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ABSTRACT

Are Chinese industrial policies making the targeted Chinese firms more productive? Alternatively, are efforts to promote productivity undercut by efforts to maintain or expand employment in less productive enterprises? In this paper, we attempt to shed light on these questions through the analysis of previously underutilized microdata on direct government subsidies provided to China's publicly traded firms. We categorize subsidies into different types. We then estimate total-factor productivity (TFP) for Chinese listed firms and investigate the relationship between these estimates of TFP and the allocation of government subsidies. We find little evidence that the Chinese government consistently "picks winners". Firms' ex-ante productivity is negatively correlated with subsidies received by firms, and subsidies appear to have a negative impact on firms' ex-post productivity growth throughout our data window, 2007 to 2018. Neither subsidies given out under the name of R&D and innovation promotion nor industrial and equipment upgrading positively affect firms' productivity growth. On the other hand, we find a positive impact of subsidy on current year employment, both for the aggregated and employment-related subsidies. These findings suggest that China's increasingly prescriptive industrial policies may have generated limited effects in promoting productivity.

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1. Introduction

Each year, governments worldwide spend an enormous amount of money subsidizing businesses. The principal economic rationale for these policies is the market failure explanation (Schwartz and Clements, 1999). The problem, however, is that giving firms taxpayers' money is often not a simple remedy for market failures. Mis-calibrated government subsidies can actually cause even more market distortions, as put by Krugman (1983, p. 132), "… in economics two wrongs do not make a right."

In this paper, we try to peek into the black box of government subsidies to businesses in the context of China. Many countries have criticized China for playing favorites with indigenous Chinese firms when giving out subsidies (Haley & Haley, 2013). They argue that Chinese governments' preference to indigenous firms gives them an unfair advantage over foreign companies in the race to dominate the technological frontier of the future. Within China itself, government subsidies to firms remain equally controversial. While supporters argue that corporate subsidies are necessary for China to upgrade its industries, critics say that the Chinese government's strong preference for large state-owned enterprises and national champions has put private companies and small and mid-sized enterprises in a disadvantaged position.

Despite the growing intensity of these domestic and international debates, many of the claims advanced by Chinese government subsidy proponents and critics have yet to be subjected to serious empirical scrutiny. While the English language literature seeking to evaluate these subsidies is growing rapidly, and some of that work will be reviewed in the next section, much work remains to be done to provide more insights into the nature, scale, and purpose of these subsidies. The limitations of this literature reflect, in part, the difficulty of accurately measuring the existence and incidence of Chinese subsidies at the firm level.

In this paper, we try to shed light on these controversies by exploiting a heretofore underutilized source of firm-level data. Since 2007, companies listed on any of China's stock exchanges have been required to disclose all direct government subsidies received, along with a brief description of the nature of these subsidies. Based on these disclosures, we find that the total amount of direct government subsidies to Chinese listed companies increased by more than 7-fold from 2007 to 2018, rising from $4 billion to $29 billion.[1] Lardy (2019) has used an earlier version of these data to show that direct subsidies have grown substantially over time, from an amount equivalent to only 5 percent of listed firms' profits prior to receiving subsidies in 2010 to almost 14 percent in 2015. Lardy's work also demonstrated that almost all listed companies are receiving some subsidies, with state-owned enterprises getting 70% of the total in 2015. However, while Lardy's work provides some important facts about the aggregate growth and average incidence of these direct government subsidies, it provides few insights regarding the impact of these subsidies at the firm level.

We seek to fill this gap in the literature by analyzing firm-level subsidy data for companies listed on the Chinese stock exchanges. Using Google BERT, along with manual validation, we categorize these subsidies into seven groups according to the brief descriptions of their nature.[2] We then relate these aggregated and categorized subsidies to firm's productivity and other firm-level characteristics. Specially, we explore the following questions. Which firms are likely to get

[1] The exchange rate used in this paper is 1 USD = 7 RMB (Yuan). Unlisted companies account for the vast majority of firms in the Chinese economy, but they are not required to disclose how much government subsidies they receive. As a result, it is difficult to calculate the total corporate subsidies disbursed in China. That said, a recent estimate put the total value of direct corporate subsidies in 2017 at $61 billion (Financial Times, 2019), or 3.6 times the amount disclosed by listed companies in the same year.

[2] Google BERT (Bidirectional Encoder Representations from Transformers) is a neural network-based tool for natural language processing (NLP) originally developed by Google to improve its response to search queries. It has since been released to the public and has been widely used to help computes parse and decode human language more effectively.

higher subsidies—those with higher productivity or lower productivity? Does the receipt of subsidies, especially those related to R&D and innovation or industrial and equipment upgrading, raise firms' productivity in subsequent years? Alternatively, does the receipt of subsidies raise employment?

Our results provide little evidence to support the view that government subsidies have been given to more productive firms or that they have enhanced the productivity of the Chinese listed firms. First, at the aggregate level, subsidies seem to be allocated to less productive firms, and the relative productivity of firms' receiving these subsidies appears to decline further after disbursement. Second, using the categorized subsidy data, we find that neither subsidies promoting R&D and innovation promotion nor subsidies promoting industrial and equipment upgrading are positively associated with firms' subsequent productivity growth. On the other hand, we find there is a positive association between subsidy and employment, both for aggregate and employment-related subsidies.

These results are subject to a number of caveats and limitations. We acknowledge throughout the paper that our subsidy data are limited, reflecting only one of the many policy instruments the Chinese government is actively using to shape the nation's industrial evolution. In addition, our analysis is largely descriptive; strong claims concerning causality will require further analysis. Nevertheless, our results cast doubt on the view that the rising wave of government subsidies will deliver the rising productivity that the Chinese economy will need to counter the pending decline in its labor force, the aging of its population, and the diminishing returns to capital accumulation it will face in coming decades.

The rest of the paper is organized as follows: Section 2 provides an overview of the prior literature on which we seek to build; Section 3 introduces our data and empirical methods;

Section 4 presents our main empirical results; Section 5 concludes and draws policy implications.

2. Government Subsidies, Chinese Industrial Policy, and Productivity

2.1 Government subsidies in China

Government subsidies can take various forms and be implemented for many reasons. Schwartz and Clements (1999) classify government subsidies into seven categories:

(1) *Direct government payments to producers or consumers (cash subsidies or cash grants);*

(2) *Reductions of specific tax liabilities (tax subsidies);*

(3) *Government equity participation (equity subsidies);*

(4) *Government credit guarantees, interest subsidies to enterprises, or soft loans (credit subsidies);*

(5) *Government provision of goods and services at below-market prices (in-kind subsidies);*

(6) *Government purchases of goods and services at above-market prices (procurement subsidies);*

(7) *Implicit payments through government regulatory actions that alter market prices or access (regulatory subsidies).*

In China, all seven of these categories have been used by the government to support businesses (Lim, Wang, and Zeng, 2018; OECD, 2019).[3] Using this broad definition of government subsidies, early work suggests that government subsidies have long been one of the four most important sources of external finance for Chinese firms, along with commercial bank

[3] Other well-documented government interventions have arguably had economic effects similar to subsidies, including tariffs, nontariff barriers, currency interventions, infringement of foreign intellectual property, requirements that foreign firms form equity joint ventures with local firms, and efforts to coerce foreign firms to sell or transfer technology to local enterprises on especially favorable terms. Many of these interventions have had important impact on the development of our sample firms, but they are beyond the scope of this paper.

loans, firms' self-fundraising, and foreign direct investment (Allen, Qian, and Qian, 2005). However, non-monetary subsidies or indirect subsidies of the kind enumerated in categories 2-7 above are usually not specifically reported by Chinese firms in their financial statements, even after the legal requirement to disclose direct subsidies went into effect.

Direct cash payments from governments to producers—part of category #1 in the Schwartz and Clements taxonomy—is a different story. Our research takes advantage of the information disclosure requirements regarding these direct subsidies for listed firms in China: starting in 2007, Chinese law has required listed companies to disclose government subsidy information in the notes to their financial reports. [4] The information includes the amount of the subsidies the company received during the relevant financial period and the reasons for those subsidies.[5] Since these financial statements are reviewed by independent auditors before being released to the public, our subsidy data should be more reliable than other self-reported data sources.[6]

To the best of our knowledge, this is the first paper to submit these reported direct subsidy data to large-sample statistical analysis. These subsidies have grown in magnitude over time, reaching aggregate levels high enough to have a measurable impact on the behavior of at least some of our sample firms. On the other hand, we fully acknowledge that the direct subsidy amounts formally disclosed by our sample firms and used in our data analysis are likely to be only part of the total direct and indirect subsidies received by Chinese firms. Our analyses of the magnitude and impact of government subsidies in China will therefore be necessarily incomplete.

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

[5] It is notable that not all subsidies come with a reason.

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

Government subsidies can serve multiple functions, including the correction of market failures (such as underinvestment in R&D), the promotion of social policy objectives (Krugman, 1983; Schwartz and Clements, 1999), or the support of interest groups aligned with the ruling party. The text describing the purpose of subsidies received by our sample firms appears to point to a wide range of objectives. For example, for the first purpose of offsetting market failures, we observe various subsidies specifically described as supporting R&D activities（重大科技创新项目）. For the purpose of accomplishing social policy objectives, we find in our data "employment stabilization subsidies"（稳定就业补贴）, subsidies for "national unity"（民族团结）, and subsidies for "employment of disabled individuals"（残疾人就业）, etc. We also see subsidies that are provided for reasons that are not easy to interpret: for example, "credit report subsidies"（信用报告补贴）. [7] Feeding this information into Google BERT and using manual validation, we categorize subsidies into seven types, which we will explain in more detail in the next section.

However, money is likely to be fungible—firms receiving a subsidy designated for a specific purpose have substantial opportunity to reallocate the expenditure of the firm's own funds in order to pursue the firm's own objectives. These could differ from the government's objectives.[8] Recognizing this, in our empirical analysis, we will run regressions using total subsidies as well

[7] Unfortunately, there is relatively little standardization or consistency in the textual description of the purposes of subsidies received, making it difficult, at least so far, to group subsidies into consistent categories, based on their objectives, across firms and years.

[8] The government's objectives may also not be clear—different levels of government could pursue different, conflicting objectives (a frequent occurrence in China's political system). Subsidies in China are provided by both the central government and local governments. In fact, our data suggests the subsidy providers involve all hierarchical levels of the Chinese governments, including central, provincial, prefecture, county, township and even village governments.

as regressions using specific subsidy types, and see how these subsidies covary with key characteristics and outcomes of the firm, especially productivity.

