Scientific research and technical service
N76	Water, Environment and Public Facilities Management	Water management industry	Public service
N77	Water, Environment and Public Facilities Management	Ecological protection and environmental governance	Public service
N78	Water, Environment and Public Facilities Management	Public facilities management	Public service
O79	Residential services, repairs, and other services	Resident Services	Other service

Table A.1: CSRC Industry Concordance

CSRC Industry Code	CSRC Industry Category Name	CSRC Industry Name	Collapsed Industry Name
O80	Residential services, repairs, and other services	Repair of motor vehicles, electronics and household products	Other service
O81	Residential services, repairs, and other services	Other services	Other service
P82	Education	Education	Public service
Q83	Health and Social Work	Health	Public service
Q84	Health and Social Work	Social work	Public service
R85	Culture, sports and entertainment industry	Journalism and publishing	Entertainment
R86	Culture, sports and entertainment industry	Radio, television, film and film recording operations	Entertainment
R87	Culture, sports and entertainment industry	Culture and art industry	Entertainment
R88	Culture, sports and entertainment industry	Sports industry	Entertainment
R89	Culture, sports and entertainment industry	Entertainment industry	Entertainment
S90	Comprehensive	Comprehensive	Other service



Notes: This Figure reports the kernel distribution of three years. I use the logarithm of subsidy after adding one to each observation. The values have been deflated by the Consumer Price Index.

Figure A.1: Kernel Density of Subsidy

Table A.2: Top Two Industries Subsidized on Average by Province

Industry	Province	Subsidy	Decile
Mineral Products	Anhui	39	99
Transportation Equipment	Anhui	36	99
Mining	Beijing	158	100
Transportation	Beijing	53	100
Metal Products	Chongqing	31	98
Transportation Equipment	Chongqing	21	97
Mining	Fujian	14	94
Finance	Fujian	14	93
Electronic	Gansu	17	95
Mineral Products	Gansu	8	82
Transportation	Guangdong	25	98
Transportation Equipment	Guangdong	23	97
Energy Supply	Guangxi	10	87
Machinery	Guangxi	9	86

Transportation	Guizhou	65	100
Real Estate	Guizhou	19	96
Transportation	Hainan	26	98
Agriculture	Hainan	13	92
Transportation Equipment	Hebei	45	100
Mineral Products	Hebei	27	98
Pharmaceutical	Heilongjiang	9	85
Energy Supply	Heilongjiang	5	70
Agriculture	Henan	31	98
Transportation Equipment	Henan	11	88
Construction	Hubei	24	97
Metal Products	Hubei	11	90
Finance	Hunan	14	94
Electronic	Hunan	11	89
Food	Inner Mongolia	37	99
Metal Products	Inner Mongolia	23	97
Entertainment	Jiangsu	13	91
Finance	Jiangsu	10	87
Transportation	Jiangxi	31	98
Transportation Equipment	Jiangxi	20	97
Other Service	Jilin	21	97
Mineral Products	Jilin	13	92
Information Technology	Liaoning	12	91
Gas and Chemistry	Liaoning	8	82
Apparel	Ningxia	12	91
Mineral Products	Ningxia	11	88
Information Technology	Qinghai	8	83
Gas and Chemistry	Qinghai	8	82

Electronic	Shaanxi	10	86
Transportation Equipment	Shaanxi	9	85
Electronic	Shandong	13	91
Printing	Shandong	11	90
Transportation	Shanghai	49	100
Transportation Equipment	Shanghai	32	99
Mining	Shanxi	8	81
Machinery	Shanxi	7	80
Food	Sichuan	7	77
Pharmaceutical	Sichuan	6	74
Transportation	Tianjin	34	99
Mining	Tianjin	17	95
Gas and Chemistry	Tibet	7	81
Finance	Tibet	7	78
Machinery	Xinjiang	19	96
Mineral Products	Xinjiang	16	95
Metal Products	Yunnan	9	84
Mining	Yunnan	6	76
Transportation	Zhejiang	11	90
Electronic	Zhejiang	10	88

Note: This Table reports the top two industries subsidized by province with their value in a million $US and their position in the global distribution. Values are expressed in deflated $US using the Chinese Consumer Price Index. I take the average of subsidies each province gives to industries operating in their jurisdiction and keep the first two.

