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ABSTRACT

WHO WINS AND WHO LOSES FROM STATE SUBSIDIES?

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China is perceived to rely on subsidizing firms in targeted industries to improve their performance and stay competitive. We implement an approach that allows for the joint estimation of direct and indirect effects of subsidies on subsidized and non-subsidized firms. We find that firms that receive subsidies experience a boost for productivity. However, our approach highlights the importance of indirect effects, which are generally neglected in the literature. We find that, in general but not always, non-subsidized firms experience reductions in their productivity growth if they operate in a cluster where other firms are subsidized. These negative externalities depend on the share of firms that receive subsidies in the cluster. Aggregating direct and indirect effects into a (weighted) total effect shows that this negative indirect effect tends to dominate. We interpret our results in the light of a simple heterogenous firm type model, which highlights that subsidization, in a competitive environment of firms, may potentially harm non-subsidized firms.

Keywords: Subsidies, Firm performance, Treatment effects, Externalities, China

JEL classification: H25; H32; L25

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1 Introduction

China is frequently noted for its policy of subsidizing firms in targeted industries. Some recent examples include electric cars, steel, and solar panels, all of which were discussed as controversial in the media.[1] Indeed, as commonly expressed in public, this use of state intervention may be one of the reasons for the recent US trade dispute with China, as it is perceived as unfair competition in China's trade practices. Underlying this policy of strong and targeted government support is, presumably, the assumption on the part of Chinese policy makers that subsidies help Chinese firms improve performance and thus competitiveness. Yet, neither the theoretical nor empirical base for such an assumption is clear-cut (see Haley and Haley, 2013a, and references therein).

This paper provides fresh evidence on this issue using data on subsidy receipts from a large-scale firm level panel dataset for the Chinese manufacturing sector. We estimate the effect of subsidization on firm level productivity, paying particular attention to the fact that, while *subsidized firms* may benefit, *non-subsidized firms* may be harmed by such a policy as a consequence. Specifically, we adapt an estimation approach (developed by Girma et al., 2015) that provides a unified framework for the estimation of direct effects (on subsidized firms) and indirect effects (on non-subsidized firms) of subsidization. Uniquely, this framework allows us to estimate these effects depending (possibly non-linearly) on the level of subsidization in a local cluster.[2]

Importantly, our identification strategy recognizes that there are two levels of selection. The first issue, as is well recognized in other studies, is that the selection of subsidized firms is unlikely to be random. However, there is a second selection problem that previous work has overlooked. When modelling the levels of subsidization in a cluster, say, as the number or share of treated firms within a province or industry, the distribution of treated firms across such clusters is also unlikely to be random. There may, for example, be deliberate government policy towards attracting certain types of firms to certain provinces or sectors, which also provide subsidies. Or there may be other non-random factors determining the location of subsidized firms. This selection problem has generally not been recognized in the literature thus far. The approach implemented here allows us to deal with both selection problems using generalized propensity score techniques at the two levels.[3]

Our empirical analysis, which distinguishes private owned, state-owned and foreign-owned enterprises, identifies a positive direct effect: Chinese state subsidies have evidently benefited recipients by enhancing their productivity, irrespective of their ownership. Importantly, the magnitude of this positive direct effect depends on how many firms received subsidies in a cluster. However, the direct effects of subsidies do not tell the whole story. The estimation of indirect effects of subsidies reveals mainly negative effects on unsubsidized firms. Aggregating direct and indirect effects into a (weighted) total effect shows that this negative indirect effect tends to dominate. For all three firm types, subsidies have an overall negative effect, especially in clusters with fairly high shares of subsidized firms.

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[1] *See, for example, the Financial Times at http://www.ft.com/cms/s/0/a55e7d36-db8a-11e5-a72f-1e7744c66818.html#axzz4BeAlJ6Ax and http://www.ft.com/intl/cms/s/0/6d4e6408-5e68-11e2-b3cb-00144feab49a.html#axzz4BeAlJ6Ax (accessed 15 June 2016), and Haley and Haley (2013b).*

[2] *In Girma et al. (2015) the estimation approach is developed studying the effect of foreign ownership on firm level productivity.*

[3] *Using propensity score techniques for selection on observables is well established in the literature on the evaluation of subsidies, e.g., Görg et al. (2008), Girma et al. (2009), Howell (2017). It is also used in related fields of economics, e.g., looking at firm level impact of domestic and international mergers and acquisitions (e.g., Geurts and Van Biesebroeck, 2019, Guadalupe et al., 2012).*