2.2. Industrial Policy and Productivity

The literature on subsidies and industrial policy goes back decades and includes hundreds, if not thousands, of papers. A full review of this literature—even of the most relevant papers—lies beyond the scope of the current paper. This stream of research remains an active one, as evidenced by the small number of recent contributions highlighted in this section. Many studies find that properly targeted subsidies can raise the productivity of small firms, at least to a limited degree (David et al., 2019; Girma, Görg, & Strobl, 2007; Rotemberg, 2019). This may be a reasonable outcome if factor markets are imperfect and small firms face special challenges accessing capital, specialized labor, or other resources. However, other studies find no evidence of a positive effect on firm productivity (e.g., Koski and Pajarinen 2015), even when the programs in question seem to be well targeted.

Subsidies may be easiest to justify when they are employed to correct a market failure, and the well-documented tendency for profit-maximizing firms to underinvest in R&D in the presence of spillovers is one such failure (Arrow, 1962). Existing work suggests that subsidies can lead to greater levels of R&D spending and innovative output, especially when targeted toward smaller, younger firms (e. g., Howell 2017). A number of recent papers have examined the impact of R&D related government subsidies in China on firm innovation and performance (e.g., Fang et al., 2018; Guo, Guo, and Jiang, 2018, 2016; Wang, Li, and Furman, 2017; Hu, 2001). Like many of the papers cited above, this literature tends to focus on younger, smaller enterprises rather than the more mature listed firms that are the focus of our analysis. The existing findings in this literature have been mixed, with research based on different data sources and methods pointing to different conclusions. For example, Guo, Guo, and Jiang (2016) use data for industrial firms and propensity score matching methods to investigate the impact of China's Innovation Fund for Small and Medium Technology-based Firms (Innofund), and find a positive effect on patenting, new products sales, and exports. Using the same data and similar methods, these authors found that the Innofund subsidies tend to support more productive firms and contribute to the receiving firms' *ex post* productivity improvements (Guo, Guo, and Jiang, 2018). However, using Innofund internal administrative data and a regression discontinuity design, Wang, Li, and Furman (2017) find that receiving Innofund grants does *not* boost firm survival, patenting, or venture funding.[9]

Other recent studies have tended to cast Chinese industrial policy in a negative light. One of the most ambitious recent evaluations of Chinese industrial policy and related subsidies can be found in the work of Kalouptsidi (2018). Using a sophisticated structural model and detailed information on the global shipping industry, Kalouptsidi *infers* the magnitude of subsidies by observing the behavior of subsidized Chinese shipbuilding firms, some of which have become quite large. Barwick, Kalouptsidi, and Zahur (2019) build on this work, concluding that subsidies yielded large increases in output and global market share, but little increase in long term profits, innovation, or positive spillovers to other Chinese industries. Welfare analysis suggests the costs of these interventions outweigh the benefits. Barwick et al., (forthcoming) and Bai et al. (2020) examine Chinese industrial policy in the auto industry—now the world's largest—finding evidence that government intervention generated significant market distortions. Chen et al., (2021) study China's InnoCom program, which rewards a tax cut to firms with R&D

[9] Many Western critics of Chinese investment policy have considered requirements placed on foreign firms in some industries to serve the Chinese market through equity joint ventures as a kind of implicit subsidy, reducing the cost paid by the Chinese partner for access to advanced technology (Jiang et al., 2018). Howell (2018) finds that this policy backfired in the auto sector.

investments above a certain threshold. They find that firms relabeling expenses as R&D accounts for a substantial fraction of reported R&D, and this kind of relabeling may lead to misallocation of R&D toward firms with less innovative projects. Cao et al. (2022) develop a Schumpeterian growth model and decomposes quantity-based innovation subsidies' impact on growth and welfare into quantity and quality channels. The model-based quantitative analysis shows that quantity-based subsidies in China both suppress the country's TFP growth rate and reduce the aggregate welfare. An OECD (2019) study of the global aluminum industry also came to the conclusion that massive Chinese government subsidies were distorting the market inside and outside of China.

2.3 Earlier Lessons from Japanese Industrial Policy

Today's debate on Chinese industrial policy may remind older readers of the earlier discussion on Japanese industrial policy. In the 1980s and 1990s, an extensive and contentious literature on Japanese industrial policy drew significant attention as U.S.-Japan trade frictions were pushing the U.S. (and other Western nations) to adopt protectionist policies (Destler, 2005). Drawing upon qualitative methods and largely anecdotal evidence, a group of noneconomists, business experts, and policymakers argued that Japan's rapid recovery and robust growth after WWII could be explained by skillful industrial policy (Johnson, 1982; Prestowitz, 1988; Vogel, 1979) .[10] Japan's "government-led" economic model came to be viewed as a threat to U.S. prosperity by some participants in these debates. By the end of the 1980s, some policy makers and influential experts were calling for a policy of "containing Japan," lest its unbalanced growth undermine the economy of the United States (Fallows, 1989).

[10] As the success of other rapidly growing East Asian nations drew Western attention, a broader group of scholars began to make the case that these East Asian nations had collectively created a new system of state-led development that was simply superior to America's more market-led approach to economic policy (Amsden, 1988; Wade, 1990).

Economists and more empirically minded social scientists in other disciplines viewed the claims of industrial policy efficacy with skepticism and suggested that Japan's intervention in its economy tended to favor declining industries rather than growing ones (Calder, 1988; Saxonhouse, 1983).[11] Eventually, the skeptics were able to bolster their claims with hard data demonstrating that the Japanese government had offered some degree of economic support to nearly all sectors, but that the preponderance of support had *not* gone to the sectors or firms with the fastest productivity growth. An important turning point in this debate came in the form of a careful econometric deconstruction of the notion that industrial policy drove Japan's economic miracle published by Richard Beason and David Weinstein in the mid-1990s. This empirical analysis at the industry level found no relationship between productivity growth and the alleged instruments of industrial policy (Beason and Weinstein, 1996). As it turned out, the policy efforts to promote rising sectors championed by some elements of Japan's bureaucracy were undermined by countervailing efforts to buttress the employment levels and solvency of politically connected but economically weak firms and industries.

Japan's long period of economic outperformance came to an abrupt end in the early 1990s; after two decades of slow growth, few scholars now argue that Japanese industrial policy is a model worthy of emulation (Ito & Hoshi, 2020). Is it possible that, like their Japanese predecessors, the officials guiding Chinese industrial policy have found it hard to resist the political pressure to prop up losers rather than pick winners?

[11] At the same time, the coincidence of rapid Japanese growth together with what appeared to be skillful government intervention inspired a generation of North America trade theorists to construct models of dynamic comparative advantage, in which temporary government policy intervention could permanently alter trade flows (Brander and Spencer, 1983; Krugman, 1990). Nobel laureate Paul Krugman has admitted the influence of the Japanese experience on his theoretical work in that era.

The urgency of this question is heightened by growing evidence of a recent decline in Chinese GDP growth and productivity growth (e.g., Brandt et al. 2020; Bai and Zhang 2017; Chen et al. 2019; Wu 2020; Hu and Yao 2019; Lardy, 2019). Many of these authors see increasing government intervention in China as one reason for this deceleration, although there are certainly other causes.[12] In this paper, we will use our new microdata to examine the correlation between industrial policy support, as evidenced by government subsidies, and firm productivity.[13]

3 Data and Empirical Methods

3.1 Data

We obtain firm-level subsidy, other financial data from the China Securities Markets and Accounting Research Database (CSMAR). Firm ownership information is drawn from the Wind financial database. CSMAR and Wind are analogous to Compustat in the U.S. context. Both databases have been widely used by scholars to study Chinese listed firms. Our sample includes all firms listed on the Shanghai and Shenzhen stock exchanges from 2007 to 2018, but we exclude financial services firms from all of our analyses. Due to the nature of their business, these firms' financial statements are quite different from that of other industries, making it difficult to estimate reasonable production functions if we apply the same approach we use for other sectors.

[12] A recent paper that parallels some of our work finds that innovation subsidies tend to go disproportionately to politically connected firms, and these subsidies do not result in higher quality patents or higher productivity (Cheng, Fan, Hoshi, & Hu, 2019)).

[13] This work is motivated in part by the recent work of Nicholas Lardy (2019). Lardy has long maintained, in the face of growing criticism, that China was continuing to move toward a more market-oriented economic model. In Lardy (2019), however, he marshals a wide range of evidence to support the view that this progress towards a more market-oriented model has not only stopped, but gone into reverse in recent years. However, Lardy's work does not extend to regression analysis of firm-level microdata.

Our study period begins in 2007 because it was the first year in which all Chinese listed firms were required to report government subsides according to the newly revised GAAP in China. Figure 1 shows the direct subsidy distribution of our sample by firm ownership types. The surge in subsidies to state-owned enterprises in 2008 reflects part of the Chinese government's aggressive fiscal response to the beginning of the global financial crisis (Lardy, 2019). As one can see, government subsidies have generally been increasing over the past decade, the bulge in 2008 notwithstanding.

[Insert Figure 1 about Here]

Figure 2 shows the total subsidy received by firms in each industry category during this period, ranked from highest to lowest; Table 1 presents the industry distribution of firms in our analyses of direct subsidies. [14]

[Insert Figure 2 and Table 1 about Here]

Tables 2 shows the summary statistics of key variables used in our empirical analyses. The maximum value for subsidies, which was given to China Petroleum & Chemical Corporation (or Sinopec), the state-owned oil and gas company, in 2008, is quite large. The largest R&D expense was spent by ZTE. Wage is a calculated variable: we divide the lump sum of cash paid to and for employees from the Cash Flow Statement by the total number of employees in each year.[15]

[Insert Table 2 about Here]

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[14] We aggregate the China Securities Regulatory Commission's (CSRC) industry codes into broader industry categories in order to get enough observations for industry-level productivity estimation. The concordance of the CSRC codes and our classifications can be found in Appendix 3 Table A1.

[15] While cash paid to and for employees is the lump sum payment for the whole year, the total number of employees is only reported at the year's end. As such, in some extreme cases, e,g., when filing for bankruptcy, the company may report a small amount in cash paid to and for employees or a small number of employees, resulting in small and large wage numbers that seem to be out of the range of a normal wage. These outliers lie within the 1st percentile or beyond the 99th percentile of observations. In the regressions using wages as a control variable, we run robustness checks by dropping these outliers, and our results remain.

3.2 Subsidy Types

Although we believe subsidy money is likely to be fungible, we are also interested in exploring the heterogeneous effects of different types of subsidies on productivity. We used Google BERT, along with manual validation, to parse the detailed text associated with firms' disclosures of subsidies to categorize subsidies into different types.