A.3 Supplemental Results

Table A.3: Summary Statistics of Control and Treated Groups

Variables	**Mean**	**Median**	**sd**	**25%**	**75%**
Not Yet Treated					
Log Subsidy	16.187	16.236	1.871	15.085	17.435
Log of Assets	22.261	22.023	1.484	21.146	23.131
Log Employees	7.831	7.765	1.337	6.922	8.674
Never Connected					
Log Subsidy	16.188	16.268	1.574	15.359	17.141
Log of Assets	21.828	21.66	1.158	21.03	22.438
Log Employees	7.316	7.247	1.165	6.538	8.028
Local Connection					
Log Subsidy	16.176	16.259	1.698	15.238	17.236
Log of Assets	22.103	21.964	1.299	21.186	22.819
Log Employees	7.561	7.545	1.202	6.811	8.327

Notes: This Table reports the summary statistics of the two control groups, firms that have been connected at the local level at least once and never connected. *Not Yet Treated* gathers firms not yet connected (or treated) at the national level. *Assets* are total assets; *employees* is the number of employees at the end of the period, and subsidy is the total amount received. I take the logarithm of all variables.

Table A.4: Dynamic Effect of National Connection on Subsidy

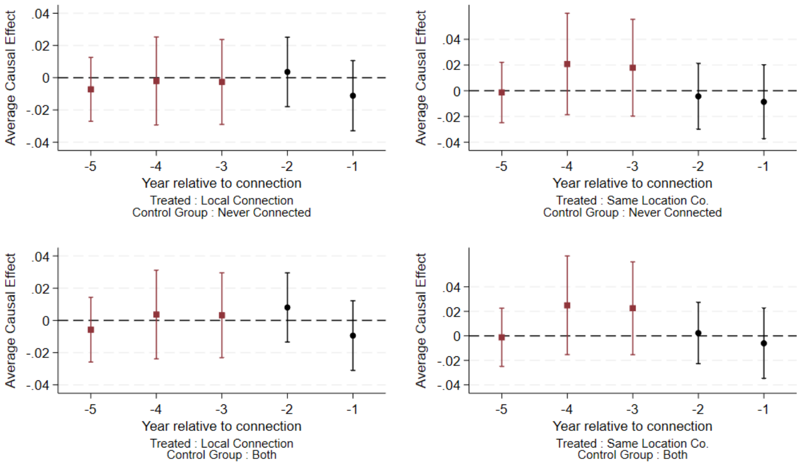
VARIABLES	(1) Never	(2) Local	(3) Both
t-5	-0.0104	-0.0536	-0.0305
	(0.110)	(0.112)	(0.110)
t-4	-0.0743	-0.118	-0.0791
	(0.117)	(0.106)	(0.107)
t-3	0.00472	-0.0465	-0.0158
	(0.116)	(0.108)	(0.108)
t-2	0.0430	0.0532	0.0555
	(0.0849)	(0.0830)	(0.0810)
t-1	0.119	0.0977	0.106
	(0.101)	(0.0952)	(0.0957)
t	0.305***	0.238**	0.272***
	(0.102)	(0.0966)	(0.0958)
t+1	0.391***	0.314***	0.355***
	(0.128)	(0.118)	(0.118)
t+2	0.448***	0.336***	0.400***
	(0.139)	(0.129)	(0.129)
t+3	0.373**	0.245*	0.318**
	(0.148)	(0.137)	(0.136)
t+4	0.388**	0.281*	0.355**
	(0.167)	(0.152)	(0.157)
Log of Asset$_{t-1}$	0.604***	0.681***	0.646***
	(0.0512)	(0.0458)	(0.0346)
Log of Employment$_{t-1}$	0.338***	0.264***	0.310***
	(0.0425)	(0.0391)	(0.0298)
TFP$_{t-1}$	0.0139	0.00807	0.0123
	(0.0129)	(0.0105)	(0.00806)
Observations	16,780	17,116	31,252
Firm FE	YES	YES	YES
Province X Year FE	YES	YES	YES
Industry X Year FE	YES	YES	YES
Cluster	Firm-level	Firm-level	Firm-level