In order to make sense of our empirical results, we build a simple theoretical model with heterogenous firms, which fits most of the observed patterns. In a related paper, Pflüger and Suedekum (2013) also have a heterogeneous firm model and show that giving subsidies to firms increases competitive pressures and allows in equilibrium only more productive firms to enter a market, thus leading to higher average productivity of operating firms. Our empirical results however show a more complicated picture, where spillover effects from subsidies can lead to deteriorating average productivity of firms. We propose some simple extensions of the heterogeneous firm model that can generate those results and provide a good fit between theory and data. Specifically, our model shows how the direct effect on subsidized firms but also the spillover effect on non-subsidized firms depend on how many firms receive subsidies in the clusters. Subsidies change the competitive environment, so the total amount of subsidies received affects firm selection into entering a market. That way subsidies affect average productivity in a cluster, without making any additional assumptions about individual firm investment in, say, productivity or innovation.

There are several empirical papers related to our study, that seek to evaluate the direct impact of public subventions on the subsidy-receiving firms' performance in a number of countries (see *inter alia* Bernini and Pellegrini, 2011; Cerqua and Pellegrini, 2014; Howell, 2017; Girma et al., 2009; Görg et al., 2008). However, subsidies, importantly, have a broader impact than just the direct impact on recipients alone. Subsidies may inflict positive or negative externalities (spillovers) on non-subsidized firms (Rotemberg, 2019, Blonigen, 2016). Externalities may arise as subsidized firms change the competitive environment, which are likely to affect the strategy, conduct and performance of non-subsidized firms. Most empirical studies (including those cited above) on the effect of subsidies do not allow for such spillovers to firms that do not receive subsidies. Notable exceptions are De Mel et al. (2008) who look at the impact on returns to capital of small cash grants to microenterprises in Sri Lanka, Cerqua and Pellegrini (2017) who examine a policy targeted at small and medium sized firms in Italy, and Rotemberg (2019) who analyses firms eligible for small firm subsidies in India.[4]

Our paper also relates to the broader literature on so-called place-based policies - a governmental tool used to enhance the economic performance of a particular area. This literature, as summarized by Neumark and Simpson (2015) is also concerned with estimating effects on economic actors within the targeted zone and those in the vicinity, i.e., direct and indirect effects in our parlance. We contribute to this literature by proposing a novel estimation approach for identifying direct and indirect effects of a policy intervention.

Another issue that is generally not considered in the literature on the evaluation of subsidies is that the strength of externalities generated by subsidization may in turn impact on the relative magnitudes of the direct or indirect effects of the subsidy. For example, the more subsidized firms we have in a particular geographic area, the lower may be the gain for the treated firm from receiving a subsidy, or the stronger may be the negative externality on the non-subsidised firms.[5]

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[4] *De Mel et al. (2008) adopt a field experiment approach where a small number of grant recipient firms were randomly chosen to avoid the problem of selectivity in subsidy receipt, before going on to estimating the direct effects of receiving the subsidy by comparing recipient and control group firms. Spillovers are taken into account by controlling for the number of treated firms within a limited geographic radius (i.e. a co-location). Cerqua and Pellegrini (2017) use selection-on-observables in a coarsened exact matching framework. Rotemberg (2019) uses changes in the eligibility criteria for his identification strategy.*

[5] *The existence of indirect spillover effects, or the dependence of the effects on the strength of the externality, are usually ruled out in the microeconometric evaluation approaches commonly employed in the literature by assumption: they implicitly assume no interactions between firms; or in the parlance of the econometric literature, the Stable Unit Treatment Value Assumption (SUTVA). This assumption essentially posits that an individual outcome does not depend on the treatment status of others. Hence, the estimation of the spillover effects described above are ruled out by assumption – an assumption that is unlikely to hold in practice, given the very plausible arguments and arising evidence as to why one may expect subsidies to have externalities on non-subsidized firms.*

The novel estimation approach employed in this paper allows us to tackle these issues, and hence address an important gap in the literature that debates the role of the state through subsidizing businesses. In contrast to De Mel et al. (2008) and Rotemberg (2019) our identification strategy does not rely on a small-scale field experiment or idiosyncratic changes in government policy but uses observational data and methods based on selection on observable pre-treatment characteristics to deal with selection problems. Hence, our approach can be easily applied by other researchers using similar data for other countries and through this external validity can be established.