As the first step, a subsample of 10,000 subsidy disclosure entries was randomly selected, and then divided into 4 groups of 2,500 entries each. Teams of research assistants carefully read the detailed description of each subsidy disclosure in each of these subsamples and classified them into one of seven categories described below. This human-classified subsample was then used as a base to construct a training dataset for automated classification, using the well-known Google BERT model. A validation testing dataset was randomly selected from the remaining data for AI classification, in order to examine its accuracy. After running Google BERT, the research assistant team judged the accuracy of AI classification and made necessary corrections. Then, the BERT model was run for the second time using corrected data. After three rounds of this iterative process, the statistical accuracy rate of AI for the testing dataset reached more than 88%. Then, the algorithm was applied to the whole dataset. After classifying all the data with the BERT model, a research assistant team manually reviewed all results and made the final round of manual corrections. After these procedures, we group subsidies into seven major categories, including:

1. R&D and innovation subsidies;
2. Industrial and equipment upgrading subsidies;
3. Employment stabilization and promotion subsidies;
4. Environment protection subsidies;

5. General business subsidies;
6. Other subsidies;
7. Unknown;

More detailed information about the subsidy categorization methods and procedures can be found in Appendix 1.

Despite our best efforts, the omissions and ambiguities in the disclosure data posed some significant challenges to our efforts to assign subsidies to these categories. Even though Chinese accounting rules require firms to provide details on the purpose and nature of the subsidies, many do not disclose these details and apparently pay no penalty for these omissions. In other cases, some details were disclosed, but not enough to enable unambiguous assignment of the recorded subsidy to one of the categories listed above.

These disclosure issues may reflect the underlying complexities and ambiguities in Chinese government subsidy programs themselves. Confidential interviews conducted with consultants and firm managers based in three eastern Chinese cities reveal that Chinese firms increasingly rely on specialized government subsidy application agents and brokers to navigate the complicated web of subsidy programs. These agents and brokers are responsible for figuring out their clients' eligibility for various subsidies offered by multiple levels of government and preparing all the paperwork on clients' behalf. If a subsidy application succeeds, the clients usually pay a certain percentage of the subsidy amount as a commission to the broker; if the application fails, the clients either do not need to pay or just a small amount. Given these practices, company managers may themselves have a limited understanding of exactly which subsidy programs their firm is benefitting from or what the original policy goals of those programs were. Instead, firms are relying on consultants to milk the subsidy system, without necessarily altering their real business plans in the ways the local and national government architects of the subsidy programs may have intended.

Identifying the subsidies meant to support R&D and innovation may have an especially interesting impact on measured firm productivity. The disclosures we associate with “R&D and innovation subsidies” contain keywords such as “innovation,” “R&D,” “patent,” “science”, “technology,” and “intellectual property.” Here are some examples: “patent fee subsidy” (专利费补助), “2015 Technology Invention Award” (2015年度技术发明奖), and “Subsidy for the research and development project of high-clean aluminum-titanium-boron alloy for aerospace aluminum”(航空航天铝材用高洁净铝钛硼合金研发项目补助款).

We created a separate category for “industrial and equipment upgrading subsidies” that were less focused on innovation, invention, or new technology and more focused on the acquisition of or investment in more advanced capital goods, machinery, and equipment. These subsidies may also have a positive impact on productivity, especially if competition among capital goods producers prevents the full value of improvements in capital goods from being fully captured in their prices. The disclosures we associate with this category often contain keywords such as “industry,” “equipment,” and “industrial transformation.” Here are some examples: “subsidies for investment projects in key industrial industries in Heilongjiang province” (黑龙江省重点工业产业投资项目补助), “Shenzhen industrial transformation special fund for the integration of industrialization and informationization project” (深圳市产业转型专项资金两化融合项目资产资助), “equipment purchase subsidy for Xinjiang mining industry technological transformation project” (新疆矿业工业技改项目设备购置补助). While we believe the data support the need for these two intellectually distinct categories, we acknowledge that some subsidy disclosures are difficult to uniquely assign to one or the other.

The next category is “employment stabilization and promotion subsidies.” The Chinese government, at all levels, is well known for placing a high value on “social stability” and seeking to avoid unemployment. Disclosures associated with this category often contain keywords such as “employment,” “internship,” and “labor.” Here are some examples: “college student employment internship subsidy” (大学生就业实习补助), “reward for the employers that have arranged the employment of disabled persons in excess of the required proportion in 2011” (2011年度超比例安排残疾人就业单位奖励), “subsidy for the series of activities of the Futian District Labor Bureau to care for migrant workers” (福田区劳动局关爱外来建设者系列活动补贴).

The next category is “environment protection related subsidies.” Disclosures associated with this category contain keywords such as “energy saving,” “environment protection,” “clean energy,” “clean production,” “recycle,” and “emission reduction.” Here are some examples: “Government financial subsidy for energy saving”(政府财政节能补贴), “Renewable energy special subsidy fund”(可再生能源专项补助资金), “Chimney demolish subsidy”(烟筒拆除补助).

The previous four categories include subsidies designed to reward firms, at least in principle, for undertaking particular changes in their business practices such as investing in R&D, using more advanced equipment, or reducing their pollution levels. The next category of subsidies is not directly associated with a change in business practices reflecting some specific policy goal. Instead, this category reflects a mix of subsidies that appear to be supporting the day-to-day operations of the firm. We call this category “general business subsidies.” Disclosures associated with this category contain a wide range of keywords related to the firm's business operations, such as "business," "export," "brand," "tax," "development" and "market." Here are some examples: "special funds for the development of small and medium-sized enterprises" (中小企业发展专项资金), "special subsidy for business promotion"(商务促进专项补助), "funds for market development" (市场开拓资金).

The next category contains subsidy disclosures with meaningful textual descriptions, but ones which do not fit into any of the first five categories. Because the number of observations of these disclosures is relatively small and divided across a number of apparent objectives, we aggregate them into this miscellaneous category, which we refer to as "other subsidies."

Finally, the "unknown" category contains subsidy disclosures with only minimal text descriptions such as "total subsidy amount," "government subsidy," "subsidy," and other brief descriptions that cannot be used for meaningful classification.

Figure 3 shows the subsidy amount distribution by subsidy type from 2007 to 2018. The "Unknown" category accounts for the largest amount of subsidies, and "general business subsidies" accounts for the second largest. The 2008 surges in subsidies are especially notable in these two categories, indicating that during the financial crisis, substantial subsidies were given to firms for either no particular reason or for supporting general business operations.

In our empirical analyses, we mainly focus on the subsidy categories 1-3 and 5 because they are most likely related to productivity and employment. We also want to remind our readers to be cautious about the conclusions that can be drawn from these analyses: they only apply to the subsamples of firms that disclose the nature of their subsidies.

[Insert Figure 3 about Here]

3.2 Estimation Framework for Government Subsidies

To understand how government subsidies can be related to firm productivity in China, we conduct a two-stage analysis: in the first stage, we estimate standard Cobb-Douglas production functions separately by industry, and compute total-factor productivity (TFP) as the residual calculated for each firm in each year. In the second stage, we seek to understand the relationship between government subsidies and firm productivity in China. In some specifications, we also use employment or R&D investments as a dependent variable.

In the first stage, we rely on work by Wooldridge (2009) to estimate the total-factor productivity (TFP) of firms from 2006 to 2018.[16] The correct estimation of total-factor productivity is crucial to this study, because it will be our main dependent variable in the second stage. One major econometric concern in estimating TFP is the potential existence of important demand or productivity shocks that are unobservable to the econometrician but are observed by the managers of the firms in our data set. In this case, firms will respond to these positive or negative shocks by increasing or decreasing their input levels, and there will be a positive correlation between the input variables and the unobservable shocks, leading to biased ordinary least squares (OLS) estimates of the production function coefficients.

Various methods have been proposed to tackle this simultaneity issue. Over the past 25 years, techniques proposed by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP) to address this endogeneity problem have been extensively used in the empirical literature. Wooldridge (2009) proposed a further improvement, showing how the Levinsohn–Petrin (LP) estimator can be obtained in a generalized method of moments (GMM) econometric framework, and that joint estimation of the parameters leads to better inference and more efficient estimation.

[16] We begin our estimation one year before 2007 in order to have valid estimates for lagged productivity which are used in the second stage analysis. This second stage analysis proceeds from the year 2007, when mandatory disclosure of government subsidies is implemented for all listed firms.

Two advantages of using this method include that (1) it overcomes the potential identification issue highlighted by Ackerberg, Caves, and Frazer (2015) in the first stage, and (2) robust standard errors can be easily obtained, accounting for both serial correlation and heteroskedasticity. Therefore, we rely on this method and use the total-factor productivity levels estimated by this method in our second-stage analyses.

As is common in the literature, we compute a firm's total-factor productivity as the residual of the firm-level regression:

$$y_{it} = \alpha + \beta l_{it} + \gamma k_{it} + \delta m_{it} + \varepsilon_{it} \quad (1)$$

Where y_{it} is the logarithm of the sales of firm i during year t, l_{it} is the logarithm of the number of workers of firm i during year t, and k_{it} is the logarithm of the total assets of firm i during year t, and m_{it} is the logarithm of the expenses for material and other inputs of firm i during year t.[17] We separately estimate production functions by industry, so our estimate of TFP effectively captures a firm's deviation from the average TFP level within its industry. We follow GMM method proposed by Wooldridge (2009) using intermediate inputs m_{it} as our proxy variable for unobserved productivity to obtain consistent estimates for coefficients of all input variables. All variables other than labor input are deflated by their appropriate deflators in each year published by China's National Bureau of Statistics.[18]

[17] We use "cash payments for raw materials and services" in the cash flow statements of our sample firms to capture variation in materials and other variable inputs. We follow the lead of other empirical researchers who have estimated production functions with the Chinese micro data in using recorded measures of "total assets of the firm" as our proxy for our sample firms' capital stocks (Giannetti, Liao and Yu, 2015). Other measures of the firms' capital stocks available in the CSMAR data suffer from well-documented distortions, and the absence of an accurate investment series prevents us from building our own capital stock measures using the standard perpetual inventory method. To the extent that we measure variations in capital services with error, this could lead to a systematic downward bias in the capital coefficient.

