Government Subsidies and the Landscape of Industrial Sectors

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Abstract

Do government subsidies shift the performance of targeted sectors? In this paper, we address this question by measuring the broad effects of more than 30000 subsidy programs across 121 countries and 105 3-digit manufacturing sectors over the period 2012-2019. We find that the impact of subsidies on the performance (size, capital investments, liquidity, productivity) of firms pre-existing to the treatment is modest at best. If anything, government subsidies affect sectoral outcomes by attracting new firms with certain characteristics. In doing so, subsidy attributes matter significantly, with loans and export promotion initiatives attracting capital-intensive firms in targeted sectors, and labour-intensive firms mostly entering sectors targeted by tax breaks. We also find that direct transfers reduce market concentration and that subsidies targeted at smaller firms attract companies with less than 25 employees without increasing average firm-level employment. Innovation oriented subsidies are found to improve R&D activity among pre-existing firms, with remarkable differences across sectors. Finally, we find evidence that in quasi-monopolistic markets, dominant firms may translate subsidies into greater revenue shares without improving innovation and productivity.

Keywords: Government subsidies; Market performance; Diff-in-diff methods

JEL codes: C20, H20, L52

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1 Introduction

Industrial policies, intended as government actions directed at changing the structure of economic activity within sectors and countries, have been extensively used in the 19th century to shape the business sector and to promote industrialization, capital accumulation and economic growth (Juhász and Steinwender, 2024). Today, despite diffused skepticism (e.g., IMF, OECD, World Bank, and WTO (2022), Van Heuvelen (2023), Dabla-Norris *et al.* (2024)), industrial policies are still largely implemented, in order address newer and more specific challenges, about innovation, the green transition and firms resilience (particularly, of small firms) in front of macroeconomic shocks of various sorts (Van Reenen, 2023; Bown, 2024; Juhász *et al.*, 2024; Rodrik, 2024; Evenett *et al.*, 2024).

Modern industrial policy is complex and can touch any sector of the economy while taking different forms, including capital controls and exchange rate interventions, export and import measures, initiatives related to foreign investments and public procurement, and other instruments. Within this broad spectrum, recent data show that, far most commonly, industrial policies are subsidies and state aids (e.g. export and production subsidies, grants, tax reliefs and government loans), typically focused on manufacturing industries (Juhász *et al.*, 2023).

Government subsides have attracted significant attention in previous economic research, as they are a major item of government expenditure in many countries (Schwartz and Clements, 1999). Like most of the literature on other industrial policies, much of the work on government subsides is devoted to isolate some specific causal effects of subsidies in highly stylized settings. For example, Criscuolo *et al.* (2019), Cingano *et al.* (2023) and Branstetter *et al.* (2023) analyze investments and employment effects in firms targeted by specific subsidy programs in given countries. Other works adopt similar case-focused approaches (Slattery and Zidar, 2020).

This literature greatly contributed to our understanding of the nuances of particular subsidy programs and to the identification of the direct effects of subsidies on recipient firms in specific empirical contexts. At the same time, however, the ability of existing research to make informative comparisons between different subsidy programs and to speak to country and sector-wide counterfactuals remains limited, and less is what we know about the extent to which event-specific results can be generalized outside of case studies. This gap in the literature is puzzling, because evidence in this direction would be a key compass for industrial policy-makers, particularly for what concerns large-scale industrial plans at the international level which often are implemented by encompassing many countries and sectors under a single policy initiative (e.g., European Commission (2023)).

In this paper, we take such a broad perspective. Do government subsidies have significant effects on sectoral outcomes beyond the impact on individual recipient firms? Are these effects general enough to remain significant across different countries and sectors? And what are the most relevant attributes shaping the effectiveness of subsidy programs? We address these questions by looking at the relationship between the supply of different subsidy programs and a number of sectoral dimensions, spanning from firm demography to productivity and innovation, from industry concentration to market leaders' performance.

There are several reasons why looking at sectoral outcomes may indeed be important for the optimal design of subsidies. Subsidy programs may cause positive (or negative) spillovers and externalities that affect also non-eligible firms. These indirect, external effects may be in the form of market distortions influencing competition mechanisms, from both demand and supply sides. Moreover, when subsidies are selective (i.e. directed to a specific group of firms), they may spur input reshuffle from non-eligible to eligible firms. Finally, certain subsidies may attract new firms and may alter firm selection. Some of these mechanisms are difficult to isolate and to measure. Nevertheless, overlooking them altogether may be misleading, because the very purpose of many subsidy programs is precisely to transform the composition of economic activity and its dynamics on a large scale.

We take advantage from the Corporate Subsidy Inventory 2.0 of the Global Trade Alert database (CSI-GTA, hereafter), which tracks subsidy initiatives at the country, sector, and year levels, for more than one hundred countries over the last fifteen years, thereby offering the most comprehensive compilation of subsidy measures available (Evenett and Martín Espejo, 2023). The CSI-GTA database covers 31116 subsidy measures, providing, for each measure, a detailed description of the measure itself, including the jurisdiction responsible for the subsidy, implementation and removal dates, and the list of sectors where the measure applies. We aggregate subsidy measures for country-sector-year tuples (with sectors at 3-digit), while exploring the description of each subsidy program with text analysis in order to keep the records separated for initiatives of a different type (e.g., production subsidies, direct transfers, tax breaks, loans, export promotion interventions), selectivity (e.g., targeting firms of different size) and objective (e.g., the development of new technologies). We then match this data with country-sector-year data on a number of sectoral characteristics obtained by elaborating information from Orbis (Bureau van Dijk), which contains company accounts for a very large sample of firms distributed worldwide. As a result, focusing on the years 2012-2019, 121 countries and 105 3-digit manufacturing sectors, and after removing empty tuples, we obtain a dataset of 31408 country-sector-year observations, with 14722 (46.87%) being those for which a subsidy is active.

The main challenge that makes evaluating the effects of subsidy programs difficult is the inherent endogeneity that these policies entail. Governments do not sprinkle subsidies on different sectors randomly. Instead, the selection of the industry to be subsidized is often driven by the need to correct market failures and at times by lobbying and rent-seeking (Juhász *et al.*, 2024). We deal with this identification threat by leveraging on the combination of the very large coverage of our dataset and the multiple implementation of different subsidy programs across different countries and sectors with different periods of treatment, which allows us to exploit three-way fixed-effect estimators in a difference-in-differences (DiD) framework in order to absorb time-variant unobservable attractors of subsidy policies at the country and sector levels.

The structure of our data is best suited to ascertain the general effects of different government subsidies on industry-wide outcomes. In setups with a single treatment period, a typical concern is that contemporaneous trends driven by factors other than the treatment could confound the effect of the treatment itself, violating the parallel trends assumption, as highlighted by previous literature (Baker *et al.*, 2022). Our multiple subsidies and multiple periods design plausibly alleviates concerns that the estimated treatment effects are driven by contemporaneous trends and provides more credible and robust evidence with respect to single event studies.

Our analysis delivers some important results.

Taken together (i.e. without distinction based on selectivity and objectives), government subsidies have modest effects on sectoral performance. When significant, these effects are shown to depend on the type of subsidy programs and seem to be mainly driven by the attraction of new firms with certain characteristics rather than by an impact on pre-existing firms. We find that direct transfers, loans and export promotion initiatives tend to attract capital-intensive firms in targeted sectors, while labour-intensive firms seem to be more likely to enter sectors targeted by tax breaks. Loans attract also younger firms and firms with greater Total Factor Productivity (TFP), with firm entry being associated to some reduction in market concentration (as measured by the Herfindahl-Hirschman Index - HHI). Export promotion initiatives, on the other side, may be attracting larger firms thereby leading to higher market concentration. Finally, direct transfers may reduce market concentration also among pre-existing firms.

When looking at subsidy programs targeting small and medium enterprises (SMEs), which are often implemented with the objective of sustaining employment levels in smaller production units, we find that such initiatives do not have positive effects on employment. If anything, SME-specific subsidies attract smaller firms in targeted sectors and discourage the creation of larger firms. Universal subsidies, implemented without firm-size restrictions, may be more effective to sustain average employment.

Innovation subsidies seem to generate more desirable effects. In particular, sectors targeted by innovation oriented measures show a significant increase in the average intensity of R&D investments. If targeted sectors are strongly patent-intensive, however, this effect may become negative. Furthermore, in patent-intensive sectors, innovation oriented subsidies may increase R&D volumes without favoring R&D diffusion across firms, something that might suggest that firms merge together their innovative efforts to exploit economies of scale in highly innovative markets.

Finally, we use our data also to explore possible capture of subsidies by dominant firms to the detriment of the relative performance of the rest of the industry. We find that, on average, subsidies do not have a significant effect on the revenue share of the market leader. However, in monopolistic or quasi-monopolistic industries, subsidies disproportionately increase the market share of the dominant firm, without this increase in relative revenues reflecting in higher TFP or R&D performance of the leader. These results suggest that subsidies may generate rents that could be captured by dominant firms, thereby creating a wedge between cross-firm asymmetries in market power and asymmetries in dynamic efficiency.

Our three-way fixed-effect model produces very rigorous estimates, as it allows absorbing confounding factors over all the combinations of the three sources of variation that we can exploit in the data (country-sector, country-year, sector-year). Moreover, the effect of subsidy programs with a certain design is estimated after controlling for the possible simultaneous adoption of subsidies with a different design at the country-sector-year level. Nevertheless, we further test the statistical robustness of our estimates by using the method proposed by Callaway and Sant'Anna (2021), that we adapt to our setting in order to deal with multiple (possibly simultaneous) treatments. Our main results are confirmed: general subsidies have a modest impact on sectoral performance, particularly on pre-existing firms, while subsidies with specific objectives have more significant effects (with SME-specific subsidies attracting small firms in targeted sectors and innovation oriented subsidies having positive impact on R&D investments).

Related literature

Beyond the question on whether governments should supply subsidies in specific contexts, which has gathered most of the attention by previous literature, the issues of whether subsidies can be effective industrial policies on broader scales and how they should be carried out over such broader scales have been left relatively unexplored in current research. Our study, going through a wide array of subsidy initiatives with a variety of attributes, contributes to fill this gap. If our findings could be wrapped in a single takeaway message, this would be that in general the impact of government subsidies on sectoral performance of pre-existing firms (e.g. employment, capital investments, liquidity, productivity) is modest at best. If anything, government subsidies shift sectoral outcomes by attracting new firms with certain characteristics. Thoughtful examination of subsidy attributes, moreover, shows that subsidy design and targets may matter, and that subsidies with specific objectives (particularly, innovation oriented subsidies) may have more desirable effects than general subsidies. In these terms, our study improves on different lines of research within the very broad economic literature on government subsidies.

First and closest is the body of very recent work documenting the empirical patterns of industrial policies, including subsidies, with the same GTA data used in the present paper (e.g., IMF, OECD, World Bank, and WTO (2022), Juhász *et al.* (2023), Evenett *et al.* (2024)). In particular, Rotunno and Ruta (2024) use GTA data to investigate the effects of domestic subsidies on international trade flows, with diff-in-diff techniques similar to ours. They find that the implementation of government subsidies is associated with higher export and import levels in targeted markets relative to non-targeted ones. Behind this average effect, Rotunno and Ruta (2024) also show that subsidy programs of a different type may exert different effects, with tax breaks having more important effects than direct transfers (e.g. state aids and grants) and loans. Our paper complements this line of study by delivering a novel set of findings on the broad impact of government subsidies on business performance and sectoral outcomes overlooked in previous literature using GTA data.