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. I use OLS model with Borusyak, Jaravel, and Spiess (2024) package. The dependent variable is the logarithm of the subsidy. Coefficients in $t-5$, $t-4$, and $t-3$ test the parallel trend assumption, and coefficients $t-1$ and $t-2$ control for anticipation.

Table A.5: Dynamic Effect of Connection on Subsidy: 2007-2019

	(1)
VARIABLES	Never
t-5	-0.0279
	(0.104)
t-4	-0.0896
	(0.116)
t-3	0.00684
	(0.112)
t-2	0.0701
	(0.0934)
t-1	0.174
	(0.123)
t	0.334**
	(0.131)
t+1	0.559***
	(0.161)
t+2	0.567***
	(0.171)
t+3	0.398**
	(0.188)
t+4	0.323
	(0.212)
Log of Assets$_{t-1}$	0.664***
	(0.0602)
Log of Employment$_{t-1}$	0.216***
	(0.0495)
TFP$_{t-1}$	0.0157
	(0.0131)
Observations	11,472
Firm FE	YES
Province X Year FE	YES
Industry X Year FE	YES
Cluster	Firm-level

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. I use OLS model with Borusyak, Jaravel, and Spiess (2024) package. The dependent variable is the logarithm of the subsidy. This Table excludes COVID-19 years. Coefficients in $t-5$, $t-4$, and $t-3$ test the parallel trend assumption, and coefficients $t-1$ and $t-2$ control for anticipation.



Notes: The Figure reports pre-trend estimates using Borusyak, Jaravel, and Spiess (2024)'s methodology. The dependent variable is the interest rate paid by the firm. The treated group includes firms connected at the local level. *Same Location Co.* restricts the connection to the same locality as the headquarters of the firm. The coefficients prior to connection are estimated with untreated observations only. Red squares stand for the pretrend test, and the black dotes test for anticipation. 95% confidence intervals are shown using standard errors clustered by firm.

Figure A.2: Pre-treatment Effect of Local Connection on Interest Rate

Table A.6: Dynamic Effect of Connection on Interest Rate

VARIABLES	(1) National Connection	(2) Local Connection	(3) Same Local Co.
PostXConnection	-0.0123	-0.0250**	-0.0251*
	(0.0111)	(0.0107)	(0.0135)
Log of Employment$_{t-1}$	-0.00121	-0.00359	-0.00214
	(0.00488)	(0.00473)	(0.00481)
TFP$_{t-1}$	-0.00125	-0.00107	-0.000936
	(0.00196)	(0.00195)	(0.00190)
Log of Revenue$_{t-1}$	-0.000779	-0.00110	-0.00122
	(0.00500)	(0.00444)	(0.00449)
ROA$_{t-1}$	-0.0545***	-0.0536***	-0.0544***
	(0.0165)	(0.0166)	(0.0163)
Tangible Assets$_{t-1}$	0.0305	0.0443*	0.0360*
	(0.0210)	(0.0243)	(0.0211)
Observations	14,898	18,632	16,303
Firm FE	YES	YES	YES
Province X Year FE	YES	YES	YES
Industry X Year FE	YES	YES	YES
Cluster	Firm-level	Firm-level	Firm-level

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. I use OLS model with Borusyak, Jaravel, and Spiess (2024) package. The dependent variable is the interest rate paid. The treated group changes depending on the specification. *Same Location Co.* restricts the connection to the same locality as the headquarters of the firm.