[18] Sales revenue (y_{ijt}) is deflated by the producer price index by industry, capital value (k_{ijt}) is deflated by the official capital price index, and intermediate material input (m_{ijt}) is deflated by the industrial producer input price index in each year. Note that we measure revenue, not physical output. To the degree that Chinese firms exercise market power, our measures of productivity will be contaminated by the ability of some firms to price above

In our second stage analysis, we attempt to answer the following three questions. First, *ex ante*, which firms are likely to get more subsidies, firms with high or low productivity? To answer this question, we regress total subsidies received by listed firms in each year on lagged total-factor productivity estimates and control for firm characteristics that might be important determinants of subsidy allocation. We use the Pseudo-Poisson Maximum Likelihood (PPML) model to contend with the large number of zero realizations in the dependent variable.[19] When we take the natural log of the values of our independent variables, we can interpret the coefficients generated by the PPML model as elasticities. The full regression specification is written below:

$$\begin{aligned} Subsidy_{it} = \alpha_i + \gamma_t + \beta_1 TFP_{i(t-1)} + \beta_2 Sales_{i(t-1)} + \beta_3 Assets_{i(t-1)} \\ + \beta_4 Profit_{i(t-1)} + \beta_5 Employment_{i(t-1)} + \beta_6 IPO_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where $Subsidy_{it}$ is the total subsidy or categorized subsidy [20] received by firm i during year t, α_i is a firm fixed effect, γ_t is a year fixed effect, $TFP_{i(t-1)}$ is the total-factor productivity calculated by Wooldridge GMM method in Stage 1 for firm i during year $t-1$, and the other variables are sales revenue, total assets, net profit, number of workers hired in year $t-1$, and IPO status in year t. We take natural logs of all independent variables except for the IPO status indicator. IPO status is a dummy variable indicating whether the firm completed an initial public offering status in year t. Firms going through the IPO process might get an additional subsidy from the government in that year, so we can control for this extra "IPO bonus." All regressors are lagged one period to ameliorate simultaneity bias. To explore how the relationship between

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marginal cost; given our data constraints (in particular, the absence of firm-specific price deflators) there is no effective way to control for this in our econometric estimation.

[19] The paper by Bellégo and Pape (2019) introduced the method in detail, and we use the package ppmlhdfe in Stata to deal with high-dimensional fixed effects.

[20] Subsidy amounts are deflated by the Consumer Price Index.

subsidy and TFP varies across firm types, we rerun these regressions separately for each of the major five firm ownership types: central state-owned enterprises, local state-owned enterprises, private enterprises, foreign-funded enterprises, and enterprises whose ownership type cannot be conclusively determined from public disclosures, and compare results across groups.[21]

Next, does receipt of a subsidy help improve the receiving firm's productivity *ex post*? Alternatively, do subsidies increase firm R&D investments or employment? To answer these questions, we regress total-factor productivity, R&D expenditure and employment on subsidies received by the firm in the most recent three years, controlling for firm and year fixed effects. When the dependent variable is R&D expenditure, we use the Pseudo-Poisson Maximum Likelihood (PPML) model again to contend with the large number of zero realizations in measured R&D expenditure. When the dependent variable is employment, measured as logarithm of the number of workers, we use the Arellano–Bond approach to address potential endogeneity issues since a lagged dependent variable is included in the set of regressors, and we follow Arellano and Bond (1991) to control for other important variables affecting employment. When the dependent variable is productivity (firm-level TFP), we use OLS regressions and a specification similar to that used in the R&D expenditure model.

The model for productivity is as follows:

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 S_{it} + \beta_2 S_{i(t-1)} + \beta_3 S_{i(t-2)} + \delta X_{i(t-1)} + \varepsilon_{ijt} \tag{3}$$

where Y_{it} are the total-factor productivity residuals calculated using the Wooldridge GMM method in Stage 1 for firm i during year t, α_i is a firm fixed effect, γ_t is a year fixed effect, S_{it}

[21] Wind determines the company's ownership type according to the nature of the controlling shareholder(s) disclosed by the company. Appendix 2 describes the definitions of the five firm ownership types. Under Chinese law, publicly traded companies are required to disclose the identity of controlling shareholders. However, there are a small number of companies whose equity ownership is so dispersed that no controlling shareholders are identified. These publicly traded companies can therefore not be conclusively assigned to any of the other ownership categories. We refer to these as "ambiguous ownership companies."

is the logarithm of the subsidy received by firm i during year t, and $S_{i(t-1)}$ and $S_{i(t-2)}$ are logged subsidies received in the previous two years. It is possible that not all subsidies have an effect on productivity. Taking this into consideration, we also run regressions using R&D and innovation subsidies as well as industrial and equipment upgrading subsidies. $X_{i(t-1)}$ is a vector of additional control variables for firm i during year $t-1$. We use a similar specification to examine the impact of subsidies on R&D expenditure and employment levels (logarithm of the number of workers). The alternative specification focused on employment was inspired by an extensive literature suggesting the emphasis placed by the government on securing social stability through the provision of jobs to Chinese citizens.[22] Again, it is possible that not all subsidies have an effect on employment. As such, we also run regressions using solely employment stabilization and promotion subsidies.

4 Results

4.3 First Stage Results

In the first stage, we estimate the total-factor productivity (TFP) of firms in each year from 2007 to 2018 at industry level, so our estimate of TFP captures a firm's deviation from the TFP within its industry. Table 3 shows the industry-level production functions for all industries listed in Table 1. The TFP values obtained from these regressions are used in our second stage estimation. As robustness checks, we also present the pooled regression results for both OLS and Wooldridge GMM methods (Appendix 3 Table A2). The coefficients of OLS and

[22] Here are two examples of policies to secure social stability through employment subsidy in China:
Ministry of Education of the People's Republic of China, http://www.moe.gov.cn/jyb_xwfb/s5147/202006/t20200612_46532224.html, accessed June 6, 2021;
The State Council of the People's Republic of China, http://www.gov.cn/zhengce/content/2019-12/24/content_5463595.htm, accessed June 6, 2021.

Wooldridge estimates are quite similar, with the fixed-effects model (column 3) generating slightly different results than other methods.

[Insert Table 3 about Here]

Inspection of the estimated coefficients reveals labor and capital coefficients that are lower than many readers might expect. However, other researchers estimating similar production functions using Chinese data (e.g., Yu, 2015) have obtained similar results. To understand these outcomes, recall that our output measure is sales, not value-added, and that we are directly measuring material inputs (and purchased services) other than capital and labor. For many firms, a substantial fraction of the value of sales consists of these purchased inputs. The direct measurement of purchased inputs other than capital and labor will naturally tend to drive the measured magnitudes of these coefficients down. These issues are not unique to China; inclusion of materials in production function analysis tends to lower the regression coefficients associated with labor and capital.

The political sensitivities surrounding layoffs and operating cost reduction considerations have led many listed Chinese firms in labor-intensive industries to rely quite heavily on so-called “labor dispatch” to provide labor. “Labor dispatch” is an arrangement under which an employee is hired by an employment agent (i.e., nominal employer) and then dispatched to work for another firm (i.e., actual employer). This arrangement allows the listed purchasing firm to reduce labor input, when necessary, by simply purchasing less from employment agents. Smaller, unlisted employment agents may be forced to lay off workers, but these entities are less visible to the political authorities than the listed firms that are in the public eye. As such, much of the variation in labor actually deployed in a listed firm’s projects could wind up in the “purchased materials and services” variable rather that our measure of firm full-time employees (Xu, 2009).

These practices are likely to be common to listed firms in certain industries, which means that our approach of estimating production functions separately by industry may enhance our ability to estimate firm productivity with reasonable accuracy.

4.4 Second Stage Results with Direct Subsidies

In Table 4, we regressed total subsidies received on a broad range of firm characteristics, including measures of firm productivity, size, and profitability. The chief guiding question behind this set of regressions is what sort of firm characteristics are associated with the receipt of subsidies. We incorporate firm fixed effects to control for time-invariant, unmeasured characteristics not captured by our existing firm-level controls, and we include year fixed effects to control for macro fluctuations in subsidies associated with countercyclical fiscal policy efforts. In general, we find a negative correlation between subsidies and lagged TFP that is statistically significant at the 5% level in most specifications. There appears to be a robust positive correlation between subsidies and firm size, as measured by the firm's total assets. The relationship between subsidies and net profit is also positive and significant at the 5% significance level. These results suggest that, overall, subsidies are given to larger and more profitable, but less productive firms.

[Insert Table 4 about Here]

In Table 5, we regressed different types of subsidies on firm characteristics, using the specification of Column 4 in Table 4. Although we find heterogenous effects of lagged productivity on different types of subsidies received, there is no statistical evidence that subsidies have been given to more productive firms. R&D and innovation subsides and industrial and equipment upgrading subsidies appear to be positively associated with lagged total assets, lagged net profit, and lagged employment, but the coefficient of lagged TFP is not significant.

Employment stabilization and promotion subsides appear to be positively associated with lagged employment, but the coefficient of lagged TFP is not significant. General business subsidies appear to be positively associated with lagged total assets, lagged net profit, and lagged employment, and negatively associated with TFP, all effects significant at the 5% level. Notably, our categorized subsidies do not contain zero values—we can only classify subsidies where firms reveal enough information for classification. As robustness checks, we repeat these categorized subsidy regressions by adding zeros to “no subsidy” firm-year-type pairs. The results from this practice are present in Appendix 3 Table A3 (corresponding to Table 5), Table A4 (corresponding to Table 7), Table A5 (corresponding to Table 9), and Table A6 (corresponding to Table 11). As we can see from these regressions, our main results hold. There is no statistical evidence that subsidies have been given to more productive firms and have caused ex-post productivity increases.

[Insert Table 5 about Here]

We experimented with running regressions separately by ownership type,[23] the results of which are presented in Appendix 3 Table A7. We find there is a negative correlation between subsidy allocation and firm productivity for foreign-funded firms, but no statistically significant correlation for other types of firms. We also find profit and employment level to be positively correlated with the cash subsidy received by private firms, but not other types of firms, suggesting that private firms are being rewarded for improving profitability and hiring more workers. This conjecture is further confirmed by a positive relationship between employment stabilization and promotion subsidies and lagged employment for private firms, as seen in Appendix 3 Table A8.

[23] In results not shown, we also experimented with the inclusion of ownership type dummy variables, finding no statistically significant effects once we control for other firm characteristics.