Second, our paper contributes to an heterogeneous econometric literature on specific subsidy programs, which is mostly based on event-focused studies. Slattery and Zidar (2020) review some of this literature with emphasis on the wage and employment effects of certain subsidy programs in the US.[1] Outside the US context, Criscuolo *et al.* (2019) evaluated job creation effects in plants targeted by a major subsidy program in the United Kingdom, by exploiting policy changes in the allocation of investment subsidies in economically disadvantaged areas of the country. Similarly, Cingano *et al.* (2023) measured the employment effects in firms benefiting from a public investment subsidy program deployed in underdeveloped areas in Italy, by leveraging on regression discontinuity techniques applied to the specific context of subsidy allocation in the program under study. Other works looked at the effects of subsidies by leveraging size-related eligibility criteria to isolate causal effects of specific subsidy programs on employment of targeted firms. For example, Garicano *et al.* (2016) studied the impact of a subsidy program reducing labour costs for small firms in France between 1995 and 2007 and measured the increase in the relative labour costs of large firms relative to small ones. In line with this, Bloom *et al.* (2019) argued that subsidies favorable to small firms may discourage firms from growing, as expanding beyond a certain point would disqualify such small firms from accessing SME-specific subsidies. Focusing on the Small Scale Reservation Laws in India, Garcia-Santana and Pijoan-Mas (2014) found that the elimination of a regime favorable to SMEs would have increased production by 6.8% in the manufacturing sector and by 2% in the overall economy, and would have spurred TFP to grow by 2% and 0.75% respectively. Similar results are showed by Martin *et al.* (2017), pointing the removal of subsidies for SMEs in India as a possible driver of employment growth. The case of SME-specific subsidies in India received attention also by other works, including Rotemberg (2019). Brown *et al.* (2024), very recently, studied the effect of an increase in the size thresh-

[1] Older studies are surveyed in Schwartz and Clements (1999).

old relevant for accessing a subsidy program in the US and estimated the decline in the survival probability of smaller firms, with this inducing targeted sectors to become more concentrated. Going beyond employment and market structure effects, various other lines of research evaluated the impact of subsidies on a number of other measures of business performance. Recently, most of the attention has focused on the impact of innovation oriented subsidies on productivity, R&D efforts and innovation outcomes (see, e.g., Branstetter *et al.* (2023) and Banares-Sanchez *et al.* (2024) on the impact of specific Chinese subsidy programs). In particular, Banares-Sanchez *et al.* (2024) showed that production subsidies caused large increases in innovation and productivity with a synthetic-difference-in-differences approach applied to a subsidy program targeting the solar photovoltaic sector in China. We add on this literature by giving a sense of scale of the extent to which event-specific results can be generalized outside highly stylized settings. Our broad-based analysis, covering many countries and sectors, shows that government subsidies are unlikely to shift the performance of targeted sectors significantly, particularly if one focuses on the performance of firms pre-exisiting the government intervention. If anything, we find that sectoral performance may change on some margins (e.g. capital deepening, firm age, TFP, market concentration) after the implementation of a subsidy program because of the different characteristics of newborn firms and new entrants attracted in the targeted sectors relative to pre-existing firms. Hence, an important message of our study is that previous estimates obtained in stylized settings are not directly usable to anticipate what could be the impact of subsidy programs implemented over more countries and sectors at the same time, as often it is the case for policies conceived at the international level (e.g., European Commission (2020) and (2023)). On another side, our study also shows that the positive impact of innovation-oriented subsidies is more likely to survive outside narrow experiments and the results provided by previous literature on innovation subsidies can be used more safely to guide policy actions on broader scales.

Incidentally, our empirical strategy based on combining a three-way fixed-effect model and the method of Sant'Anna and Zhao (2020) and Callaway and Sant'Anna (2021) in a two-step unified framework, as described in the robustness check section of our paper, may contribute to the refinement of available diff-in-diff methods in contexts with multiple different treatments (Baker *et al.*, 2022; Freedman *et al.*, 2023; de Chaisemartin and D'Haultfœuille, 2024; Borusyak *et al.*, 2024).

The rest of the paper is organized as follows. In Section 2, we present the data used in our study. In Section 3, we explain our empirical strategy. In Section 4, we collect and comment our estimation results, whose robustness is checked in 5. Section 6 concludes.

2 Data

2.1 Measuring subsidies

We gather information on government subsidies from the Corporate Subsidy Inventory 2.0 of the Global Trade Alert (CSI-GTA) database, released in May 2023 and covering 31116 subsidy programs implemented over 148 customs territories after 2008 (the first version of the database, presented in 2021, is described in Evenett and Fritz (2021)).

In the CSI-GTA database, government subsidies are identified as subsidy initiatives involving an action or a commitment to action by a public body, the actual or potential outlay of a public body's resources, an advantage on firms, and possible selectivity (e.g. across sectors) in some meaningful respect. Measures in the form of direct welfare state payments to individuals or transfers to other levels of government or to foreign governments are excluded. To be included in the database, moreover, subsidies must be meaningful, i.e. a subsidy must be an intervention with a volume exceeding USD 10 million (different thresholds may apply to interventions targeted exclusively at SMEs). Small changes in the costs of complying with regulations (e.g. in the cost of obtaining a licence) are not considered meaningful. Also regional policies are excluded, i.e. activities of local governments, constituencies, and other sub-national units. All the entries of the database are documented through credible and official statements by the acting institution. Consistency is double-checked through press clippings from multiple original sources.

For each subsidy, the CSI-GTA database provides a detailed description of the intervention, including the jurisdiction responsible for the intervention, implementation and removal dates, and the list of sectors where the intervention applies. Sectors are classified according to the 3-digit level Central Product Classification 2.1.

The spectrum of subsidy programs included in the CSI-GTA database covers a rich variety of types of intervention. Following previous work (e.g., Rotunno and Ruta

(2024)), we start by classifying government subsidies into five categories: production measures (subsidies aimed at generating positive externalities in production), direct transfers (state aids, financial assistance in a foreign market, capital injection and equity stakes, financial grants, in-kind grants), tax breaks (revenue-reducing subsidies, consisting of import incentives, tax or social insurance relief and price stabilisation subsidies), risk transfers (aiming at shifting the risk from firms to the government, e.g. interest payment subsidies, state loans, and loan guarantees), and export promotion subsidies (initiatives aimed at promoting exports to foreign markets, e.g. trade finance, export subsidies, tax-based export incentives, and other export incentive).

The CSI-GTA database not only allows differentiation between various types of subsidies but also provides information on whether the subsidy policy has selective goals across firms with different size (i.e. whether the corporate subsidy is SME-specific) and on whether the government initiatives is related to the development of low-carbon emitting technologies. Both aspect are of great interest in our research setting. In particular, we integrate the information about whether the subsidy is related to new green technologies with additional text analysis in order to include also subsidies aimed at supporting R&D investments. We go through the textual description of each subsidy measure with text analysis techniques and identify subsidy initiatives whose description involves goals associated with R&D. Then, we classify as innovation oriented subsidies those related to the development of green technologies and those aimed at supporting R&D more in general (and those which have both features).

2.2 Outcome variables

We obtain all the variables used to measure sectoral performance by elaborating firm-level information from Orbis, which is a database maintained by Bureau van Dijk. Orbis covers a large longitudinal sample of firms distributed worldwide, providing balance-sheet data on a broad set of financial items, in addition to other demographic characteristics of firms, including location and sector of main activity. Over the 2012-2019 period of our interest, Orbis covers 1706456 firm-year observations (i.e. more than 200000 firms per year, on average).

In our analysis, we use a number of time-varying variables obtained by elaborating firm-level information on firm demography, input and outputs. In particular, in different steps of our analysis we focus on average firm size (measured by both employees and revenues), capital deepening (tangible assets per employee), liquidity ratios (cash and marketable securities divided by short-term liabilities), firm age (years from incorporation date), revenue-based market shares (within countries and 3-digit sectors, based on which we compute HHI values) and R&D investments (as average volumes, per-employee amounts and shares of firms undertaking R&D investments within country-sectors).

Moreover, we also recover a time-varying measure of TFP by estimating within-sector firm-level production functions with the approach proposed by Wooldridge (2009). This is a proxy variable approach to deal with unobserved productivity and simultaneity, which is shown to be more efficient than the two-step semi-parametric procedures introduced by Olley and Pakes (1996) and Levinsohn and Petrin (2003). In words, we implement a one-step generalized method of moments (GMM) estimator, where the moment conditions are specified within a two-equations system, with the log of revenues as the dependent variable and different sets of instruments across equations used for identification. The log of intermediate inputs is used as the proxy variable required to consistently estimate the TFP term.

We construct country-sector-year indicators by elaborating these firm-level variables and take the log where appropriate. We use a 3-digit sectoral classification. Although Orbis provides a finer sectoral classification, we do not dig across sectors more granularly in order to minimize empty cells with reference to our variables of interest.

2.3 Overview of the data

We merge CSI-GTA and Orbis data at the country, sector, and years levels, by using three-step concordance chains from the Central Product Classification 2.1 used in CSI-GTA to ISIC 4 to NACE 2.1 used in Orbis. Our final dataset is composed by an unbalanced panel of 31408 country-sector-year observations, over 121 countries, 105 manufacturing 3-digit sectors, and 8 years. We focus on the 2012-2019 time-span to avoid exceptional policy events in the years around the 2009 Great Recession, on the one side, and exceptional initiatives associated with the COVID-19 pandemic, on the other. More recent years may also involve sample distortions in Orbis due to delays in balance-sheet reporting.

To describe our final database, we look at the data from three different angles.

First, we consider the pattern of the supply of government subsidies over time. To simplify the exposition, we group country-sector-year tuples depending on the main attributes of the supplied subsidies, i.e. selectivity (we distinguish universal subsidies from SME-specific subsidies), objective (whether a subsidy is innovation oriented because related to the development of green technologies or to R&D more in general) and type (whether a subsidy is a production subsidy, direct transfer, tax break, loan, or an export promotion initiative). In Figure 1 we report the time series of the shares of country-sector-year observations with at least one active subsidy belonging to each group. Overall, government subsidies are on the rise and follow a time pattern that is consistent with the general increase in the use of industrial policies shown by previous literature (Juhász *et al.*, 2023). Tax breaks in particular show a remarkable increase in their extensive margin of use at the beginning of the period. Production subsidies and direct transfers, as well as measures targeting SMEs and the green transition or R&D, are relatively less common.

[insert Figure 1 about here]

Second, we focus at the cross-sectional dimension of the database. As one might expect, subsidy interventions are sectorally selective. To help grasping sectoral differences in the supply of subsidies, we aggregate our data at the 2-digit level, as shown in Figure 2. Some sectors emerge as favourite targets both across countries and in terms of the average duration of subsidy programs. The production of vehicles and other transport products and the production of machineries and electronic products are broadly targeted by subsidies and tend to remain under treatment longer with respect to other sectors. At the opposite side of the spectrum, we find pharmaceuticals, printing and reproduction of recorded media.

[insert Figure 2 about here]

Third, we exploit the firm-level dimension of the data and look at a number of baseline indicators useful to start describing sectoral performance, with and without government subsidies (of any kind). In Figure 3, we show the country-sector-year distributions of the firm averages of revenues, capital intensity, age, liquidity ratio, and TFP, and the country-sector-year distributions of market concentration (HHI). Although descriptive, the histograms reported in Figure 3 show that there is no perfect overlap between treated and untreated country-sector-year tuples, thereby stimulating deeper econometric work on the data, presented below.

[insert Figure 3 about here]

3 Econometric strategy

Our objective is to study whether government subsidies have an effect on the structure and performance of manufacturing sectors. In our setting, our treatment is the supply of a subsidy at a country-sector-year level.

There are two main critical challenges in evaluating causal effects of government subsidies. First, the supply of subsidies is not random across countries and sectors. For example, governments may subsidize disproportionately sectors of the economy that are more exposed to international trade or that are at initial stages of technology adoption. Other sources of market failure and strategic reasons (e.g. considerations about government capacity and comparative advantages) may lead to targeting certain industries in particular. We need to account for these unobservable differences across countries and sectors. Second, different subsidies may be implemented simultaneously in the pursuit of different goals, thereby generating effects which may go in different directions. Frequently, SMEs are object of dedicated measures within broader subsidy initiatives. Moreover, in many countries and sectors governments increasingly implement interventions targeting the green transition and the development of low-carbon technologies or supporting R&D more in general. Subsidies may be implemented also in different forms, ranging from production subsidies to direct transfers, from tax breaks to loans and export promotion initiatives. We would like to capture these heterogeneous and potentially simultaneous effects.

To help address these concerns we construct a set of binary treatment variables, by disentangling treatments with subsidy programs that differ in terms of selectivity, objectives and type. More formally, depending on its characteristics, each subsidy program is classified in a category h of subsidies with similar attributes among a number H of categories. Treatment means being treated with a subsidy of category h. Let subscript c denote the country, s the sector and t the year. Treatment indicators are denoted with $D^h_{c,s,t}$, where $D^h_{c,s,t} = 1$ if a country-sector is treated in year t with a subsidy of category h and $D^h_{c,s,t} = 1$ otherwise. In a same regression model, subsidy programs are classified in mutually exclusive categories and a given subsidy is captured by a single treatment indicator $D^h_{c,s,t}$. Nevertheless, a same country-sector unit may be treated by two or more subsidies of different categories at the same time. Hence, for instance, a same subsidy cannot be classified as both direct transfer and tax break, but at time t a country-sector unit may supply both direct transfers and tax breaks.