Our paper also contributes to earlier papers that have looked at the impact of subsidies on firm performance in China. For example, Aghion et al. (2015) investigate the implications of subsidies (as one aspect of industrial policy) for firm level productivity in China. Using similar data to ours, they find that industry-city combinations where the correlation between subsidy receipt and the level of competition is higher also have firms with higher productivity growth. Also, a greater dispersion of subsidies within an industry-city combination is associated with higher firm level productivity growth. They control for subsidy receipt at the level of the individual firm, which is positively correlated with productivity growth. While our results are not strictly comparable given the different approach used, our findings on the direct effects are in line with theirs. However, they do not look at indirect effects, nor do they allow the effects to vary with the strength of subsidization. In contrast to Aghion et al. (2015), Howell (2017) finds negative direct effects when looking at the relationship between subsidies and productivity growth for Chinese firm level data using propensity score matching. However, he also does not allow for externalities, which may likely bias results.

The rest of the paper is structured as follows. The next section discusses some of the institutional background to the policy of using subsidies in China. This is followed by a brief description of our data set in Section 3. Section 4 sets out the econometric methodology, and Sections 5 and 6 present and discuss empirical results and extensions. Section 7 then discusses a theoretical framework that fits many aspects of the empirical results. Section 8 concludes.

2 Institutional background

The institutional foundation that governs China's economic dynamics can be described as a regionally decentralized authoritarian system in which the central government incentivizes local officials to promote regional economic growth (see Xu, 2011 and references therein). This has resulted in regional economic decentralization where local governments actively engage in shaping the business and economic landscape of their respective regions, and directly intervene in relation to businesses' investment and operational decisions.

A distinguishing feature of Chinese state capitalism is the use of capital controls by the government, including soft budget constraints (Kornai et al., 2003), influencing local banks (Lin and Li, 2008), or offering easy access to land and other economic resources to politically protected firms (Du and Girma, 2010). Perhaps one of the most controversial practices is the use of outright subsidies.

While government subsidies are by no means exclusive to China, the reason that the latter's case is attracting such interest stems from the fact that subsidies are spread over a large spectrum of firms and a broad range of sectors (Haley and Haley, 2013a). Shao and Bao (2011) find that over the years 2000-2006, about 13-19% of all firms reported in the Industrial Census receive subsidies and the percentage has been increasing over time. Girma et al. (2009) report that over the period 1998 to 2004, government production subsidies to manufacturing firms amounted to more than $100 billion. In a more recent study, Haley and Haley (2013a) combine official statistics with information from industry analysts and policy documents, and they estimate that China may have spent well over $300 billion on its largest SOEs between 1985 and 2005.

As in Howell (2017) and Girma et al. (2009), we use data on production-related subsidies that are allocated to firms. There are generally several reasons why governments subsidize enterprises:

industrial development, export promotion, supporting firms to innovate and securing a national advantage in leading industries (WTO, 2006). An additional specific motivation for the Chinese government to subsidize SOEs is to avoid a worsening of unemployment rates and social riots due to possible bankruptcies of SOEs (Luo and Golembiewski, 1996).

Having experienced a prolonged economic boom, China now faces the growing concerns of unsustainable high investment rates and soaring production costs. Despite increasing R&D spending, the country's rate of productivity growth remains relatively low, and China appears to be heading towards the "Middle Income Trap" (Woo et al., 2012). Recent evidence suggests that resource misallocation problems both within and between firms, can partly explain the slow aggregate productivity performance (Hsieh and Klenow, 2009; Du et al., 2014). As Hsieh and Klenow (2009) point out, government policies may well have a role to play to account for such misallocation. We therefore investigate the link between government intervention through subsidies and firm productivity, considering both the direct impact of receiving a subsidy on the firm's own performance as well as the indirect spillover effects on other firms.

3 Data and exploratory analysis

3.1 Data

We draw on firm level data from the Chinese manufacturing industry. The dataset is based on the *Annual Reports of Industrial Enterprise Statistics*, compiled by the China National Bureau of Statistics. The enterprises covered by this dataset account for an estimated 85–90 percent of total output in most industries.[6] Hence the data are well placed to study the wider economic impact of firm subsidies. For the purpose of this analysis, we have more than 300,000 firms over the period 1998-2007. The precise definition of the variables used in the analysis is given in Table 1.