In the next round of regression analyses, we ask whether receiving a subsidy is correlated with subsequent growth in recorded TFP, R&D expenditure, or employment. We first run regressions at a total subsidy level, and then across different subsidy types. Table 6 shows the regressions of TFP on total subsidies. We find that total subsidies appear to have a *negative* and statistically significant impact on TFP, albeit a very modest one in terms of economic size. In Table 7, we regress TFP on R&D and innovation subsidies, industrial and equipment upgrading subsidies, employment stabilization and promotion subsides, and general business subsides respectively using the full model of Column 4 in Table 6. Across all specifications, the coefficients of subsidy variables are not statistically significant at the 5% level. To the extent that we can draw conclusions from these results, it appears that even subsidies that appear to be closely related to productivity, i.e., R&D and innovation subsidies and industrial and equipment upgrading subsidies, do not contribute to productivity growth.

[Insert Table 6 and 7 about Here]

Using R&D expense as an alternative indicator of innovation input, in Table 8, we regress R&D expense on total subsidies and find that 2-year lagged direct subsidies appear to have a very modest but positive and statistically significant impact on subsequent R&D spending. In Table 9, we regress R&D expense on different types of subsides using the full model of Column 4 in Table 8. Results presented in Column 1 suggest that R&D and innovation subsidies do not seem to have an effect on firms' R&D expense, which is quite surprising. Column 2 and 4 show that current industrial and equipment upgrading subsidies and current general business subsides appear to have a positive effect on firms' R&D expense, an effect that is significant at the 1% and 5% levels, respectively. Column 3 shows that 1-year lagged employment stabilization and promotion subsides seem to have a negative impact on firms' R&D expense, which is significant at the 5% level.

[Insert Table 8 and 9 about Here]

In Table 10, we regress employment on total subsidies. Current direct subsidies appear to have a positive impact on current employment levels while 1-year lagged subsidies seem to have a negative impact, potentially indicating that firms might be strategically manipulating employment numbers to get subsidies—temporarily increasing hiring during the period of receiving subsidies and then cutting it back during the next period. In Table 11, we repeat the analyses in Table 10 but use employment stabilization and promotion subsidies as a depend variable. While 1-year lagged employment stabilization and promotion related subsidies are no longer significant this time, current employment stabilization and promotion related subsidies' positive effect remains and significant at 5% level. That said, these employment effects are also fairly modest in size.

[Insert Table 10 and 11 about Here]

Taken together, Tables 6–Table 11 do not seem to support the view that direct subsidies, as measured at an aggregated level or across different types, are raising the productivity levels of Chinese firms. They provide some support for the view that subsidies may be boosting temporary employment, but this may come at the expense of productivity, inducing firms to hold on to more than the efficient level of employees and inhibiting, rather than enhancing, the flow of human and financial resources to the most efficient enterprises.

5 Conclusion

In this paper, we estimate total-factor productivity for listed firms in China and we investigate the relationship between the allocation of direct government subsidies and firm productivity in China, using information on total firm subsidies and disaggregating this total into different subsidy types. We find little evidence that the Chinese government picks winners—if anything, the evidence suggests that direct subsidies tend to flow to less productive firms rather than more productive firms. In addition, we find that, overall, the receipt of direct government subsidies is negatively correlated with subsequent firm productivity growth over the course of our data window, 2007 to 2018. Even subsidies given out by government in the name of R&D and innovation promotion or industrial and equipment upgrading do not show any statistically significant evidence of positive effects on subsequent firm productivity growth.

The paper contributes to a growing literature exploring the effect of government subsidies on firm productivity, and relates to a strand of literature examining the effect of R&D related government subsidies in China on firm innovation and performance. The study is limited in the sense that it only covers a very narrow aspect of government support to corporate firms—direct subsidies—and it only measures that support for listed enterprises.

That said, based on the results of this study, we find little evidence that the allocation of subsidies has improved the productivity of Chinese firms. There is more robust evidence that subsidies support slightly higher levels of employment, at least temporarily. This is consistent with the view that political considerations might outweigh efficiency considerations in the allocation of direct subsidies. In the longer run, this approach is unlikely to promote the kind of significant productivity improvements the Chinese economy will need to maintain growth in the face of an aging population, a declining workforce, and mounting evidence of diminishing returns to capital investment.

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Figure 1. Direct Subsidy Distribution by Firm Ownership Over Time