By leveraging on the triple source of variation allowed by structure of our data (at the country, sector, and year levels), we employ the following three-way fixed-effect DiD model:

$$Y_{c,s,t} = \alpha_{c,s} + \alpha_{c,t} + \alpha_{s,t} + \sum_{h=h_1}^{h_H} \delta^h D^h_{c,s,t} + \varepsilon_{c,s,t} \tag{1}$$

where our parameter of interest is denoted by δ^h, which is a variance-weighted average of cross-group treatment effects for each h-category treatment (see, e.g., Goodman-Bacon (2021)).[2] In this setting, the control group is populated by all untreated observations, i.e. never-treated and not-yet-treated. As Wooldridge (2021) notes, this may provide an advantage in the precision of the estimator with respect to when only never-treated units are in the control group, because more of the data is being used. Standard errors are heteroskedasticity robust and clustered at the country-sector level.

4 Empirical results

Baseline sectoral performance

We start by looking at how subsidies of a different type impact on the average business performance in targeted sectors. We focus on a number of baseline indicators of sectoral performance, including indicators of average firm demography and productivity, and market concentration. We estimate Equation (3), where the set of treatments $D^h_{c,s,t}$ (with $h = h_1, ..., h_H$) covers the following five mutually exclusive categories in which subsidy programs can be classified based on their type: production measures, direct transfers, tax breaks, loans (i.e. risk transfers), and export promotion initiatives. We run the model on two different samples. In the first one, we compute our country-sector-year outcome variables by using all the firms for which we have

[2] Clearly, δ^h is not easily interpretable when treatment effects evolve substantially over time. Although dynamic variations of TWFE models are popular to address this concern, it has been demonstrated that such dynamic specifications do not provide estimated parameters that can be rigorously interpreted as reliable measures of dynamic treatment effects (Sun and Abraham, 2021). In the robustness checks Section of the paper, we show some results obtained with the method proposed by Sant'Anna and Zhao (2020) and Callaway and Sant'Anna (2021), which allows accounting for dynamic effects.

data over 2012-2019. In the second, the outcome variables are computed by using only firms born before our observation period (i.e. before 2012), in order to isolate firms that were pre-existing to the possible treatment over 2012-2019 and therefore excluding newborn firms which might have been attracted by the government interventions under analysis.

Estimation results are collected in Table 1[3]. In columns [1]-[6], we report the results obtained by using all firms (newborn and pre-existing), while in columns [7]-[12] only pre-existing firms are used.

[insert Table 1 about here]

Starting from the first block of regressions (all firms), we find a few interesting results. Overall, government subsidies do not seem to have systematic effects on sectoral performance. Nevertheless, we also observe that the sign and statistical significance of some of the estimated effects change across different types of subsidies. Let us briefly report the main findings, following the order of the program types considered in this empirical exercise as reported in Table 1. Production measures are positively associated with average firm age, but do not have any significant impact on the other performance indicators. Direct transfers have some positive effect on capital deepening and reduce market concentration significantly, without having impact on average revenues, age, liquidity and TFP. Similarly, tax breaks do not affect firm size, age, liquidity and TFP, but they are associated with a reduced capital deepening. Moreover, tax breaks do not affect market concentration. Loans are more impactful on sectoral performance, as they reduce market concentration and increase average TFP and capital deepening. Loans are also associated with a lower average age of firms in targeted sectors and do not affect firm size and liquidity. Finally, export promotion initiatives increase average capital deepening and may induce some increased market concentration in targeted sectors, without generating other significant effects.

To help interpreting these estimates, we turn now our attention to the results obtained for the sectoral performance indicators constructed by using only pre-existing firms. Interestingly, we find nearly no impact of government subsidies, with the only exception of the negative effect of direct transfers on market concentration. The con-

[3]The literature offers various measures of firm size, such as the logarithm of revenues and the logarithm of employment. In Table 1, we present estimates based on revenues, as those based on employees are equivalent and available upon request. However, throughout the rest of the work, we use the logarithm of employment to assess the impact of subsidies specifically targeted at SMEs.

trast between these two blocks of estimates has very relevant implications, because it means that all the effects detected when the full sample of firms is used (i.e. including newborn and pre-existing firms) are to be attributed to the particular characteristics of the new firms that are attracted in targeted sectors rather than to a direct effect of subsidies on the characteristics of pre-existing firms. This does not mean that government subsidies do not influence sectoral performance. Indeed, government subsidies may change sectoral performance in some respects, but they do so by attracting firms from non-targeted sectors or stimulating the formation of new companies with characteristics that are different from those of the firms already active in the targeted sectors.

Coming back to the significant estimates reported above, therefore, we arguably have to impute the positive association between capital deepening and direct transfers, loans and export promotion initiatives to the attraction of capital-intensive firms in sectors targeted by these types of measures. On the other side, tax breaks may attract more labour-intensive firms. Sectors targeted by loans may be attractive for younger firms, possibly more productive, thereby inducing some redistribution of revenue shares from old to new firms. Finally, direct transfers favor a reduction of market concentration by inducing a more even distribution of market shares among pre-existing firms.

The insignificant effect of subsidies on firm size (measured in revenues), as observed in Table 1, is unsurprising in the light of previous literature showing that governments tend to address firm growth issues by SME-specific interventions rather than by specific types of programs (e.g. capital injections or export subsidies) speaking to firms of any size. In particular, a line of research on SME-specific subsidies showed that changes in eligibility criteria may have effects on employment growth and entry rates of SMEs (e.g., Garicano *et al.* (2016), Martin *et al.* (2017), Bloom *et al.* (2019), Brown *et al.* (2024)). Fortunately, the CSI-GTA database allows us to isolate subsidy interventions targeted at SMEs. We exploit this feature of the database in order to dig more into the relationship between subsidies and average firm size in targeted sectors. We estimate Equation (3) by considering two possible treatments which differ in terms of firm-size selectivity. One is the implementation of a universal subsidy program without size-related restrictions. The other is the implementation of subsidies with eligibility requirements based on firm size, namely subsidies providing more favorable economic conditions for SMEs.[4] In this exercise, we do not distinguish subsidy programs in terms of type (i.e. whether they are direct transfers, loans, or interventions of other types), but only focus on their size-related eligibility requirements.

As the outcome variables of the model, to be better aligned with previous related literature, here we use the log of the number of employees as an indicator of firm size. Specifically, we consider the average size of firms in targeted sectors, unpacking firms below 25 employees, between 25 and 250 employees, and above 250 employees. For reference, we also estimate the effect of universal and SME-specific subsidies on average firm size in a pooled sample. Moreover, using the same size categories (i.e. below 25, between 25 and 250, and above 250 employees), we look at how subsidies impact on the share of firms of different size in targeted sectors. Estimation results are collected in Table 2.

[insert Table 2 about here]

We observe that SME-specific subsidies do not have any significant effect on firm size in all the size classes considered. If anything, are universal subsidies to drive some increase in firm size both on average and, supporting the evidence of Criscuolo *et al.* (2019) and Dechezleprêtre *et al.* (2023), among smaller firms (below 25 employees). When we study sectoral composition, we find that SME-specific subsidies are associated with an increased share of small firms and with a reduction in the share of larger firms (above 250 employees). This might suggest that SME-specific subsidies attract small firms from outside targeted sectors and, as pointed out by Garicano *et al.* (2016), may stimulate firms around the size threshold relevant for eligibility to remain below the threshold to benefit from subsidies. Such a perverse effect is absent when universal subsidies are implemented.

R&D activities

Government subsidies to support private R&D activities have gained renewed momentum in recent years, particularly with the purpose to accelerate the development of low-carbon technologies for the green transition (Rodrik, 2024). Innovation oriented subsidies typically find justification in market failures associated with the incomplete appropriation of the returns to R&D investments and also in the existence of barriers

[4]The threshold, in terms of number of employees, defining SMEs may change across countries and government programs. We keep the original coding provided in the CSI-GTA database and consider SME-specific subsidies those which are labeled as such in the original database.

to entry in innovation intensive sectors, where R&D projects involve sizable fixed investments and require large scales of production to be profitable. More specifically, in relation to clean technologies, support for R&D subsidies often follows from second-best reasoning in light of the political opposition to global carbon taxes (Van Reenen, 2023).

An heterogeneous literature has evaluated whether public R&D subsidies are complements or substitutes to the private R&D spending of recipient firms. Results are mixed, often pointing to either no complementarity or crowding-out effects (Becker, 2015). Nevertheless, recent works find that innovation subsidies directed to the development of clean technologies may have positive effects on private innovation activity (e.g., Banares-Sanchez *et al.* (2024)). Against this literature background, less understood is how innovation oriented subsidies impact on research investments more broadly in targeted sectors, including both recipient and non-recipient firms. In particular, there is a dearth of evidence on whether innovation subsidies increase average R&D investment while leading to wider diffusion of R&D activities across firms or to a higher concentration of such activities in fewer, top-spending companies. Also the comparative impact of innovation subsidies across sectors with different innovation propensity has been poorly investigated so far.

We explore the impact of innovation oriented subsidies by exploiting the textual description of government subsidies provided in the CSI-GTA database. In particular, we define as innovation oriented subsidies those which are related to the development of new cleaner technologies (already identified in the original CSI-GTA database) and to R&D activities more in general (as resulting from a text analysis that we conducted on subsidy descriptions). In order to estimate the differential effect of innovation subsidies across sectors with different innovation propensity, we exploit the Intellectual Property extension of the Orbis database, containing information on patent portfolios at the firm-level. We compute a measure of patent intensity, defined as active patents per employee, for each firm, and then average this patent intensive measure within sectors. Finally, we identify patent-intensive sectors as the top 5% sectors in terms of average patents per employee.

As the outcomes of interest, relevant for evaluating the impact of innovation subsidies, we focus on the within-sector averages of R&D volumes (total R&D expenditure per firm), R&D intensity (ratio between R&D expenditure and employees per firm) and R&D diffusion (i.e. the share of firms, within sectors, which undertake positive R&D investments). Again, the outcome variables vary at the country, sector, and year levels. Formally, we estimate a regression model similar to Equation (3), where R&D performance indicators are considered on the left-hand-side and innovation oriented subsidies (and their interaction with a dummy variable identifying patent-intensive sectors) are considered on the right-hand-side. Besides the full sets of fixed effects, we also control for the possible simultaneous implementation of any other subsidy programs unrelated to innovation.[5] Estimation results are collected in Table 3.

[insert Table 3 about here]

Our estimates show that innovation-oriented subsidies do not spur average R&D volumes in general, something that seems to be consistent with previous evidence that innovation subsidies tend not to generate systematic crowding-in effects. However, innovation subsidies may lead to increased R&D intensity. In patent-intensive sectors, innovation subsidies have a negative effect on R&D intensity (although statistically insignificant) and a positive and significant effect on average R&D volumes, without improving R&D diffusion. Taken together, these estimates might point to innovation subsidies in patent-intensive sectors as possibly inducing firms to merge their R&D efforts to exploit economies of scale in innovative activities. As a result of these possible merges, average R&D volumes rise while firm size, if anything, increases less than proportionally.

Capture by market leaders

Previous analysis of GTA data shows that industrial policies often are aimed at specific firms (Juhász *et al.*, 2023). This firm-specific targeting may be justified by the existence of market failures. For example, subsidies may be common in infant industries, at an initial stage of development, to realize external economies of scale. At the same time, also firm pressures and lobbying may play a role (Kerr *et al.*, 2014), particularly by firms seeking to capture rents (Baldwin and Robert-Nicoud, 2007).

We look for indirect evidence of "powerful" firms capturing subsidies by exploiting the firm-level dimension of our data. First, we identify market leaders. We compute the revenue market share of each firm for each year throughout the 2012-2019

[5] We focus on pre-existing firms. However, unreported estimates conducted over newborn and pre-existing firms together show very similar results.

period and identify the market leader, in each country-sector-year cell, with the firm having the largest revenue share. Then, we estimate the effect of subsidies on the revenue share of the leader and on its relative TFP and R&D with respect to the industry average. We specify the model in a way that also allows us to isolate these effects in quasi-monopolistic markets, intended as markets where the leader has a revenue share higher than 90%. We estimate

$$W_{c,s,t} = \alpha_{c,s} + \alpha_{c,t} + \alpha_{s,t} + \beta D_{c,s,t} + \gamma D_{c,s,t} \times M_{c,s,t} + \eta_{c,s,t} \tag{2}$$

where $W_{c,s,t}$ is the performance of the market leader, $M_{c,s,t}$ is a dummy variable equal to 1 for quasi-monopolistic markets, and where β and γ are our parameters of interest. Fixed effects α and the subsidy indicator $D_{c,s,t}$ have the same meaning as in Equation (3). Here, in particular, $D_{c,s,t}$ boils subsidies of any kind together. Estimation results are collected in Table 4.