[Table 1 about here]

Table 2 shows the value of total subsidies and the number of subsidized firms by ownership category, distinguishing private firms, foreign invested firms and state-owned enterprises (SOEs). It is noticeable that all categories of firms received substantial amounts of subsidies. For example, in 2007, more than 23 Billion USD was paid to 25,673 private firms, and just 4,077 state-owned enterprises (SOEs) received 6.7 Billion USD worth of production subsidies. Figure 1 reveals that the proportion of firms receiving subsidies has been increasing steadily from 1998 to the middle of the 2000s. Also, time series plots of the average amount of subsidy amongst subsidized firms given in Figure 2 show that, not surprisingly, SOEs enjoyed the largest number of subventions over the study period.

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[6] This data is the largest Chinese firm level dataset that is available for research to date. Its advantage also lies in the accumulated knowledge and experience of using the data among researchers through exploiting its potentials and mitigating its pitfalls (see for example Du and Girma, 2010; Nie et al., 2012; Brandt et al., 2012). We follow Brandt et al. (2012) and Du et al. (2014) to construct industrial concordances to account for industrial specification changes. We also clean the data thoroughly and carefully check the consistencies and completion of the information of firm identification and ownership registration over the period, and of the firm identification, industrial concordances and ownership classification, as well as the measurement issues of output and capital stock of production function. Further, to ensure rigorous estimation of TFP, we also adopt the previous work by Jefferson et al. (1996) and Brandt et al. (2012) which developed a procedure to construct firm's original capital stock at birth year (up to 1978), and firm's incremental net fixed capital of each year, using calculated industrial historical capital stock annual growth rate by province and two-digit level industry based on the 1993 annual enterprise survey for the period of 1993-1998, and the calculated growth rates based on the NBS data since 1998. A more detailed account of the data issues was provided in our previous work (Du et al., 2014).

[Table 2 about here]

Table 3 gives some summary statistics on variables of interest by subsidy status. The most noteworthy difference is that firms that are subsidized in year *t* are about 10 times more likely to have received a subsidy also in *t*-1 and *t*-2. This suggests that subsidy receipt tends to be path-dependent.

[Table 3 about here]

3.2 Selection into subsidy

Given the above statistical observations, in order to better understand the pattern of subsidy distribution, we estimate the determinants of subsidy receipt amongst Chinese firms over the period 1998-2007, conditional on variables that are all measured in the period prior to subsidy receipt. Drawing on the literature of firm subsidies discussed in the previous sections (Bernini and Pellegrini, 2011; Cerqua and Pellegrini, 2014; Howell, 2017; Görg et al., 2008), the regression model includes the following pre-subsidy firm level characteristics: past history of subsidy receipt, firm size (level of employment), TFP, TFP growth trend, firm age, debt (a proxy for access to formal financing channels). We also include important firm characteristics that have been identified specifically in the Chinese context (Girma et al., 2009; Du and Mickiewicz, 2016): existence of political connections, history of loss-making, and ownership type (private being the baseline group). These variables capture the selective nature of subsidy receipt (see Table 1 for details of variable definitions).

Moreover, taking into account the regionally decentralized nature of China's policy making milieu, we include a second group of conditioning variables that are the cluster-level averages of the firm-level variables, excluding the firm's own value. For the purpose of our empirical implementation geographic clusters are based on three-digit administrative division codes which roughly identify prefectures. The manufacturing enterprises in our dataset are located in 74 such prefectures which we henceforth simply refer to as town-clusters. These are designed to capture the spatial dependence amongst firms given that subsidies in China are largely administered by local government authorities. The model is estimated using a logistic regression which also includes time, ownership and industry dummies.

The log odds ratios from the logistic regression are reported in Table 4. The strongest predictor of subsidy both at the firm and spatial levels is subsidy receipt in the past, as also suggested in the simple summary statistics in Table 3. Interestingly, young and larger firms are more likely to receive subsidies all else equal, as are loss-making and politically connected ones. Moreover, state-owned enterprises are significantly more likely to receive subsidies than private or foreign firms. Overall, the results from this exploratory regression show that the decision to allocate subsidies amongst firms is not a random process, but rather one that is systematically correlated with firm and cluster level variables. This observation motivates our empirical strategy which we discuss in detail below.

[Table 4 about here]

4 Estimating the effects of subsidy

The aim of the empirical exercise is to estimate direct and indirect treatment effects at cluster level of subsidy receipt on productivity. As noted in the descriptive analysis in Section 3, firm's selection into subsidy is unlikely to be random. Hence, controlling for selection at firm <u>and</u> cluster level is essential. In this section, we set out our basic identification strategy.