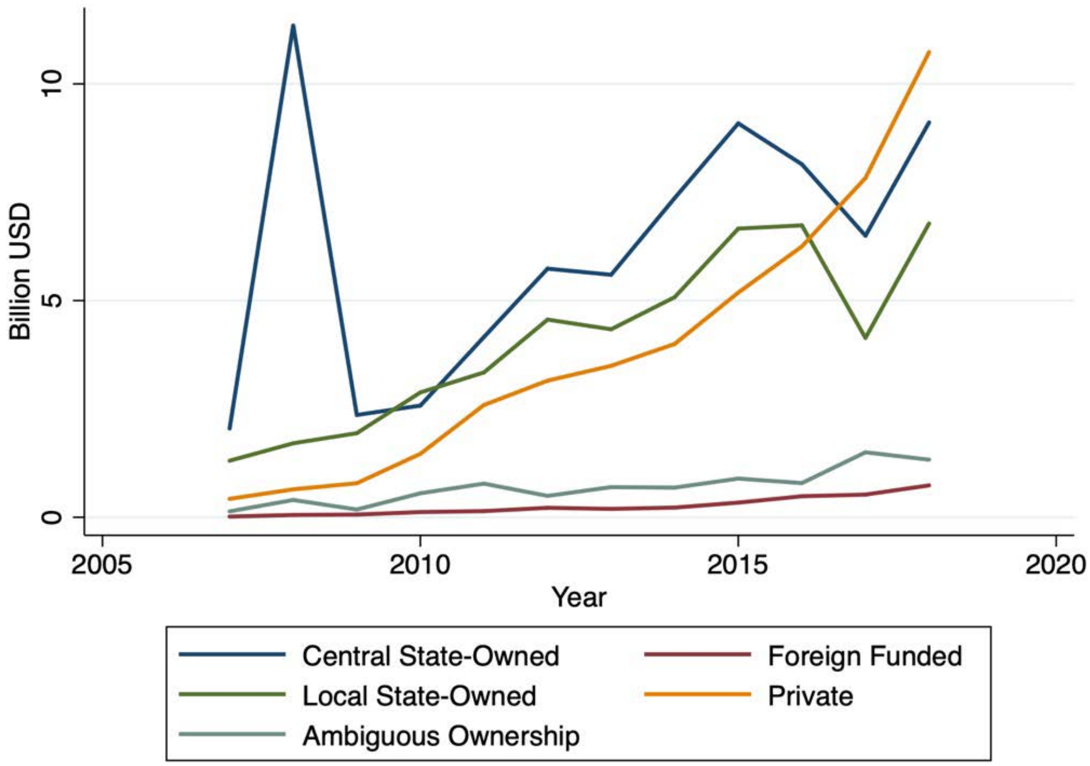

Figure 2. Total (Direct) Subsidies Received by Industries from 2007 to 2018

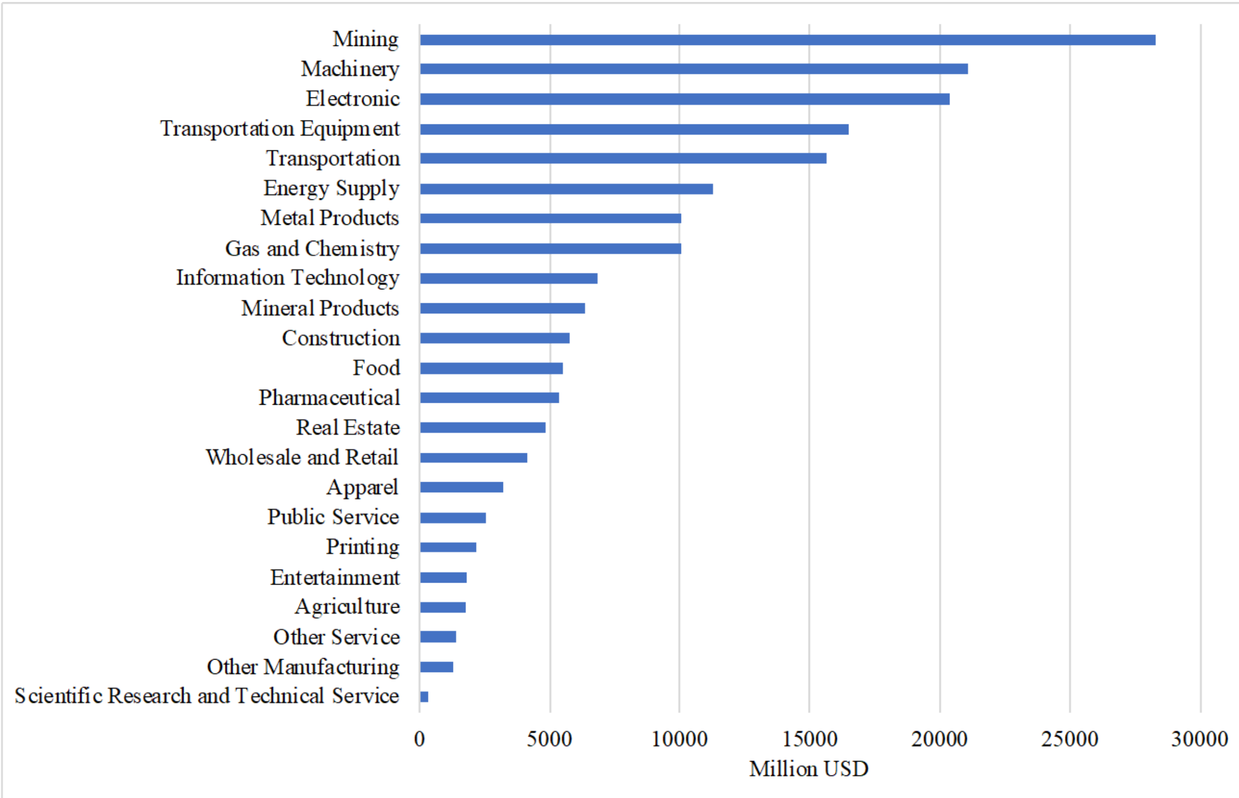

Figure 3. Direct Subsidy Distribution by Types Over Time

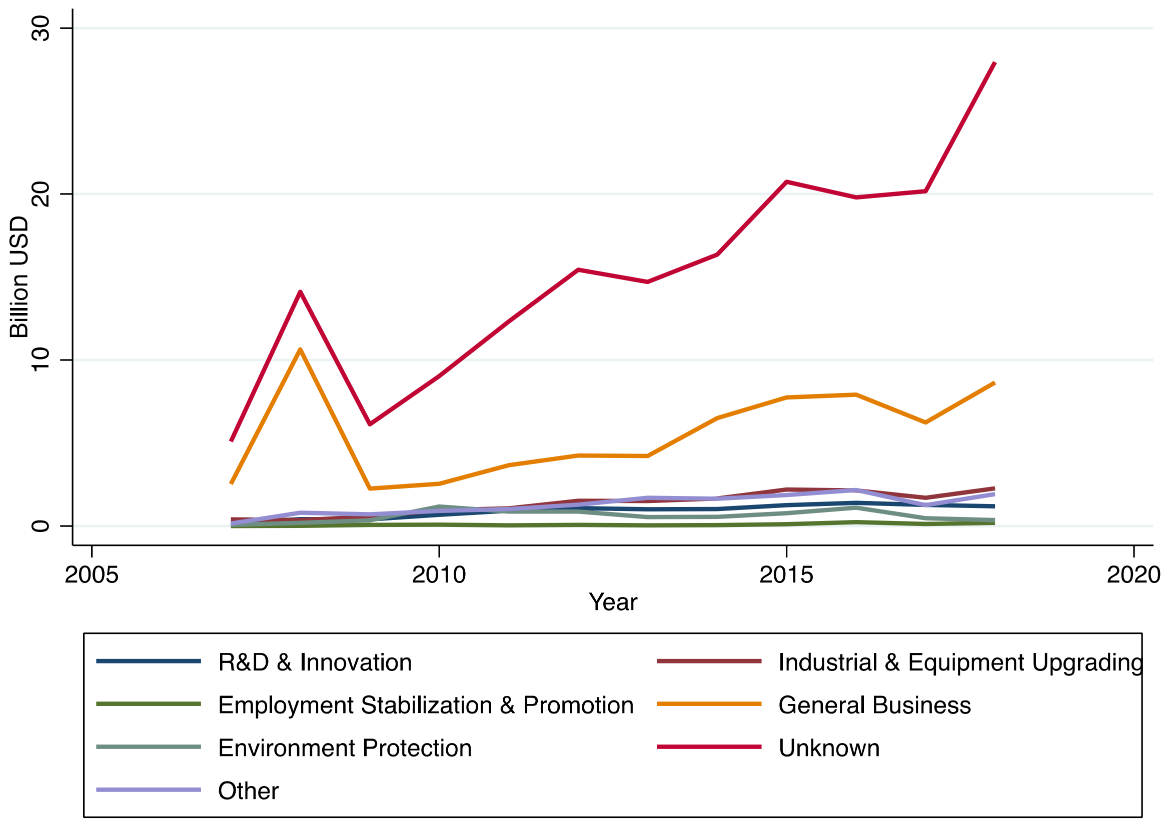

Table 1. Industry Distribution of Sample Firms in Empirical Analyses

Industry Type	Freq.	Percent
Agriculture	531	1.71
Apparel	977	3.14
Construction	801	2.58
Electronic	3,033	9.76
Energy supply	922	2.97
Entertainment	328	1.06
Food	1,222	3.93
Gas and chemistry	3,271	10.52
Information Technology	1,761	5.66
Machinery	4,553	14.64
Metal products	1,572	5.06
Mineral products	916	2.95
Mining	746	2.4
Other manufacturing	485	1.56
Other service	718	2.31
Pharmaceutical	1,873	6.02
Printing	563	1.81
Public service	499	1.61
Real estate	1,895	6.1
Scientific research and technical service	219	0.7
Transportation	1,053	3.39
Transportation equipment	1,429	4.6
Wholesale and retail	1,723	5.54
Total	31,098	100

Note: Sample data from 2006 to 2018, with subsidy data only available from 2007 to 2018.

Table 2. Summary Statistics for Direct Subsidy Analyses

Variable	Obs	Mean	Std.Dev.	Min	Max
Log Subsidy (Yuan)	29,654	14.69	4.391	0	24.54
Log Employment (Person)	30,993	7.496	1.387	0	13.22
Log Sales Revenue (Yuan)	31,033	21.08	1.577	8.928	28.67
Log Total Assets (Yuan)	31,085	21.69	1.360	10.72	28.31
Log Material Input (Yuan)	30,981	20.54	1.753	6.454	28.42
Log Net Profit (Yuan)	27,907	18.36	1.580	10.07	25.64
Age	30,585	16.15	5.762	0	63
IPO indicator	31,090	0.0712	0.257	0	1
Log R&D Expense (Yuan)	31,090	10.50	8.705	0	25.03
Log R&D Persons (Person)	31,090	1.860	2.679	0	10.65
Log Wage (Yuan/person)	30,989	11.33	0.704	4.347	17.20

Note: For subsidies, 94.3% of observations have positive reported subsidies from 2007 to 2018, and we assume zero subsidy for the 5.7% of observations that did not report subsidy in the original financial reports, and, in order to take logs, we add 1 to all observations of subsidies, and then take the logarithm. We only use logged subsidies in models where subsidy is an independent variable. We treat R&D expense and persons with the same method.

Table 3. Wooldridge GMM Estimation of Production Functions at Industry Level

Industry	Agriculture	Apparel	Construction	Electronic	Energy Supply	Entertainment
lnl	0.107***	0.118***	0.152***	0.180***	0.0467***	0.217***
	(0.0152)	(0.0129)	(0.0125)	(0.00769)	(0.00858)	(0.0127)
lnk	0.163**	0.281***	0.672***	0.335***	0.333***	0.350***
	(0.0723)	(0.0372)	(0.0471)	(0.0209)	(0.0367)	(0.0470)
lnm	0.486***	0.559***	0.533***	0.482***	0.487***	0.457***
	(0.0404)	(0.0277)	(0.0302)	(0.0161)	(0.0274)	(0.0417)
Observations	459	833	671	2,537	808	265
No. of Groups	64	132	124	466	110	64

Industry	Food	Gas and Chemistry	Information Technology	Machinery	Metal Products	Mineral Products
lnl	0.146***	0.0528***	0.288***	0.185***	0.113***	0.204***
	(0.0120)	(0.00839)	(0.00790)	(0.00578)	(0.00935)	(0.0143)
lnk	0.368***	0.320***	0.351***	0.356***	0.258***	0.399***
	(0.0470)	(0.0229)	(0.0255)	(0.0173)	(0.0280)	(0.0369)
lnm	0.742***	0.592***	0.387***	0.569***	0.585***	0.507***
	(0.0274)	(0.0157)	(0.0169)	(0.0125)	(0.0174)	(0.0238)
Observations	1,062	2,811	1,417	3,879	1,363	792
No. of Groups	153	442	311	649	201	118

Industry	Mining	Other Manufacturing	Other Service	Pharmaceutical	Printing	Public Service
lnl	0.212***	0.172***	0.135***	0.291***	0.0316	0.236***
	(0.0104)	(0.0126)	(0.0101)	(0.0119)	(0.0219)	(0.0151)
lnk	0.381***	0.0909**	0.309***	0.496***	0.0837	0.255***
	(0.0471)	(0.0404)	(0.0474)	(0.0409)	(0.0592)	(0.0891)
lnm	0.454***	0.821***	0.444***	0.433***	0.637***	0.604***
	(0.0255)	(0.0343)	(0.0309)	(0.0214)	(0.0319)	(0.0480)
Observations	646	380	571	1,605	485	400
No. of Groups	95	96	126	249	73	97

Industry	Real Estate	Scientific Research and Technical Service	Transportation	Transportation Equipment	Wholesale and Retail
lnl	0.175***	0.289***	0.156***	0.145***	0.0400**

	(0.0107)	(0.0185)	(0.00754)	(0.0124)	(0.0159)
lnk	0.122**	0.155	0.271***	0.253***	0.123*
	(0.0540)	(0.0953)	(0.0372)	(0.0369)	(0.0721)
lnm	0.380***	0.473***	0.401***	0.663***	0.708***
	(0.0225)	(0.0512)	(0.0202)	(0.0282)	(0.0514)
Observations	1,600	162	924	1,213	1,487
No. of Groups	256	55	126	202	230

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Determinants of Firm-Level Total Subsidies, Including Firm Fixed Effects

VARIABLES	(1) Total Subsidy	(2) Total Subsidy	(3) Total Subsidy	(4) Total Subsidy
Lagged TFP	-0.0215	-0.0408**	-0.0518***	-0.0457***
	(0.0261)	(0.0179)	(0.0160)	(0.0155)
Lagged Sales Revenue		-0.114	-0.193*	-0.225**
		(0.118)	(0.105)	(0.113)
Lagged Total Assets		0.732***	0.834***	0.788***
		(0.0689)	(0.182)	(0.164)
Lagged Net Profit			0.0948***	0.0933***
			(0.0273)	(0.0274)
Lagged Employment				0.108
				(0.0720)
IPO				0.160
				(0.102)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	26,869	26,869	24,218	24,218

Note: Column (1)–(4) are Pseudo-Poisson Maximum Likelihood (PPML) regressions with firm fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All independent variables are in logged values except for IPO indicator. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Determinants of Firm-Level Subsidies by Types, Including Firm Fixed Effects

VARIABLES	(1) R&D & Innovation Subsidy	(2) Industrial and Equipment Upgrading Subsidy	(3) Employment Stabilization & Promotion Subsidy	(4) General Business Subsidy
Lagged TFP	-0.0275	-0.0171	-0.00847	-0.0339**
	(0.0217)	(0.0175)	(0.0261)	(0.0163)
Lagged Sales Revenue	0.109	0.118*	0.152	0.196***
	(0.0721)	(0.0625)	(0.119)	(0.0569)
Lagged Total Assets	0.221***	0.261***	0.222*	0.364***
	(0.0802)	(0.0659)	(0.116)	(0.0616)
Lagged Net Profit	0.0542**	0.0669***	-0.0471	0.0885***
	(0.0240)	(0.0202)	(0.0343)	(0.0192)
Lagged Employment	0.184***	0.112**	0.259***	0.103**
	(0.0496)	(0.0471)	(0.0813)	(0.0431)
IPO	-0.0488	0.0465	0.0433	0.630***
	(0.124)	(0.107)	(0.168)	(0.103)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	12,853	13,475	5,814	18,118
R-squared	0.567	0.568	0.670	0.597

Note: Column (1)–(4) are OLS regressions with firm fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All variables are in logged values except for IPO indicator. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Impact of Total Subsidies on Firm-Level TFP