[insert Table 4 about here]

On average, across all the countries and sectors, we do not find a significant association between the implementation of subsidy programs and the relative performance of market leaders (whether it is measures in terms of revenues, TFP or R&D). These findings appear to be in line with those of Criscuolo *et al.* (2019), according to whom larger firms are able to "manipulate" the system and take the subsidy without changing their economic performance. Clearly, where markets are very concentrated, the revenue share of the market leader is significantly higher than the average of the other sectors, while the same does not hold for the leader's relative TFP and R&D efforts. In quasi-monopolistics markets, moreover, subsidies are associated with a disproportionately larger increase in the revenue share of the dominant firm, without this reflecting in improvements of TFP and R&D. These estimates seem suggesting that subsidies may be used by the dominant firm to increase its market position in terms of revenues, but only in very concentrated markets. At the same time, dominant firms do not tend to exploit the economic benefits associated with subsidies to improve their productivity with respect to other firms. In other words, in concentrated markets, subsidies may generate rents that could be captured by dominant firms, thereby creating a wedge between cross-firm asymmetries in market power and asymmetries in dynamic efficiency.

5 Robustness checks

Our three-way fixed-effect estimation deviates from the canonical DiD setup because it has multiple treatment periods and variation in treatment timing. This means that the estimated parameters of our three-way fixed-effect model have to be interpreted as some average treatment effects, without precise identification of possibly relevant dynamic effects. This issue may be important for policy, since the impact of subsidies may vary over time. For instance, firms may increase R&D investments or employment only after some years of government transfers. On the other hand, other dimensions of market structure and performance of an industry may react more immediately to the introduction of a subsidy program. As a result, an estimated parameter which is found statistically insignificant as an average effect over our entire observation period may actually turn out to be significant in some sub-period after treatment. A policy maker may want to be informed about these potential dynamic effects.

To test the robustness of our results to these issues, we employ the method discussed in Sant'Anna and Zhao (2020) and Callaway and Sant'Anna (2021), which extends two-way fixed-effect (TWFE) estimation in settings with differential treatment timing by implementing doubly-robust multiple periods DiD estimators. At the core of this approach is the disaggregation of causal parameters in group-time average treatment effects on the treated (ATTs), i.e. the average treatment effects for each group at each time, where a group is defined by the time period when units are first treated. Callaway and Sant'Anna (2021) propose to estimate each group-time ATT using the doubly-robust estimator introduced by Sant'Anna and Zhao (2020), to then aggregate the ATTs with appropriate weights. In our empirical setup, this means that we compute every group-time ATTs, relative to the year of first treatment between 2012-2019, and turn them into a weighted ATT, by aggregating cohort-specific ATTs into event study estimates. Aggregation is based on stabilized inverse probability weighting. In our empirical exercise, we use not-yet-treated observations as the control group, a strategy that allows us to fully exploit variations in the treatment status while being less robust to violations of the no anticipation assumption (Freedman *et al.*, 2023). Standard errors are clustered at the country-sector level.

As such, however, the method of Callaway and Sant'Anna (2021) cannot be directly implemented with our data. We deal with treatments belonging to different categories (i.e. subsidy programs with different attributes) and the effect of implementing a subsidy of a given category may depend on the simultaneous adoption of another subsidy belonging to a different category. Clearly, being treated with other subsidy measures is a time-varying variable which cannot be used as a control in the algorithm of Callaway and Sant'Anna (2021).

We address this limitation of the method of Callaway and Sant'Anna (2021) by proceeding in two steps. Suppose we are interested in the causal effect of a subsidy belonging to category $h_j \in [h_1, h_H]$. We estimate a three-way fixed-effect model where we exclude measures h_j from the right-hand side, while including all other measures $h \neq h_j$ as explanatory variables together with country-sector, country-year and sector-year dummies. Hence, the residuals of the regression can be interpreted as outcome values purged from the effect any treatment different from h_j and from all the fixed effects. Then, we use the purged outcome as the outcome of interest in a setting *à la* Callaway and Sant'Anna (2021).

Formally, in the first step we estimate the model:

$$Y_{c,s,t} = \alpha_{c,s} + \alpha_{c,t} + \alpha_{s,t} + \sum_{h=h_1}^{h_H} \zeta^h D^h_{c,s,t} + v_{c,s,t} \quad \text{with} \quad h \neq h_j \tag{3}$$

where ζ are the parameters associated to subsidy programs different from the one of interest (h_j), $v_{c,s,t}$ are the residuals and all the other symbols and letters have the same meaning as in Equation 3. In the second step, we analyze the residuals $v_{c,s,t}$ as outcomes in the method of Callaway and Sant'Anna (2021), where subsidies of category h_j are the ones of interest. Let e the event-time, $t \in 1, ..., \mathcal{T}$ the current period and $g \in \mathcal{G}$ the time of first treatment. Hence, $e = t - g$ measures the time elapsed since the subsidy was introduced. Moreover, $G_{c,s,g}$ is a binary variable that takes value 1 if a country-sector unist is first treated in period g (and 0 otherwise), while C is a binary variable that equals 1 for units that do not participate in the treatment in any time period, i.e. $C = 1$ defines the not-yet-treated comparison group. We recover the ATT as

$$\text{ATT}(g,t) = \mathbb{E}[v_t - v_{g-1} | G_g = 1] - \mathbb{E}[v_t - v_{g-1} | C = 1] \tag{4}$$

Then, we aggregate the ATT(g,t)'s with the following weighting scheme:

$$\vartheta_e(e) = \sum_{g \in \mathcal{G}} \mathbf{1}\{g + e \leq \mathcal{T}\} \text{ATT}(g, g+e) \mathbb{P}(G = g | G + e \leq \mathcal{T}, C \neq 1) \tag{5}$$

where $\vartheta_e(e)$ is the average effect of participating in the treatment for the group of units that have been exposed to the treatment for exactly e time periods.

An important aspect that should be highlighted is that the method of Callaway and Sant'Anna (2021) is most appropriate in staggered treatment designs, where the treatment is "irreversible", i.e. once a unit is treated, it is forever treated. In our setting, a subsidy measure could be withdrawn during the period of analysis, implying that the empirical treatment variable can switch back to zero one or more years after the subsidy measure came into force for the first time. In order to circumvent this problem while avoiding forcing the binary treatment to be absorbing (see de Chaisemartin and D'Haultfœuille (2024)), we remove country-sector-year tuples after they return untreated (when it is the case). The results are reported graphically in Figures from 4 to 8.

[insert Figures 4, 5, 6, 7, 8 about here]

The dynamic effects estimated in this exercise are consistent with the results of our three-way fixed-effect models. Although of a lower statistical significance, on average, the sign of the parameters estimated here are in line with those presented in Tables 1-4. We find that direct transfers have a negative effect on market concentration among pre-existing firms. Tax breaks attract more labour-intensive companies, while loans and export promotion initiatives attract capital-intensive firms. Loans also attract younger firms. In addition, we find that, among pre-existing firms, export promotion initiatives increase liquidity ratios and production measures may reduce TFP, something that was statistically insignificant in the three-way fixed-effect models.

SME-specific subsidies are confirmed to be incapable to generate employment effects, and again they seem to increase the share of firms below 25 employees. The statistical significance of the effect of SME-specific subsidies on the sectoral composition is somewhat weaker here than in the three-way fixed-effect model, however it is close to the 90% threshold and the sign is in line with our prior that SME-specific subsides may be attractor for SMEs in targeted sectors.

The effects of innovation oriented subsidies are corroborated to a broader extent. In targeted sectors, we find a significant increase in R&D intensity in the first year of subsidy implementation. Moreover, targeted sectors show greater diffusion of R&D activities. In patent-intensive sectors, innovation subsidies increase significantly average R&D volumes and may reduce R&D intensity, without significant impact on R&D diffusion.

Finally, the effect of government subsidies on the leader's revenue shares appears again to be positive in quasi-monopolistic markets, at least at the end of the observation period, while relative TFP and R&D expenditures remain unaffected.

6 Conclusions

Over the last decade, industrial policies have re-gained attention in empirical economic research, stimulating the construction of broad-based datasets for evaluating the deployment of industrial policies and helping to orient government intervention on a wide range of areas (Evenett *et al.*, 2024). With the use of these fresh broad-based data sources, recent research has focused its interest in particular on government subsidies (e.g., Rotunno and Ruta (2024)), in an attempt to complement a dense previous econometric literature which analyzes subsidy programs in highly stylized settings, without clear conclusions about the extent to which the results from such case-specific studies can be generalized over broader and more heterogeneous contexts. Indeed, it is important to notice that a single subsidy program can be well implemented over many countries and many sectors at a same time, as it is often the case for initiatives sponsored by public multinational institutions (e.g., European Commission (2023)).

In this paper, we add on this line of study by using the CSI-GTA database, which is the most comprehensive compilation of subsidy measures available today (Evenett and Martín Espejo, 2023), to explore whether government subsidies shift the performance of targeted sectors over a range of relevant outcomes. We analyzed data on more than 30000 subsidy programs across 121 countries and 105 3-digit manufacturing sectors over the period 2012-2019, with cutting-edge diff-in-diff techniques for causal identification in multiple treatment designs. We found that the impact of subsidies on the performance (employment, capital investments, liquidity, productivity) of firms pre-existing to the treatment is modest at best. If anything, government subsidies affect sectoral outcomes by attracting new firms with certain characteristics. In doing so, subsidy attributes matter significantly, with loans and export promotion initiatives attracting capital-intensive firms in targeted sectors, and labour-intensive firms mostly entering sectors targeted by tax breaks. We also found that direct transfers reduce market concentration and that subsidies targeted at smaller firms attract companies with less than 25 employees without increasing average firm-level employment. Innovation oriented subsidies are found to improve R&D activity among pre-existing firms, with differences across sectors. Finally, we found evidence that in quasi-monopolistic markets, dominant firms may translate subsidies into greater revenue shares without improving innovation and productivity.

Taken together, our results suggest that government subsidies are not an effective industrial policy if one wants to re-orient business activity and to drive firm employment and growth. Government subsidies may shape the composition of targeted sectors rather than affecting the activity of firms that pre-exist to the subsidy intervention. Fortunately for policy-makers, this seems to be less true for innovation oriented subsidies, which seem to exert positive and more robust effects on R&D activities in targeted sectors, sectoral composition being equal. In any event, policy design must address possible rent-seeking and subsidy capture, when market are concentrated and dominated by relatively very large (quasi-monopolistic) firms.