Table A.7: Tax Avoidance & Political Connections

VARIABLES	(1) 3-YEARS	(2) 3-YEARS	(3) 3-YEARS
All Connection	-0.001*		
	(0.001)		
National Connection		0.002	0.002
		(0.002)	(0.002)
Local Connection		-0.003***	
		(0.001)	
Same Location Co.			-0.003***
			(0.001)
Log of Revenue	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
TFP	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)
Intangible Assets	0.058***	0.057***	0.057***
	(0.006)	(0.006)	(0.006)
Ratio R&D Expense	-0.085***	-0.084***	-0.085***
	(0.015)	(0.015)	(0.015)
Observations	6,789	6,789	6,789
Firm FE	YES	YES	YES
Province X Period FE	YES	YES	YES
Industry X Period FE	YES	YES	YES
Cluster	Firm-level	Firm-level	Firm-level
F test	0	0	0
Adjusted R-squared	0.645	0.645	0.645

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. All columns are OLS regressions with fixed effects. The dependent variable is the tax avoidance measure $\Delta_{i,r}$. It follows the methodology of Henry and Sansing (2018) (see the text for more details). The period r used in the Table is three years, from 2007 to 2021. A firm is defined as connected if it is connected in the last year of the period. For the control variables, I take the mean over the period r.

A.4 Individual Level Analysis

A Return of Being Connected

As an additional test of the benefits of being politically connected, I estimate the differences in remuneration between connected and non-connected managers. The data is reshaped at the individual-firm-year level, allowing to test the effect of connection on total compensation. Although it is not possible to track whether an individual manages multiple firms, I assume that each manager is associated with a single firm.

The following equations estimate the gains from being politically connected:

$$Compensation_{k,t} = \beta_1 Connection_{k,t} + \beta_2 X_{kt} + \alpha_{i_{(k)},t} + \delta_{l_{(k)}} + (\omega_k) + \epsilon_{k,t} \tag{6}$$

where $Compensation_{k,t}$ is the logarithm of total compensation received by the individual k in year t. $Connection_{k,t}$ is a dummy variable equaling one if the individual is a former or current politician. $\beta_2 X_{kt}$ includes controls for the logarithm of age and gender. I include firm-year ($\alpha_{i(k),t}$), position in the firm ($\delta_{l_{(k)}}$) and individual fixed effects (ω_k) in the model. I

Table A.8 reports the results. Columns 1-4 estimate the effect of connection on compensation. In Model 2, after controlling for individual fixed effects, switching to connected status is associated with a 6.8% increase in compensation. The effect is uniform between types of connection (Model 4).

B 2013-Anti-Corruption Campaign

Given that the campaign specifically targeted the relationship between the private sector and policymakers, I hypothesize that the compensation awarded to connected individuals may decrease post-2013 first because their power to reach rulers was curbed because of the campaign, second because compensation may be seen as a potential red flag for the authorities.

The analysis follows an event study framework, treating the campaign as an exogenous shock. I construct a new individual-firm-year dataset for this purpose. For the treated group, I focus on individuals who were always connected before 2013, excluding those who established connections after 2013 (or joined a firm after 2013) and managers switching from non-connected to connected. I also require that the connected manager was in the firm at the latest in 2010 to control for the pretrend and anticipation. The control group comprises individuals with no political connections. A two-way fixed effects model is run, and since all treated observations are affected at the same point in time, it eliminates concerns related to negative weights. In my DID setting, 2012 is the reference year.

The following equations are estimated to assess the post-campaign effect:

$$Compensation_{k,t} = \beta_1 Post2013_t \ X \ Connection_{k,t} + \beta_2 X_{k,t} + \alpha_{i_{(k)},t} + \delta_{l_{(k)}} + \omega_k + \epsilon_{k,t} \tag{7}$$

where $Compensation_{k,t}$ is the logarithm of total compensation received by the individual k in year t. $Post2013_t \ X \ Connection_{k,t}$ captures the post-campaign effect of being a connected manager on remuneration. $X_{k,t}$ is the control, the logarithm of the manager's age. I finally include firm-year ($\alpha_{i_{(k)},t}$), individual (ω_k) and position in the firm ($\delta_{l_{(k)}}$) fixed effects.