VARIABLES	(1) TFP	(2) TFP	(3) TFP	(4) TFP
Current Total Subsidy	-0.0135***			-0.0112**
	(0.00508)			(0.00494)
1-Year Lagged Total Subsidy		-0.0141***		-0.0118***
		(0.00493)		(0.00439)
2-Year Lagged Total Subsidy			-0.0109**	-0.00776*
			(0.00503)	(0.00454)
Lagged Total Assets	0.389***	0.363***	0.355***	0.377***
	(0.0661)	(0.0658)	(0.0676)	(0.0681)
Lagged Employment	-0.271***	-0.230***	-0.220***	-0.209***
	(0.0558)	(0.0569)	(0.0586)	(0.0578)
Lagged R&D Expense				-0.00463
				(0.00308)
Lagged R&D Persons				-0.000717
				(0.00968)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	26,894	25,492	22,130	22,130
R-squared	0.849	0.861	0.875	0.876

Note: All columns are OLS regressions including firm and year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All variables are in logged values. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7. Impact of Subsidies by Types on Firm-Level TFP

VARIABLES	(1) TFP	(2) TFP	(3) TFP	(4) TFP
Current Innovation Subsidy	-0.00628			
	(0.00796)			
1-Year Lagged Innovation Subsidy	-0.0131*			
	(0.00733)			
2-Year Lagged Innovation Subsidy	-0.00680			
	(0.00783)			
Current Upgrade Subsidy		-0.00583		
		(0.00799)		
1-Year Lagged Upgrade Subsidy		-0.00667		
		(0.00871)		
2-Year Lagged Upgrade Subsidy		-0.0130		
		(0.00926)		
Current Employment Subsidy			-0.0216	
			(0.0164)	
1-Year Lagged Employment Subsidy			-0.0199	
			(0.0163)	
2-Year Lagged Employment Subsidy			-0.0215*	
			(0.0114)	
Current Business Subsidy				-0.0157*
				(0.00942)
1-Year Lagged Business Subsidy				0.000468
				(0.00858)
2-Year Lagged Business Subsidy				-0.00759
				(0.00924)
Lagged Total Assets	0.155	0.257**	0.204	0.232***
	(0.104)	(0.113)	(0.184)	(0.0892)
Lagged Employment	0.0211	-0.0475	-0.233	-0.0719
	(0.0797)	(0.0833)	(0.165)	(0.0721)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	8,596	8,579	1,731	13,166
R-squared	0.923	0.925	0.968	0.919

Note: All columns are OLS regressions including firm and year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All variables are in logged values. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Impact of Subsidies on Firm-Level R&D Expenditure

VARIABLES	(1) R&D Expense	(2) R&D Expense	(3) R&D Expense	(4) R&D Expense
Current Total Subsidy	-0.0152*			-0.00677
	(0.00902)			(0.00500)
1-Year Lagged Total Subsidy		-0.0198*		-0.0296**
		(0.0108)		(0.0151)
2-Year Lagged Total Subsidy			0.0524***	0.0563***
			(0.0143)	(0.0170)
Lagged Total Assets	0.485***	0.496***	0.408***	0.433***
	(0.0899)	(0.101)	(0.0812)	(0.0820)
Lagged Employment	0.0892	0.111**	0.0960*	0.110**
	(0.0590)	(0.0508)	(0.0512)	(0.0499)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	23,427	22,292	19,214	19,214

Note: All columns are Pseudo-Poisson Maximum Likelihood (PPML) regressions, including firm and year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All independent variables are in logged values. *** p<0.01, ** p<0.05, * p<0.1.

Table 9. Impact of Subsidies by Types on Firm-Level R&D Expenditure

VARIABLES	(1) R&D Expense	(2) R&D Expense	(3) R&D Expense	(4) R&D Expense
Current Innovation Subsidy	-0.000184			
	(0.0127)			
1-Year Lagged Innovation Subsidy	-0.00566			
	(0.0120)			
2-Year Lagged Innovation Subsidy	-0.0137			
	(0.00962)			
Current Upgrade Subsidy		0.0323***		
		(0.00953)		
1-Year Lagged Upgrade Subsidy		0.00629		
		(0.0122)		
2-Year Lagged Upgrade Subsidy		0.0247		
		(0.0154)		
Current Employment Subsidy			0.0127	
			(0.0341)	
1-Year Lagged Employment Subsidy			-0.0628**	
			(0.0248)	
2-Year Lagged Employment Subsidy			-0.0184	
			(0.0165)	
Current Business Subsidy				0.0189**
				(0.00916)
1-Year Lagged Business Subsidy				0.00778
				(0.00748)
2-Year Lagged Business Subsidy				-0.00678
				(0.0104)
Lagged Total Assets	0.345***	0.475***	0.462***	0.392***
	(0.0618)	(0.0587)	(0.118)	(0.0643)
Lagged Employment	0.287***	0.135***	0.174	0.168***
	(0.0497)	(0.0411)	(0.130)	(0.0489)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	8,508	8,043	1,566	12,035

Note: All columns are Pseudo-Poisson Maximum Likelihood (PPML) regressions, including firm and year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All independent variables are in logged values. *** p<0.01, ** p<0.05, * p<0.1.

Table 10. Impact of Subsidies on Firm-Level Employment (Arellano–Bond Estimator)

VARIABLES	(1) Employment	(2) Employment	(3) Employment	(4) Employment
Current Total Subsidy	0.00595***			0.00484***
	(0.00126)			(0.00126)
1-Year Lagged Total Subsidy		-0.00421***		-0.00342***
		(0.00127)		(0.00127)
2-Year Lagged Total Subsidy			0.000387	-0.000747
			(0.00112)	(0.00101)
Current Wage	-0.780***	-0.780***	-0.789***	-0.790***
	(0.0202)	(0.0203)	(0.0205)	(0.0204)
Lagged Wage	0.450***	0.460***	0.466***	0.460***
	(0.0321)	(0.0326)	(0.0331)	(0.0332)
Current Total Assets	0.517***	0.524***	0.544***	0.539***
	(0.0259)	(0.0260)	(0.0253)	(0.0251)
Lagged Total Assets	-0.248***	-0.249***	-0.274***	-0.264***
	(0.0353)	(0.0356)	(0.0331)	(0.0327)
1-Year Lagged Employment	0.720***	0.734***	0.738***	0.728***
	(0.0390)	(0.0402)	(0.0373)	(0.0375)
2-Year Lagged Employment	-0.0415***	-0.0429***	-0.0491***	-0.0467***
	(0.00835)	(0.00850)	(0.00831)	(0.00821)
Lagged Industry Sales	-0.00173	-0.00163	-0.00175	-0.00183
	(0.00178)	(0.00179)	(0.00186)	(0.00184)
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	20,709	20,709	19,327	19,327
Number of Firms	2,821	2,821	2,818	2,818

Note: All columns use Arellano–Bond GMM estimators and include year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are Arellano–Bond robust SE. All variables are in logged values. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Impact of Employment Stabilization and Promotion Related Subsidies (Employment Subsidy) on Firm-Level Employment (Arellano–Bond Estimator)

VARIABLES	(1) Employment	(2) Employment	(3) Employment	(4) Employment
Current Employment Subsidy	0.00599**			0.0129**
	(0.00275)			(0.00563)
1-Year Lagged Employment Subsidy		-0.00335		-0.00133
		(0.00277)		(0.00436)
2-Year Lagged Employment Subsidy			-0.00216	0.00209
			(0.00212)	(0.00315)
Current Wage	-0.750***	-0.720***	-0.735***	-0.654***
	(0.0409)	(0.0481)	(0.0528)	(0.0590)
Lagged Wage	0.197***	-0.107	-0.0286	0.0485
	(0.0644)	(0.0940)	(0.0600)	(0.0533)
Current Total Assets	0.420***	0.547***	0.380***	0.378***
	(0.0432)	(0.0775)	(0.0621)	(0.0567)
Lagged Total Assets	-0.0475	0.235***	0.105*	0.138***
	(0.0484)	(0.0682)	(0.0567)	(0.0436)
1-Year Lagged Employment	0.327***	-0.0149	0.139*	0.166**
	(0.0823)	(0.109)	(0.0804)	(0.0770)
2-Year Lagged Employment	-0.00963	0.0113	0.0230	-0.00338
	(0.0135)	(0.0153)	(0.0205)	(0.0194)
Lagged Industry Sales	0.000841	0.00132	-0.000135	-0.00147
	(0.00243)	(0.00260)	(0.00243)	(0.00318)
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	3,513	2,832	2,141	1,164
Number of Firms	1,424	1,282	960	532

Note: All columns use Arellano–Bond GMM estimators and include year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are Arellano–Bond robust SE. All variables are in logged values. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 1

Classifying subsidy types

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

Step 1: Manual classification of training data

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

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

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

Step 2: Artificial intelligence deep learning classification

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

Step 3: Manual review

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

Through these procedures, a total of 500,735 records of subsidies were classified.

Appendix 2

Definition of Firm Ownership

Wind determines the company's ownership type according to the nature of the actual controller disclosed in the company's shareholding structure relationship:

1. State-owned enterprises

When the actual controller of the enterprise is the State-owned Assets Supervision and Administration Commission (SASAC), a central state-owned enterprise(s), or a central government state agency(ies), the ownership of the enterprise is classified as the **central state-owned enterprise**; When the actual controller of the enterprise is a local SASAC, a local government, or a local state-owned enterprise, the ownership of the enterprise is classified as a **local state-owned enterprise**.

2. Private enterprise

When the actual controller of the enterprise is an individual(s), the ownership of the enterprise is classified as a **private enterprise.**

3. Foreign-funded enterprises

When the actual controller of the enterprise is an individual (s) and whose nationality is overseas or Hong Kong, Taiwan, or Macau, the ownership of the enterprise is classified as a **foreign-funded enterprise**.

4. Collective enterprise

When the actual controller of the enterprise is a collective enterprise(s)[24], the ownership attribute of the enterprise is classified as a **collective enterprise**.

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[24] This refers to an enterprise that was, at some point in the past, based on collective ownership of the means of production by the workers themselves. In order to list on a Chinese exchange, any collective enterprise would have to convert itself into a joint-stock company.

5. Ambiguous ownership enterprise

When there is no actual controller and there is no other basis for the above-mentioned types of enterprises, the ownership of the enterprise is classified as an **ambiguous ownership enterprise**.

Appendix 3

Table A1. Concordance of CSRC Industries to Collapsed Industries

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
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
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
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
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
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

Note: The collapsed industries are used in our industry-level TFP estimation.