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Table 1: Effects of subsidies (by type) on business performance.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	All firms (newborn and pre-existing)						Only pre-existing firms					
	Revenues	Capital deep.	Age	Liquidity ratio	TFP	HHI	Revenues	Capital deep.	Age	Liquidity ratio	TFP	HHI
Production measures	-0.041	0.011	0.014*	0.008	-0.035	0.001	-0.027	0.065	-0.001	-0.003	-0.015	-0.002
	(0.035)	(0.040)	(0.008)	(0.019)	(0.035)	(0.010)	(0.032)	(0.049)	(0.003)	(0.019)	(0.034)	(0.008)
Direct transfers	-0.016	0.054*	-0.001	0.012	-0.001	-0.011**	-0.015	0.024	-0.001	0.007	-0.016	-0.012**
	(0.020)	(0.031)	(0.005)	(0.014)	(0.023)	(0.005)	(0.018)	(0.026)	(0.002)	(0.013)	(0.019)	(0.005)
Tax breaks	-0.005	-0.065*	0.001	-0.002	0.002	-0.001	-0.002	-0.048	0.001	-0.009	0.011	-0.002
	(0.018)	(0.033)	(0.004)	(0.013)	(0.020)	(0.006)	(0.016)	(0.033)	(0.002)	(0.012)	(0.019)	(0.006)
Loans	0.014	0.049*	-0.010**	0.004	0.036*	-0.012**	0.013	0.020	0.001	0.002	0.023	-0.002
	(0.019)	(0.027)	(0.005)	(0.011)	(0.021)	(0.005)	(0.016)	(0.022)	(0.001)	(0.011)	(0.022)	(0.005)
Export promotion	-0.004	0.084***	0.006	0.017	-0.025	0.014*	-0.014	0.044	0.002	0.018	-0.016	0.002
	(0.022)	(0.032)	(0.005)	(0.015)	(0.020)	(0.007)	(0.020)	(0.027)	(0.001)	(0.013)	(0.018)	(0.007)
Constant	10.83***	3.881***	3.046***	0.922***	6.805***	0.0266***	10.89***	3.922***	3.277***	0.931***	6.969***	0.226***
	(0.014)	(0.023)	(0.003)	(0.009)	(0.014)	(0.004)	(0.013)	(0.020)	(0.001)	(0.009)	(0.012)	(0.002)
Country×Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector×Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country×Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
# obs.	14619	14705	15845	15528	14204	15848	14932	14089	15144	14842	13598	15144

Note. Three-stage FE DiD. Variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: revenues = log of revenues; capital deepening = log of tangible assets per employee; age = log of age; liquidity ratio = log of liquidity ratio; TFP = Total Factor Productivity recovered with Wooldridge (2009); HHI = Herfindahl-Hirschman Index. Standard errors in parenthesis. Statistical significance: * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 2: Effects of subsidies (universal/SME) on firm size and sector composition.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Average firm size				Sector composition		
	All firms	Size of firms <25 empl.	Size of firms 25-250 empl.	Size of firms 250+ empl.	Share of firms <25 empl.	Share of firms 25-250 empl.	Share of firms 250+ empl.
Universal	0.039**	0.030*	-0.017	0.005	0.003	-0.003	0.002
	(0.019)	(0.017)	(0.0103)	(0.016)	(0.003)	(0.003)	(0.003)
SME-specific	-0.099	0.023	-0.0003	-0.014	0.010*	0.007	-0.018**
	(0.067)	(0.045)	(0.032)	(0.042)	(0.006)	(0.008)	(0.008)
Constant	4.754***	2.674***	4.484***	7.113***	0.187***	0.386***	0.238***
	(0.017)	(0.014)	(0.01)	(0.016)	(0.002)	(0.003)	(0.003)
Country $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓
Sector $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓
Country $\times$ Sector FE	✓	✓	✓	✓	✓	✓	✓
# obs.	14827	10276	13436	12483	15848	15848	15848

Note. Three-stage FE DiD. Variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Size = log of employees. In columns [2]-[4], size is computed for sub-samples of firms of given size classes (below 25, between 25 and 250, and above 250 employees) within country-sector-year tuples. In columns [5]-[7], the share of firms of given size classes (below 25, between 25 and 250, and above 250 employees) is computed as the share of firms of such given size classes within country-sector-year tuples. Standard errors in parenthesis. Statistical significance: * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3: Effects of subsidies (innovation oriented) on R&D activity.

	[1] R&D volumes	[2] R&D intensity	[3] R&D diffusion
Subsidy unrelated to innovation	-0.006	0.091	-0.003
	(0.067)	(0.057)	(0.003)
Innovation oriented subsidy	-0.094	0.147*	0.002
	(0.085)	(0.077)	(0.004)
Patent-intensive sector	-0.013	0.008	-0.006
	(0.096)	(0.104)	(0.004)
Innovation oriented subsidy × Patent-intensive sector	0.191*	-0.035	-0.017
	(0.115)	(0.117)	(0.012)
Constant	7.808***	0.811***	0.183***
	(0.055)	(0.050)	(0.002)
Country×Year FE	✓	✓	✓
Sector×Year FE	✓	✓	✓
Country×Sector FE	✓	✓	✓
# obs.	6148	5888	9620

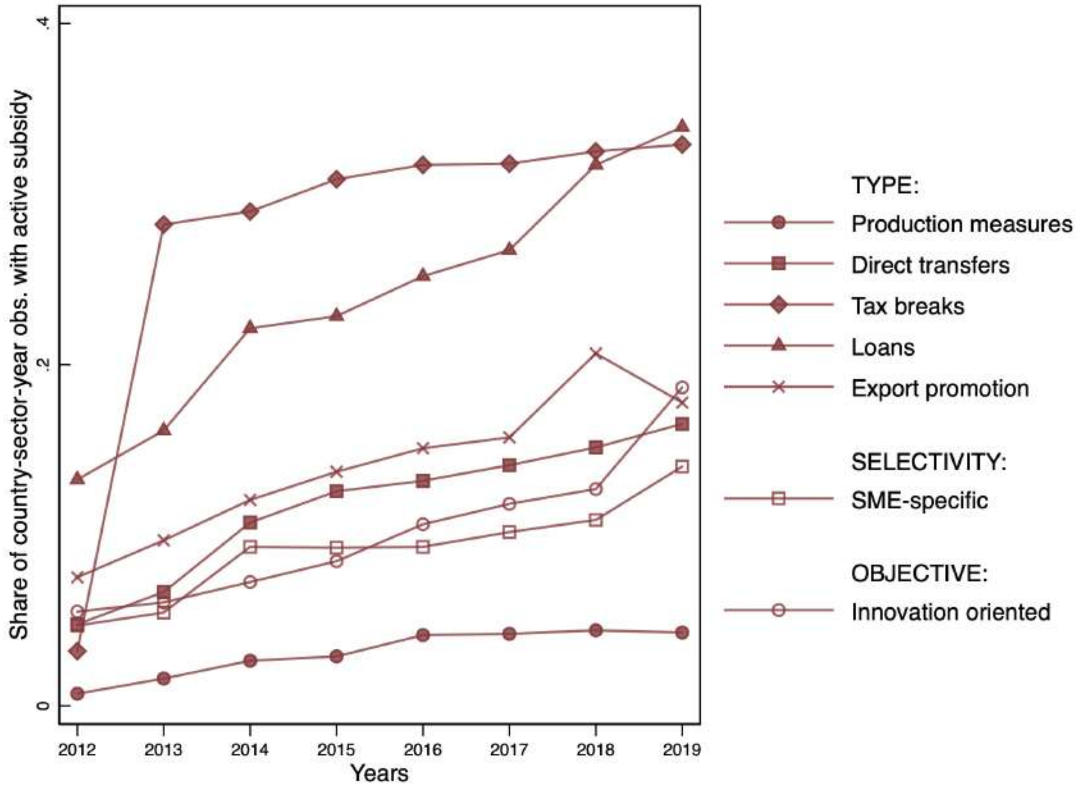
Note. Three-stage FE DiD. Variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: R&D volumes = log of R&D expenditure; R&D intensity = log of R&D expenditure per employee; R&D diffusion = share of firms with positive R&D expenditure. Patent-intensive sectors are the top 5% sectors in terms of average patents per employee. Standard errors in parenthesis. Statistical significance: * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4: Effects of subsidies (any) on leader's shares.

	[1] Leader's relative revenues	[2] Leader's relative TFP	[3] Leader's relative R&D
Any subsidy	-0.004	0.001	0.013
	(0.003)	(0.004)	(0.010)
Quasi-monopolistic market	0.265***	0.002	0.013
	(0.006)	(0.008)	(0.026)
Any subsidy × Quasi-monopolistic market	0.031***	0.009	0.009
	(0.031)	(0.011)	(0.030)
Constant	0.381***	1.345***	1.272***
	(0.002)	(0.003)	(0.008)
Country×Year FE	✓	✓	✓
Sector×Year FE	✓	✓	✓
Country×Sector FE	✓	✓	✓
# obs.	15620	14204	6148

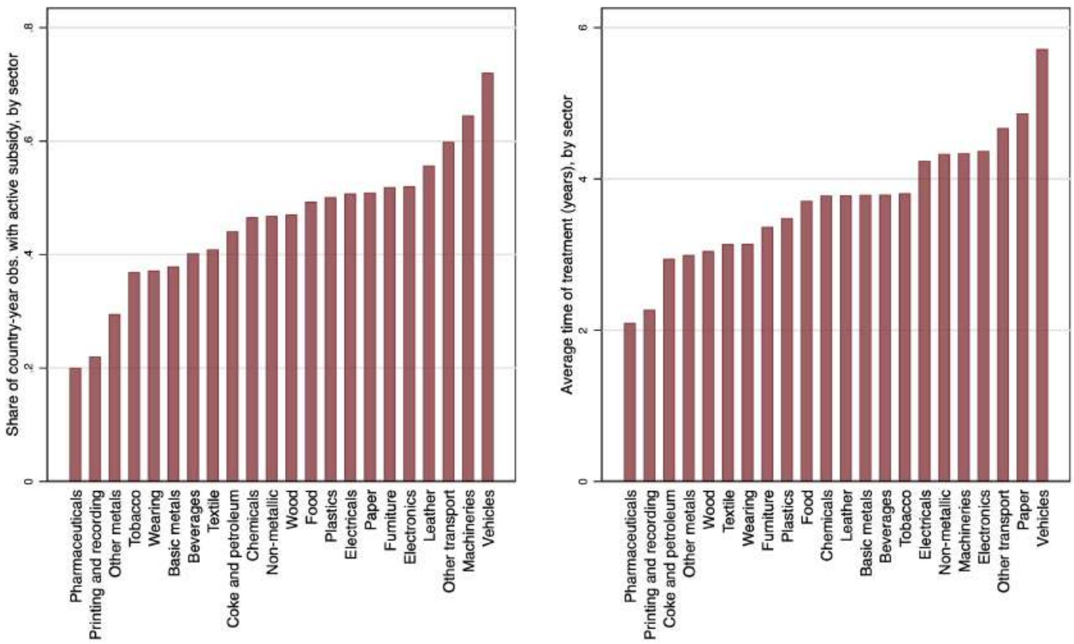
Note. Three-stage FE DiD. Variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variable is a dummy = 1 for active subsidy (0 otherwise). Outcome variables: revenues of the market leader relative to the sector-average; TFP of the market leader relative to the sector-average; R&D of the market leader relative to the sector-average. Quasi-monopolistic market is a dummy = 1 if the leading firm has a 90%+ market share (0 otherwise). TFP = Total Factor Productivity recovered with Wooldridge (2009). Standard errors in parenthesis. Statistical significance: * significant at 10%, ** significant at 5%, *** significant at 1%.

Figure 1: Implementation of subsidy programs over time.



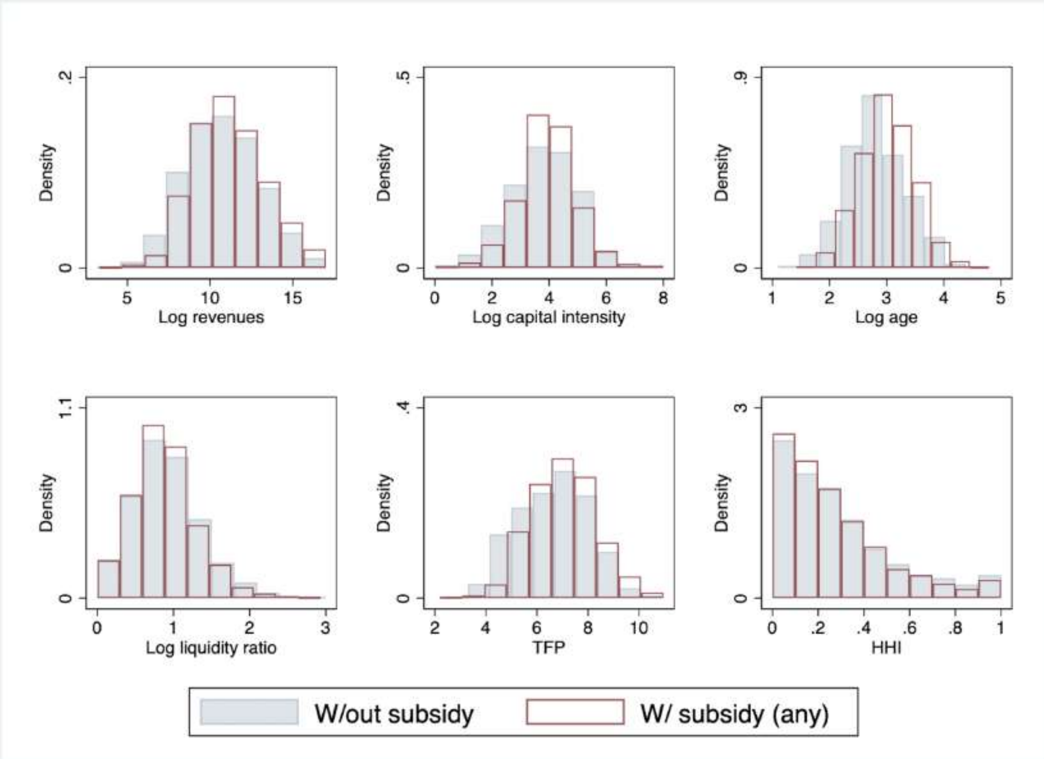
Note. Data at country-sector-year level (sectors at 3-digit). Country-sector-year observations are considered as treated if at least a subsidy program is implemented at the level of the tuple. Subsidy programs are classified based on their type, selectivity (related to size), and objective (innovation oriented). 31408 observations are used (collapsed by year of subsidy implementation).