Table A.9 shows the impact of the campaign on the wage earned by managers. In each column, the campaign is associated with a wage decrease. In Model 2, after the campaign, connected managers experience a decrease of about 8%. The effect is relatively homogeneous between the layers, even if it is no longer significant at the national level when adding firm-year FE. Figure A.3 controls for the pretrend and shows the dynamic effect of the campaign. From 2014 to 2018, connected managers' wages dropped by about 10% per year. The National People's Congress election at the end of 2008 might explain the higher coefficient in 2009.

Table A.8: Return of Being Connected

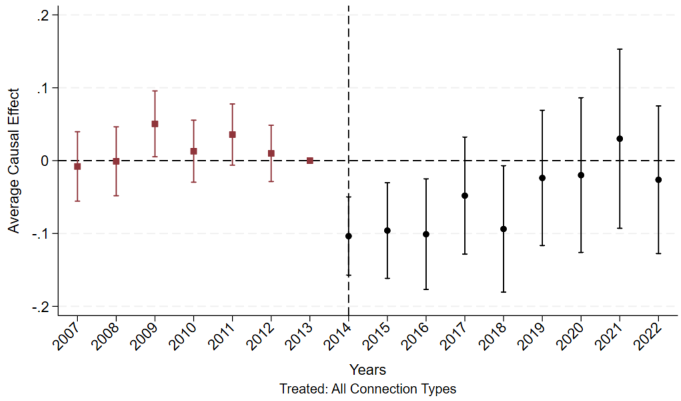
	(1)	(2)	(3)	(4)
VARIABLES	Compensation			
All Connection	0.0327***	0.0648***		
	(0.0117)	(0.0182)		
National Connection			0.0141	0.0973**
			(0.0260)	(0.0425)
Local Connection			0.0330***	0.0597***
			(0.0125)	(0.0194)
Observations	720,581	695,330	720,581	695,330
Firm X Year FE	YES	YES	YES	YES
Position FE	YES	YES	YES	YES
Individual FE	NO	YES	NO	YES
Covariates	YES	YES	YES	YES
Cluster	Individual-level	Individual-level	Individual-level	Individual-level
Adjusted R-squared	0.687	0.871	0.687	0.871

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Each column uses OLS regressions on the logarithm of total compensation received by the individual at the end of the year. The covariates include the logarithm of the individual's age and the sex of the individual.

Table A.9: 2013-Anti-Corruption Campaign & Compensation

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All		National		Local	
Post2013 X Connected	-0.146***	-0.0902***	-0.137**	-0.0717	-0.149***	-0.0947***
	(0.0294)	(0.0250)	(0.0572)	(0.0512)	(0.0331)	(0.0274)
Observations	680,701	680,679	675,314	675,293	679,257	679,234
Firm FE	YES	YES	YES	YES	YES	YES
Position FE	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm X Year FE	NO	YES	NO	YES	NO	YES
Covariates	YES	YES	YES	YES	YES	YES
Cluster	Individual-level	Individual-level	Individual-level	Individual-level	Individual-level	Individual-level
Adjusted R-squared	0.835	0.870	0.835	0.870	0.835	0.870

Notes: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. All columns are OLS regressions with fixed effects. The dependent variable is the logarithm of total compensation received by the individual. *Post2013 X Connected* is the effect of the campaign on connected individuals. The covariates include the logarithm of the individual's age.



Notes: This Figure reports the coefficients of the dynamic effect of the 2013 anti-corruption campaign. The confidence interval is given at 95%. The dependent variable is the compensation received by the manager. All coefficients are estimated using OLS regressions with fixed effects.

Figure A.3: Dynamic Effect of the Anti-Corruption Campaign on Manager's Compensation