Table A2. Pooled OLS and Wooldridge GMM Estimation of Production Functions

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) Wooldridge
lnl	0.186***	0.187***	0.112***	0.212***
	(0.00713)	(0.00717)	(0.00980)	(0.00207)
lnk	0.277***	0.266***	0.321***	0.307***
	(0.00923)	(0.00962)	(0.0148)	(0.00800)
lnm	0.565***	0.569***	0.527***	0.502***
	(0.00866)	(0.00877)	(0.0128)	(0.00515)
Constant	2.075***	2.078***	2.458***	
	(0.104)	(0.106)	(0.220)	
Year Fixed Effect	No	Yes	Yes	No
Firm Fixed Effect	No	No	Yes	No
Observations	30,888	30,888	30,802	27,245
R-squared	0.932	0.933	0.968	
Number of groups			3,578	3,578

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Determinants of Firm-Level Subsidies by Types, Including Firm Fixed Effects

VARIABLES	(1) R&D & Innovation Subsidy	(2) Industrial and Equipment Upgrading Subsidy	(3) Employment Stabilization & Promotion Subsidy	(4) General Business Subsidy
Lagged TFP	-0.0596	-0.0889	-0.105	-0.0575*
	(0.0431)	(0.0740)	(0.0661)	(0.0300)
Lagged Sales Revenue	-0.207	0.127	0.0246	-0.119
	(0.200)	(0.103)	(0.306)	(0.242)
Lagged Total Assets	0.553***	0.404***	0.320	0.739**
	(0.175)	(0.149)	(0.304)	(0.332)
Lagged Net Profit	0.0808	0.0581	-0.0266	0.145*
	(0.0542)	(0.0404)	(0.0732)	(0.0823)
Lagged Employment	-0.0190	0.0191	0.145	0.168
	(0.145)	(0.116)	(0.190)	(0.130)
IPO	0.605*	-0.0936	-0.390	0.183
	(0.359)	(0.296)	(0.472)	(0.151)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	20,533	22,022	18,227	23,893

Note: This table corresponds to Table 5 by adding zeros to “no subsidy” firm-year-type pairs. Column (1)–(4) are Pseudo-Poisson Maximum Likelihood (PPML) regressions with firm fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All independent variables are in logged values except for IPO indicator. *** p<0.01, ** p<0.05, * p<0.1.

Table A4. Impact of Subsidies by Types on Firm-Level TFP

VARIABLES	(1) TFP	(2) TFP	(3) TFP	(4) TFP
Current Innovation Subsidy	-0.00443**			
	(0.00195)			
1-Year Lagged Innovation Subsidy	-0.00450**			
	(0.00188)			
2-Year Lagged Innovation Subsidy	-0.00249			
	(0.00239)			
Current Upgrade Subsidy		-0.00365**		
		(0.00182)		
1-Year Lagged Upgrade Subsidy		-0.00484***		
		(0.00156)		
2-Year Lagged Upgrade Subsidy		-0.00269		
		(0.00198)		
Current Employment Subsidy			-0.00496***	
			(0.00191)	
1-Year Lagged Employment Subsidy			-0.00540***	
			(0.00195)	
2-Year Lagged Employment Subsidy			-0.00511**	
			(0.00232)	
Current Business Subsidy				-0.00394*
				(0.00206)
1-Year Lagged Business Subsidy				-0.00447**
				(0.00210)
2-Year Lagged Business Subsidy				-0.00388*
				(0.00228)
Lagged Total Assets	0.370***	0.373***	0.368***	0.380***
	(0.0687)	(0.0689)	(0.0686)	(0.0692)
Lagged Employment	-0.241***	-0.241***	-0.239***	-0.241***
	(0.0587)	(0.0586)	(0.0586)	(0.0587)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	23,515	23,515	23,515	23,515
R-squared	0.858	0.858	0.858	0.858

Note: This table corresponds to Table 7 by adding zeros to “no subsidy” firm-year-type pairs. All columns are OLS regressions including firm and year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All variables are in logged values. *** p<0.01, ** p<0.05, * p<0.1.

Table A5. Impact of Subsidies by Types on Firm-Level R&D Expenditure

VARIABLES	(1) R&D Expense	(2) R&D Expense	(3) R&D Expense	(4) R&D Expense
Current Innovation Subsidy	0.000864			
	(0.00238)			
1-Year Lagged Innovation Subsidy	-0.00148			
	(0.00197)			
2-Year Lagged Innovation Subsidy	0.00324			
	(0.00430)			
Current Upgrade Subsidy		0.000824		
		(0.00205)		
1-Year Lagged Upgrade Subsidy		0.000926		
		(0.00145)		
2-Year Lagged Upgrade Subsidy		-0.000535		
		(0.00226)		
Current Employment Subsidy			0.000423	
			(0.00245)	
1-Year Lagged Employment Subsidy			-0.00196	
			(0.00230)	
2-Year Lagged Employment Subsidy			0.00206	
			(0.00314)	
Current Business Subsidy				-0.00209
				(0.00374)
1-Year Lagged Business Subsidy				-0.00545
				(0.00748)
2-Year Lagged Business Subsidy				0.0221*
				(0.0124)
Lagged Total Assets	0.485***	0.483***	0.485***	0.459***
	(0.104)	(0.103)	(0.100)	(0.0922)
Lagged Employment	0.0967**	0.100**	0.0987**	0.0964*
	(0.0482)	(0.0486)	(0.0501)	(0.0511)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Observations	20,355	20,355	20,355	20,355

Note: This table corresponds to Table 9 by adding zeros to "no subsidy" firm-year-type pairs. All columns are Pseudo-Poisson Maximum Likelihood (PPML) regressions, including firm and year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All independent variables are in logged values. *** p<0.01, ** p<0.05, * p<0.1.

Table A6. Impact of Employment Stabilization and Promotion Related Subsidies (Employment Subsidy) on Firm-Level Employment (Arellano–Bond Estimator)

VARIABLES	(1) Employment	(2) Employment	(3) Employment	(4) Employment
Current Employment Subsidy	0.00104**			0.000645
	(0.000468)			(0.000444)
1-Year Lagged Employment Subsidy		-0.000897**		-0.000978**
		(0.000448)		(0.000415)
2-Year Lagged Employment Subsidy			-0.00102**	-0.00134***
			(0.000479)	(0.000483)
Current Wage	-0.779***	-0.779***	-0.779***	-0.779***
	(0.0206)	(0.0206)	(0.0206)	(0.0206)
Lagged Wage	0.459***	0.458***	0.457***	0.458***
	(0.0322)	(0.0322)	(0.0322)	(0.0322)
Current Total Assets	0.523***	0.524***	0.524***	0.523***
	(0.0260)	(0.0260)	(0.0260)	(0.0260)
Lagged Total Assets	-0.256***	-0.255***	-0.255***	-0.255***
	(0.0359)	(0.0359)	(0.0358)	(0.0359)
1-Year Lagged Employment	0.734***	0.733***	0.732***	0.733***
	(0.0398)	(0.0398)	(0.0398)	(0.0398)
2-Year Lagged Employment	-0.0437***	-0.0433***	-0.0430***	-0.0428***
	(0.00854)	(0.00854)	(0.00853)	(0.00849)
Lagged Industry Sales	-0.000671	-0.000634	-0.000679	-0.000671
	(0.00188)	(0.00188)	(0.00188)	(0.00188)
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	20,711	20,711	20,711	20,711
Number of Firms	2,821	2,821	2,821	2,821

Note: This table corresponds to Table 11by adding zeros to “no subsidy” firm-year-type pairs. All columns use Arellano–Bond GMM estimators and include year fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are Arellano–Bond robust SE. All variables are in logged values. *** p<0.01, ** p<0.05, * p<0.1.

Table A7. Determinants of Firm-Level Subsidies by Ownership Types

	Central State-owned	Foreign-funded	Local State-owned	Private	Ambiguous
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Subsidy	Subsidy	Subsidy	Subsidy	Subsidy
Lagged TFP	-0.0538	-0.0555**	-0.0141	-0.0288	-0.101
	(0.0524)	(0.0260)	(0.0320)	(0.0178)	(0.0900)
Lagged Sales Revenue	-0.464	-0.133	-0.0362	-0.261**	-0.0974
	(0.316)	(0.246)	(0.141)	(0.118)	(0.148)
Lagged Total Assets	1.161***	0.913***	0.370***	0.500***	0.788*
	(0.418)	(0.299)	(0.141)	(0.122)	(0.449)
Lagged Net Profit	0.0714	-0.133	0.0352	0.158***	0.0136
	(0.0848)	(0.102)	(0.0350)	(0.0265)	(0.0946)
Lagged Employment	0.230	-0.135	0.0191	0.163***	0.639
	(0.167)	(0.192)	(0.113)	(0.0590)	(0.397)
IPO_ind	0.110	0.156	-0.00206	0.164**	0.312
	(0.586)	(0.349)	(0.231)	(0.0804)	(0.455)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	3,193	731	6,601	12,055	621

Note: Pseudo-Poisson Maximum Likelihood (PPML) regressions with firm fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All independent variables are in logged values except for IPO indicator. *** p<0.01, ** p<0.05, * p<0.1.

Table A8. Determinants of Firm-Level Employment Stabilization and Promotion Related Subsidies (ES) by Ownership Types

	Central State-owned	Foreign-funded	Local State-owned	Private	Ambiguous
	(1)	(2)	(3)	(4)	(5)
VARIABLES	ES	ES	ES	ES	ES
Lagged TFP	0.00151	0.522	-0.147	-0.152*	0.276
	(0.0583)	(0.349)	(0.133)	(0.0867)	(0.172)
Lagged Sales Revenue	-0.0376	0.513	-0.258	0.184	-0.432
	(0.424)	(0.332)	(0.442)	(0.264)	(0.430)
Lagged Total Assets	0.621	-1.030**	0.343	-0.263	1.232**
	(0.512)	(0.493)	(0.557)	(0.290)	(0.492)
Lagged Net Profit	0.0468	0.0354	-0.0887	-0.00793	0.0660
	(0.0957)	(0.185)	(0.0905)	(0.121)	(0.141)
Lagged Employment	0.193	0.288	-0.209	0.504**	-0.370
	(0.257)	(0.308)	(0.254)	(0.206)	(0.410)
IPO_ind	-0.228		2.531***	-0.267	
	(0.621)		(0.186)	(0.343)	
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	848	185	1,558	4,124	202

Note: Pseudo-Poisson Maximum Likelihood (PPML) regressions with firm fixed effect. Data include Chinese listed firms from 2007 to 2018. Standard errors are clustered at firm level. All independent variables are in logged values except for IPO indicator. *** p<0.01, ** p<0.05, * p<0.1.