Figure 2: Sectoral distribution of subsidy programs.



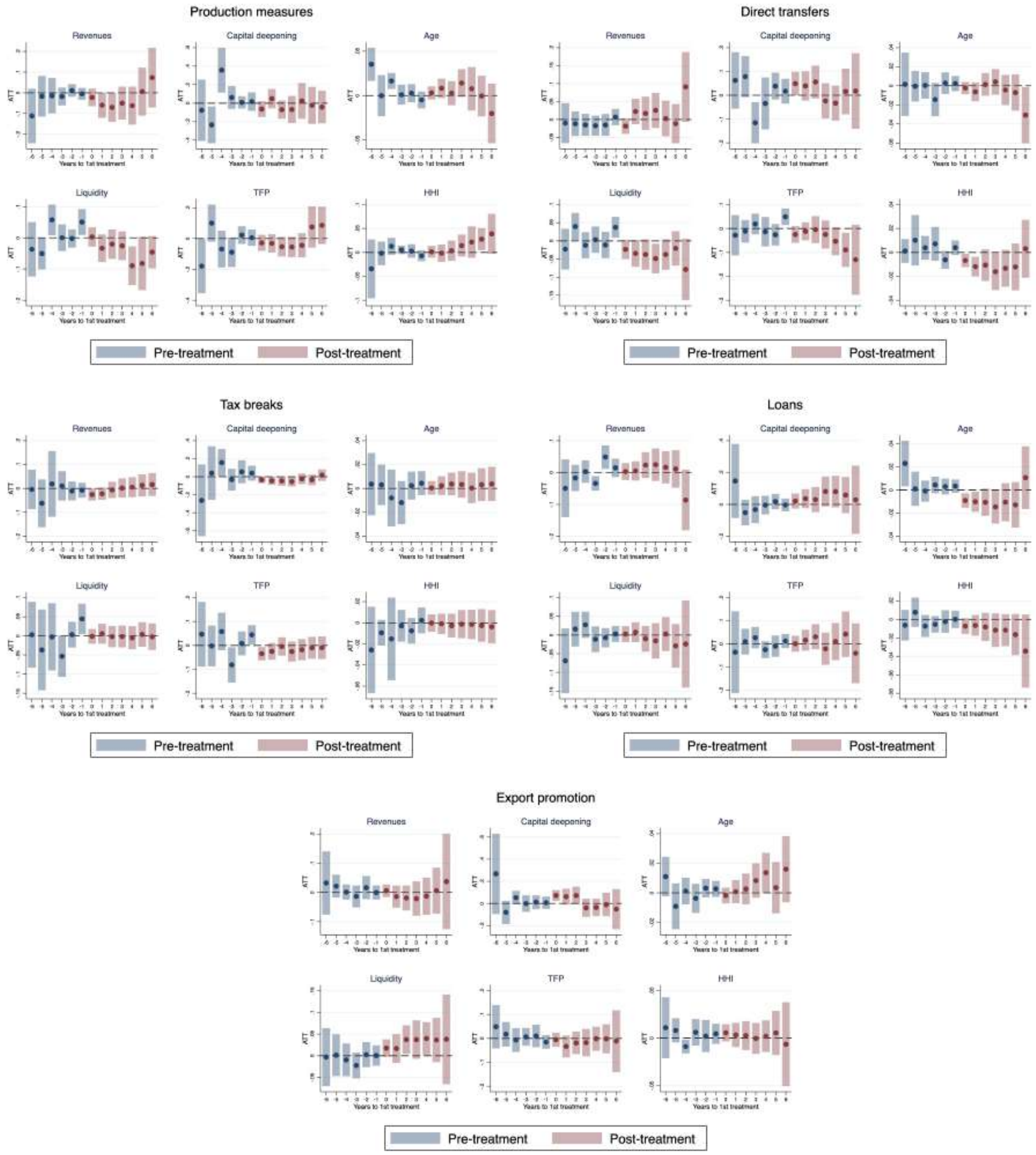
Note. Data at country-sector-year level. A sector in a country-year cell is considered as treated if at least a subsidy program (of any kind) is implemented at the level of the country-sector-year tuple. 31408 observations are used. In the left-hand-side panel, observations are collapsed by 2-digit sectors and reported as shares of country-sector observations implementing any subsidy, by sector. In the right-hand-side panel, treatment periods (in years) are collapsed by 2-digit sectors and reported as averages, by sectors.

Figure 3: Sectoral performance with and without subsidies.



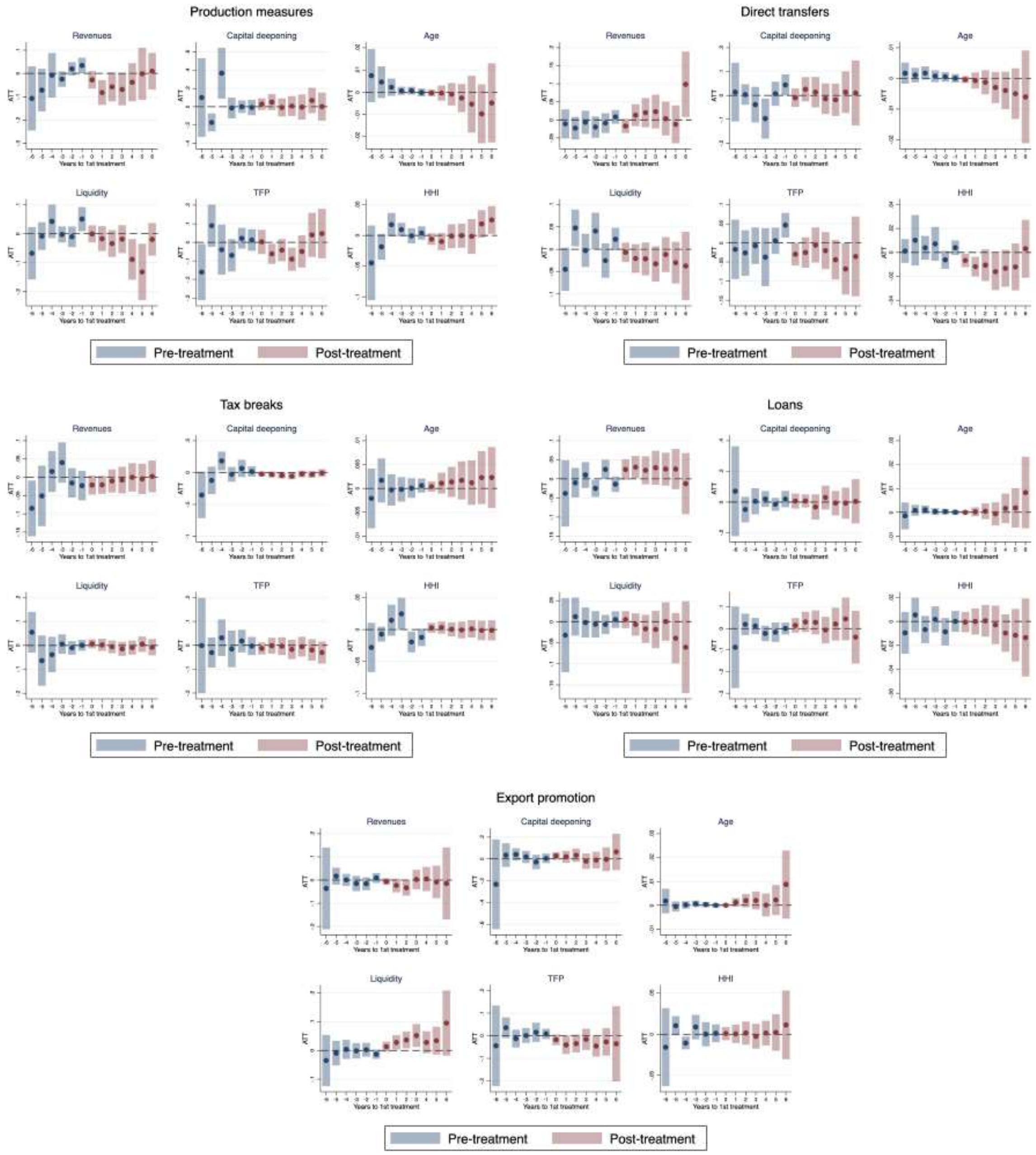
Note. Data at country-sector-year level (sectors at 3-digit). Country-sector-year observations are considered as treated if at least a subsidy program (of any kind) is implemented at the level of the tuple. 31408 country-sector-year observations are used. Performance indicators are computed at the firm-year level and then averaged at the country-sector-year. TFP is Total Factor Productivity recovered with Wooldridge (2009). HHI stands for Herfindahl-Hirschman Index.

Figure 4: Business performance (all firms): estimated dynamic effects.



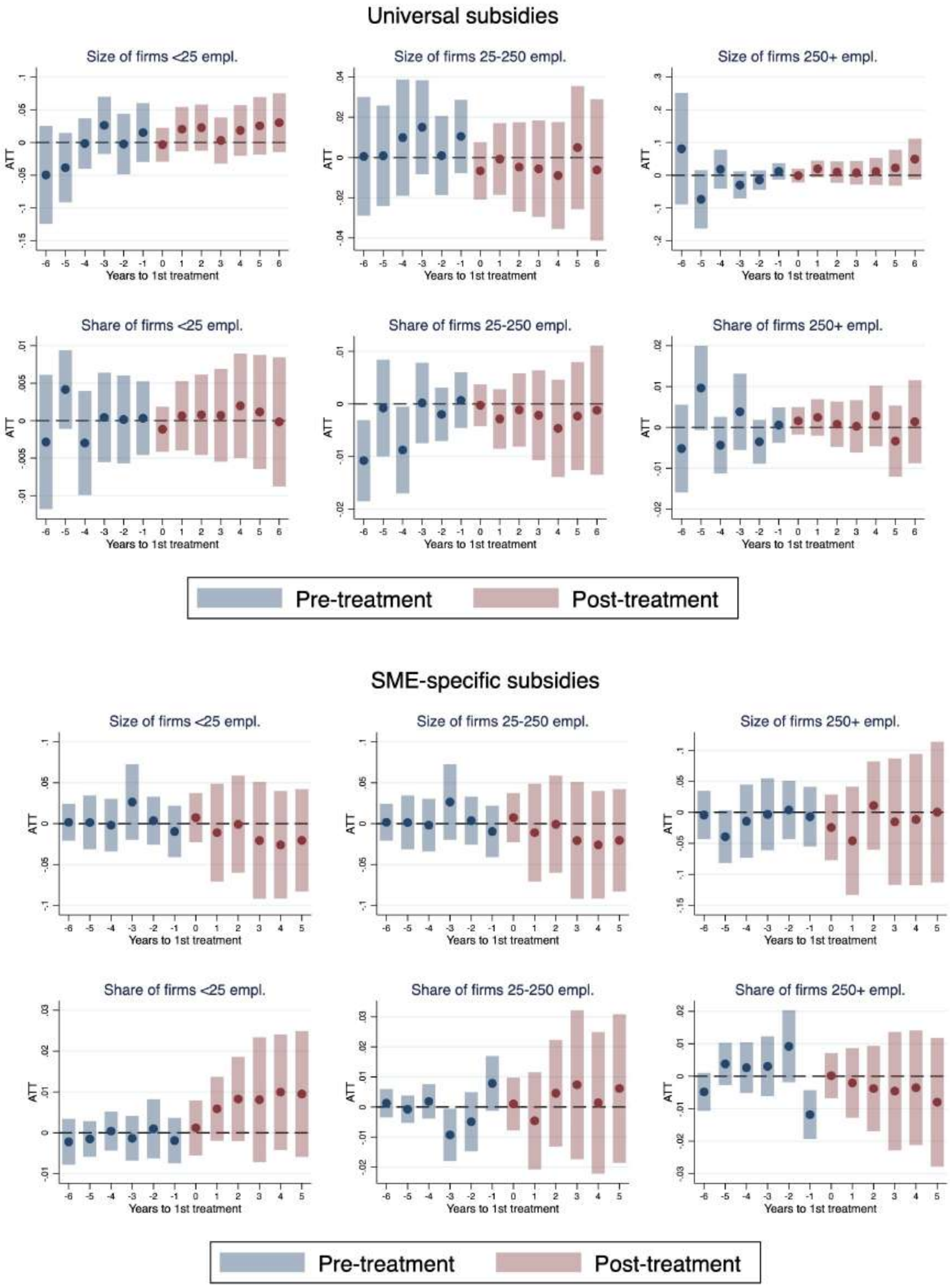
Note. Estimates obtained with the method of Callaway and Sant'Anna (2021), run on purged outcomes resulting from three-stage FE DiD (see Section "Robustness" in the paper, for details). All firms (newborn and pre-existing) are considered when computing sectoral performance variables. Final variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: revenues = log of revenues; capital deepening = log of tangible assets per employee; age = log of age; liquidity ratio = log of liquidity ratio; TFP = Total Factor Productivity recovered with Wooldridge (2009); HHI = Herfindahl-Hirschman Index.

Figure 5: Business performance (only pre-existing firms): estimated dynamic effects.



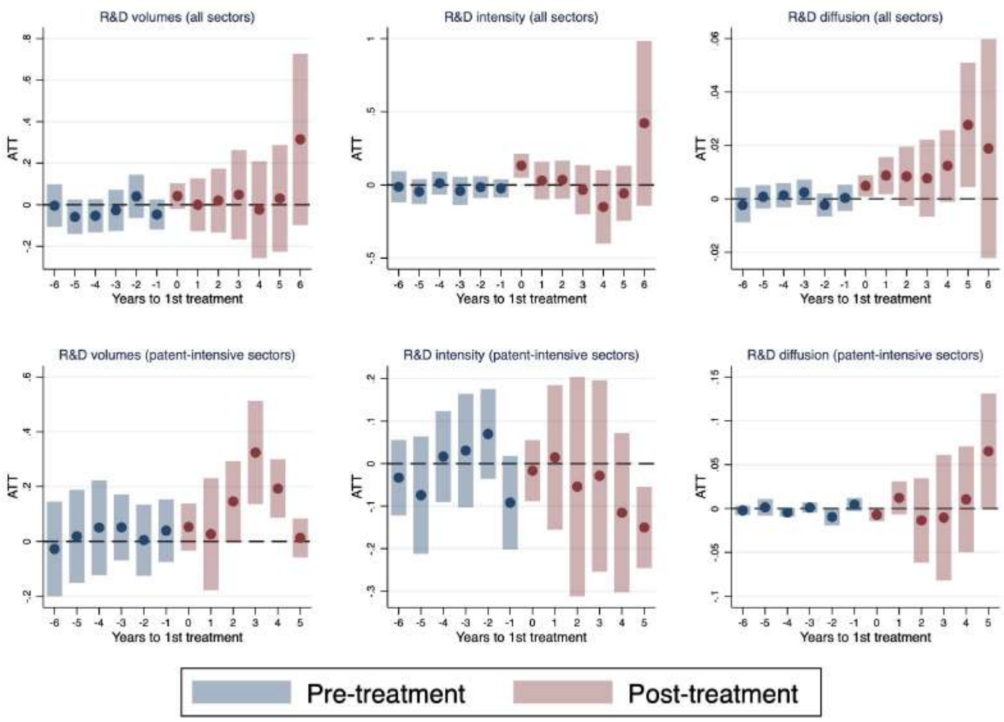
Note. Estimates obtained with the method of Callaway and Sant'Anna (2021), run on purged outcomes resulting from three-stage FE DiD (see Section "Robustness" in the paper, for details). Only pre-existing firms (i.e. born before 2012) are considered when computing sectoral performance variables. Final variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: revenues = log of revenues; capital deepening = log of tangible assets per employee; age = log of age; liquidity ratio = log of liquidity ratio; TFP = Total Factor Productivity recovered with Wooldridge (2009); HHI = Herfindahl-Hirschman Index.

Figure 6: Firm size and sector composition: estimated dynamic effects.



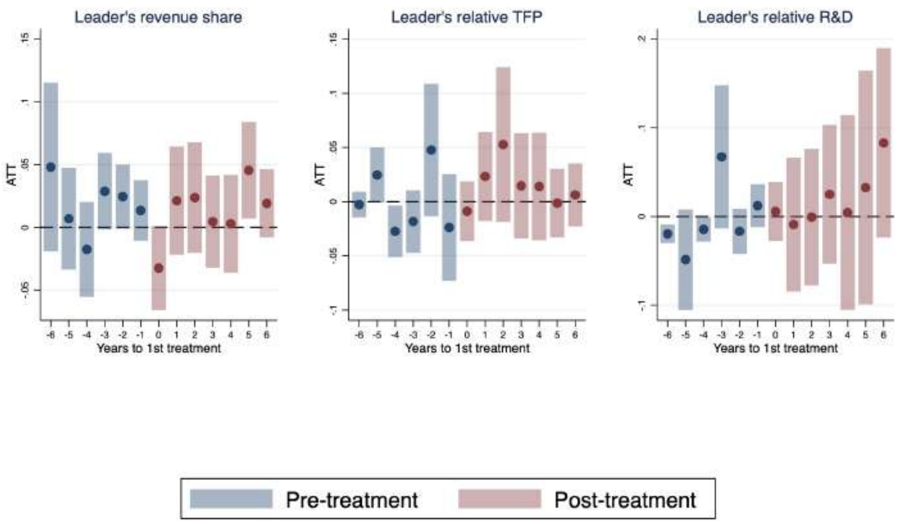
Note. Estimates obtained with the method of Callaway and Sant'Anna (2021), run on purged outcomes resulting from three-stage FE DiD (see Section "Robustness" in the paper, for details). Variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Size = log of employees. Size is computed for sub-samples of firms of given size classes (below 25, between 25 and 250, and above 250 employees) within country-sector-year tuples. Shares of firms of given size classes (below 25, between 25 and 250, and above 250 employees) are computed as the share of firms of such given size classes within country-sector-year tuples.

Figure 7: R&D activity: estimated dynamic effects.



Note. Estimates obtained with the method of Callaway and Sant'Anna (2021), run on purged outcomes resulting from three-stage FE DiD (see Section "Robustness" in the paper, for details). Only pre-existing firms (i.e. born before 2012) are considered when computing sectoral performance variables. Final variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: R&D volumes = log of R&D expenditure; R&D intensity = log of R&D expenditure per employee; R&D diffusion = share of firms with positive R&D expenditure. Patent-intensive sectors are the top 5% sectors in terms of average patents per employee.

Figure 8: Leader's shares in quasi-monopolisitic markets: estimated dynamic effects.



Note. Estimates obtained with the method of Callaway and Sant'Anna (2021), run on purged outcomes resulting from three-stage FE DiD (see Section "Robustness" in the paper, for details). Outcome variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. The estimated effects refer to quasi-monopolistic markets, identified as 3-digit sectors where the leading firm has a 90%+ market share. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: revenues of the market leader relative to the sector-average; TFP of the market leader relative to the sector-average; R&D of the market leader relative to the sector-average. TFP = Total Factor Productivity recovered with Wooldridge (2009).

Appendix

A Subsidies and sectoral performance heterogeneity

We deepen the analysis by examining more closely the impact of different types of subsidies on sectoral heterogeneity. To do so, we select the 25th and 75th percentiles of the distributions of the different sectoral performance indicators (revenues, capital deepening, age, liquidity, and productivity). This will allow us to show whether the subsidy has a greater effect on firms in the 25th percentile (e.g., those that are less capitalized, less productive, less liquid, and younger) than those in the 75th percentile (those that are more mature, or with high capital-labor intensity, high productivity, and more liquid) of each variable. In addition, by making the interquartile difference, we will try to understand whether, in treated sectors, subsidies reduce inequality among firms in terms of performance or increase it even more.

Table A.1 reports the results for different quartiles of performance using a sample consisting of all firms (both pre-existing and newborn) for a period from 2012 to 2019. In columns [1]-[6], there are results for the 25th percentile, and in columns [7]-[12] are those for the 75th percentile.

[insert Table A.1 about here]

To further test the robustness of our results, we also employ the method introduced in Sant'Anna and Zhao (2020) and Callaway and Sant'Anna (2021), calculating the dynamic effects of the subsidy on the two quartiles of interest, following the same econometric strategy used in the paper, and show the results in Figures from A.1 to A.3.

[insert Figures A.1, A.2, A.3, about here]

Consistent with the previously analyzed average sectoral impact, production subsidies do not appear to have a significant effect on many of the variables considered. We observe substantial significance only in their effect on the 75th percentile of TFP, suggesting that this type of subsidy may slow the productivity growth of the most productive firms without having a significant impact on less productive firms. Analyzing the effect of direct transfers on market concentration, we observe a significant and negative impact, likely attributable to the entry of new firms into the subsidized sectors. This is further supported by the negative dynamic effect of the subsidy on both percentiles of firm age (see Figure A.1). Additionally, the attraction of advanced firms by this type of subsidy is confirmed. Indeed, beyond the positive effect on the capital-labor ratio observed for the sectoral average, there is also evidence of a positive impact on liquidity across both quartiles.

In both the three-way fixed effects model and the dynamic analysis, tax breaks have a negative effect on the revenues of firms in the 25th and 75th percentiles. Additionally, the incentive to substitute capital with labour, particularly for firms in the first quartile, is confirmed (see Figure A.2). This suggests that tax breaks tend to attract less capitalized firms and exacerbate the gap between these firms and those with higher capital-to-labour ratios. If tax breaks appear to attract firms with a low capital-to-labour ratio, the average effect of loans seems to be the opposite, attracting more technologically advanced firms that reduce market concentration. The analysis of percentiles supports this evidence, showing a significantly negative dynamic response from the quartile of younger firms (see Figure A.2). The estimates in Table A.1 confirm the technologically relevant effects, with a positive response in both productivity percentiles. This productivity gain could be explained by the adoption of more capital-intensive production processes that these subsidies would induce in the sectoral average.

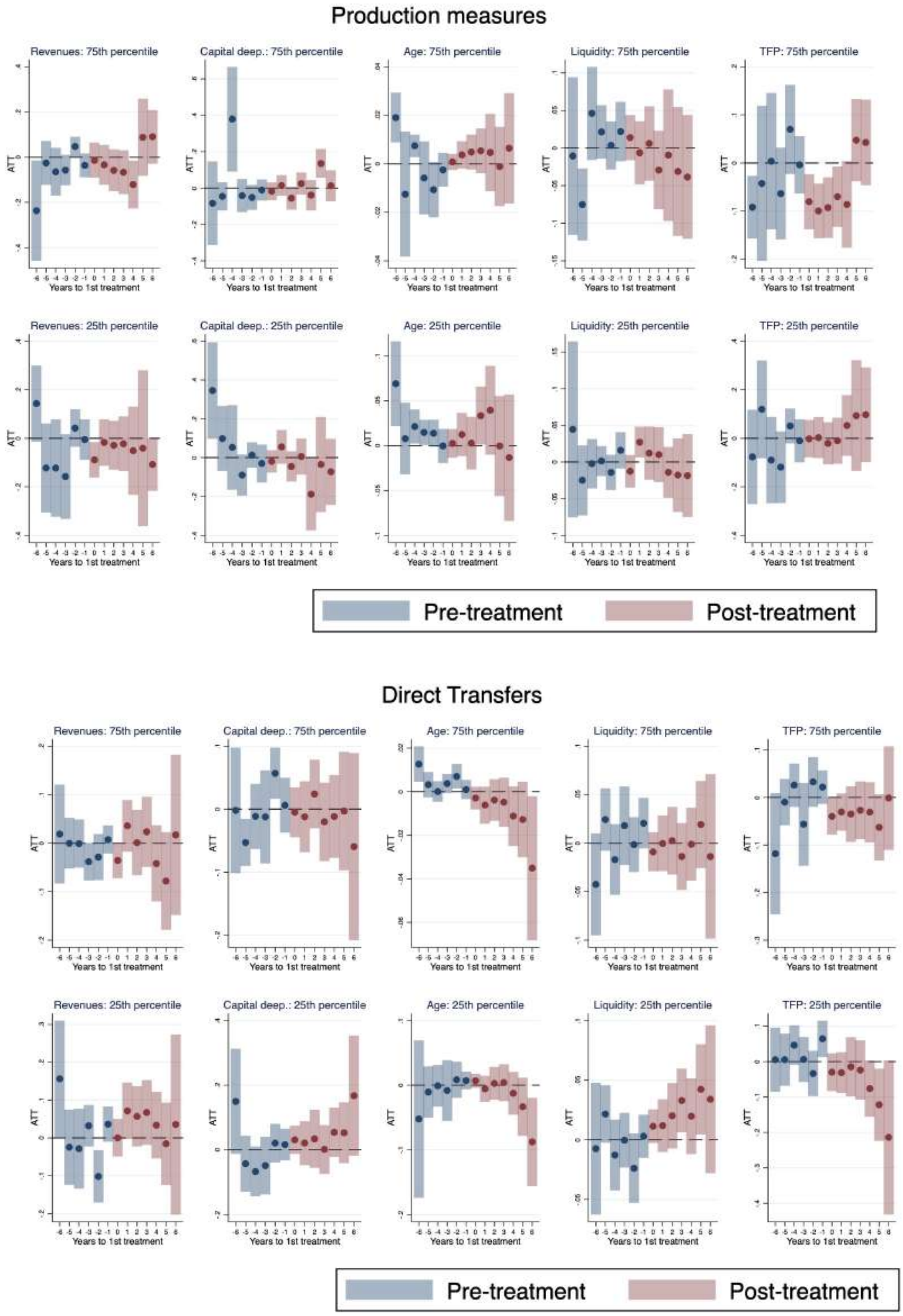
Lastly, the results in Table A.1 confirm the positive effects of export subsidies on the capital-to-labour ratio, previously observed at the sectoral average level and now also for both quartiles. The effect on firm age is also noteworthy, showing a significantly positive impact for both mature and younger firms, with a greater effect on the latter. This suggests that such subsidies not only enhance overall resilience but also reduce the age dispersion between younger and more mature firms.

Table A.1: Effects of subsidies (by type) on business performance (all firms): analysis of the 25th and 75th percentiles.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	25th percentile					75th percentile				
	Revenues	Capital deep.	Age	Liquidity ratio	TFP	Revenues	Capital deep.	Age	Liquidity ratio	TFP
Production measures	-0.082	0.005	0.028	0.013	-0.016	-0.071	-0.023	0.001	0.015	-0.085**
	(0.057)	(0.050)	(0.018)	(0.015)	(0.049)	(0.051)	(0.037)	(0.005)	(0.020)	(0.039)
Direct transfers	0.011	0.045	0.005	0.024**	-0.006	-0.023	0.032	-0.002	0.021*	-0.010
	(0.033)	(0.031)	(0.012)	(0.011)	(0.032)	(0.027)	(0.024)	(0.004)	(0.013)	(0.023)
Tax breaks	-0.070**	-0.059**	0.001	-0.011	0.006	-0.042*	-0.042	-0.002	-0.021	0.001
	(0.029)	(0.029)	(0.011)	(0.011)	(0.027)	(0.025)	(0.026)	(0.004)	(0.014)	(0.024)
Loans	0.054*	0.023	-0.017	0.005	0.060*	0.003	0.021	-0.001	0.004	0.035*
	(0.028)	(0.027)	(0.012)	(0.010)	(0.035)	(0.024)	(0.020)	(0.004)	(0.012)	(0.021)
Export promotion	-0.031	0.058*	0.036***	-0.014	-0.044	-0.021	0.041*	0.000	0.016	-0.020
	(0.036)	(0.033)	(0.013)	(0.014)	(0.032)	(0.028)	(0.025)	(0.004)	(0.016)	(0.021)
Constant	8.460***	2.373***	2.574***	0.089***	6.114***	10.620***	3.981***	3.462***	1.011***	7.560***
	(0.023)	(0.023)	(0.008)	(0.009)	(0.021)	(0.020)	(0.017)	(0.003)	(0.010)	(0.016)
Country $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country $\times$ Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
# obs.	15614	14496	15845	15528	14204	15619	14704	15845	15528	14204

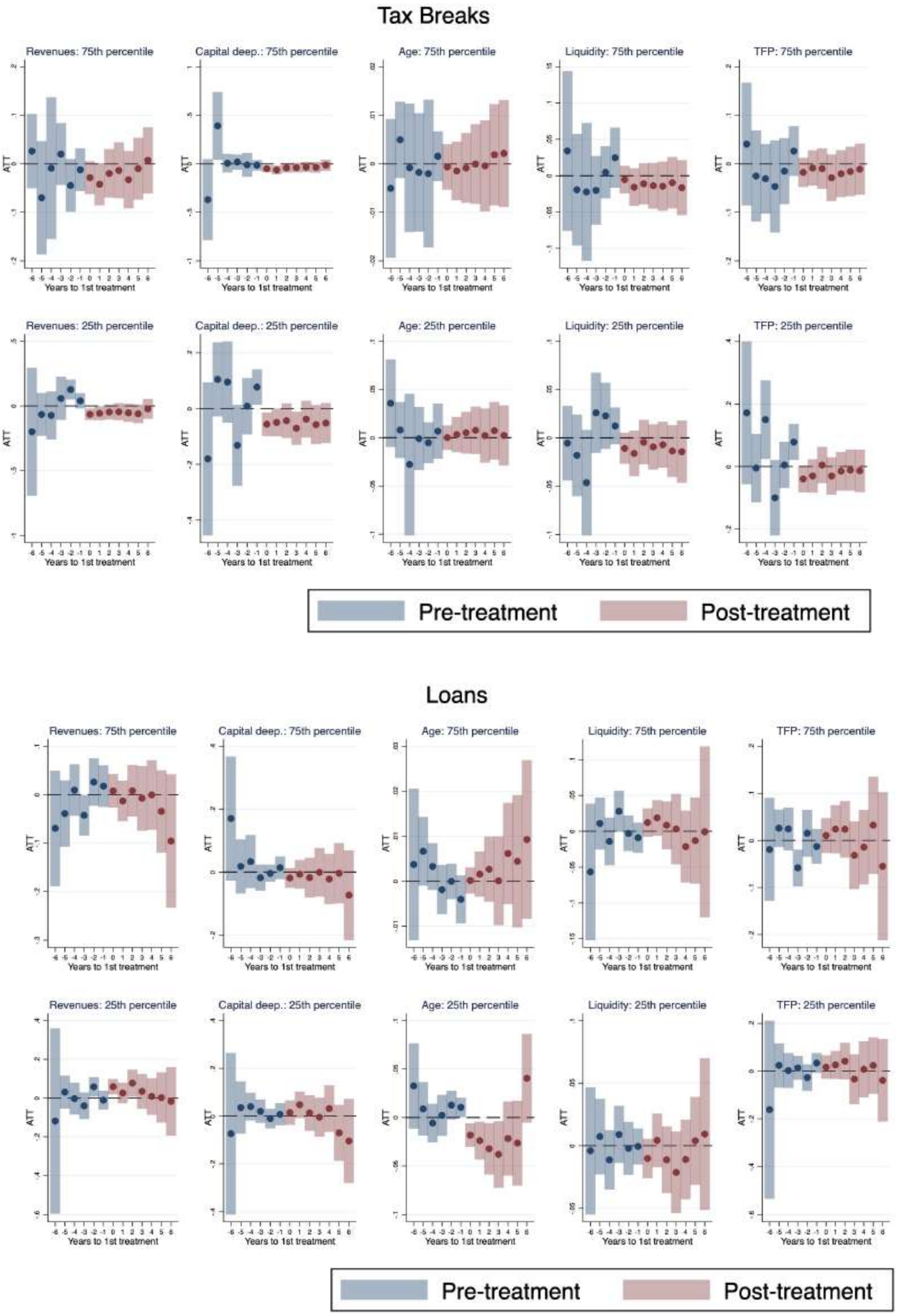
Note. Three-stage FE DiD. Variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: revenues = log of revenues; capital deepening = log of tangible assets per employee; age = log of age; liquidity ratio = log of liquidity ratio; TFP = Total Factor Productivity recovered with Wooldridge (2009); HHI = Herfindahl-Hirschman Index. Standard errors in parenthesis. Statistical significance: * significant at 10%, ** significant at 5%, *** significant at 1%.

Figure A.1: Estimated dynamic effects of subsidies (by type) on business performance (all firms): analysis of the 25th and 75th percentiles.



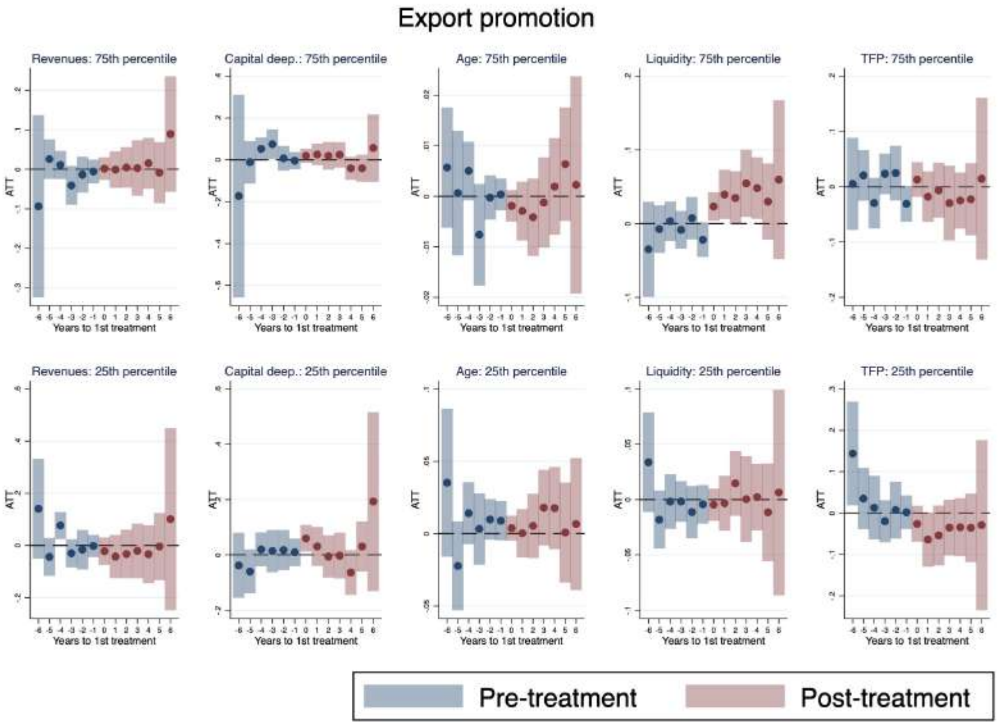
Note. Estimates obtained with the method of Callaway and Sant'Anna (2021), run on purged outcomes resulting from three-stage FE DiD (see Section "Robustness" in the paper, for details). All firms (newborn and pre-existing) are considered when computing sectoral performance variables. Final variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: revenues = log of revenues; capital deepening = log of tangible assets per employee; age = log of age; liquidity ratio = log of liquidity ratio; TFP = Total Factor Productivity recovered with Wooldridge (2009).

Figure A.2: Estimated dynamic effects of subsidies (by type) on business performance (all firms): analysis of the 25th and 75th percentiles.



Note. Estimates obtained with the method of Callaway and Sant'Anna (2021), run on purged outcomes resulting from three-stage FE DiD (see Section "Robustness" in the paper, for details). All firms (newborn and pre-existing) are considered when computing sectoral performance variables. Final variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: revenues = log of revenues; capital deepening = log of tangible assets per employee; age = log of age; liquidity ratio = log of liquidity ratio; TFP = Total Factor Productivity recovered with Wooldridge (2009).

Figure A.3: Estimated dynamic effects of subsidies (by type) on business performance (all firms): analysis of the 25th and 75th percentiles.



Note. Estimates obtained with the method of Callaway and Sant'Anna (2021), run on purged outcomes resulting from three-stage FE DiD (see Section "Robustness" in the paper, for details). All firms (newborn and pre-existing) are considered when computing sectoral performance variables. Final variables used are at the country-sector-year level, over the 2012-2019 time span. Sectors are defined as NACE 3-digit level. Subsidy variables are dummies = 1 for active subsidy (0 otherwise). Outcome variables: revenues = log of revenues; capital deepening = log of tangible assets per employee; age = log of age; liquidity ratio = log of liquidity ratio; TFP = Total Factor Productivity recovered with Wooldridge (2009).