In order to deal with the two levels of selection, our empirical approach proceeds in two steps (see Girma et al. 2015 for a more detailed description). To tackle selection at the firm level, we firstly estimate the firm-level relationship between subsidy receipt and productivity separately <u>for each town-</u>

cluster, using data at the firm level. In a second step, to allow for selection at the cluster level, we take the share of subsidized firms in a cluster as treatment, using data at the cluster level.

First step estimation – Firm level selection

We define a firm-level binary treatment variable $d_{irt} = 1$ if firm *i* in cluster *r* receives a subsidy in year *t*, and $d_{irt} = 0$ if not. This treatment variable is then used as independent variable in a productivity regression using the firm-level data for a given cluster. In order to take into account selection at the firm level, we estimate the outcome equation using inverse propensity score-weighted regression and controlling for the pre-treatment covariates (Bang and Robins, 2005; Hirano et al., 2003). Note that the outcome variable, firm-level productivity is defined as the change relative to *t*-1, akin to using a difference-in-differences strategy combined with propensity score weighting. [7]

Implementing this approach implies that we, firstly, for each cluster generate the firm-specific propensity-scores of being treated. These are estimated via logistic regressions with subsidy status as dependent variable and a rich list of pre-treatment covariates. These covariates are the same as those used in Table 4 above. [8] [9] The difference here is that the estimations are carried out separately for each cluster (as this is important for modelling selection into clusters in the second step) and that we are careful to check balancing conditions (covariate balancing tests results are summmarised in Table A1).

Using the estimated propensity scores we then, secondly, generate the average potential outcomes (under subsidy and no subsidy) for each ownership type (private, foreign and state-owned) separately.[10] This is done by running the following regression (separately for each cluster-ownership type)

$$y_{ir} = \alpha + \beta d_{ir} + F(X;\delta\,) + error;\ i=1 \ldots N. \tag{1}$$

where y is the change in firm level productivity and F(.) is a function of the pre-treatment covariates vector X. From these regressions we can then calculate the cluster specific average potential outcomes for each firm type,

$$\bar{y}_r^1 = \frac{1}{N}\sum_{i=1}^{N}\hat{\alpha} + \hat{\beta} + F(X;\delta\,)\ \ and\ \ \bar{y}_r^0 = \frac{1}{N}\sum_{i=1}^{N}\hat{\alpha} + F(X;\delta\,) \tag{2}$$

[7] *This estimation strategy provides two opportunities to adjust for selection on observables by combining inverse probability reweighting with regression covariates adjustment. The identifying assumption is selection on observables. To the extent that there are unobservables that are correlated with both the treatment conditional on observables and the change in productivity, our results would potentially be biased. To guard against extreme propensity scores exerting undue influence on our calculations, the weights are winsorised.*

[8] *Recall that in this estimation we, among other things, control for the past experience of subsidy receipt to reduce unobservable characteristics in driving the subsidy selection. Subsidies have a tendency to persist, but it is not unusual to gain or lose a subsidy. From our data, we observe that over 1998-2008, about one-third of firms that received subsidies did not have any subsidy in the previous year. There are also 29% of firms that tend to lose a subsidy in the subsequent.*

[9] *One may perhaps be concerned about the inclusion of lagged TFP levels and growth in this model, as TFP is the main outcome variable of our overall analysis. However, in this step here we model the selection into subsidization (and not the level of current TFP) where lagged firm performance is an important predictor and needs to be taken into account.*

[10] *The outcomes are generated separately for the three firm types as previous research shows clearly that there is substantial heterogeneity in performance and behavior across those three types. Note, however, that the propensity scores are not estimated separately for firm types, hence, our assumption is that all three firm types compete equally for subsidies, but that the outcome of receipt may be different.*

Second step estimation – Cluster level selection

In the second step, the cluster and firm type level average potential outcomes, $\bar{y}_r^1$ and $\bar{y}_r^0$ estimated in the first step are treated as the "outcome" variables. The proportion of subsidized firms in the cluster, s_r is taken to be the continuous "treatment" variable. Since the treatment dosage s_r is again unlikely to be randomly distributed (e.g. due to endogenous difference between local governments when it comes to the extent of subsidy usage), we employ the causal inference approach for continuous treatments (Hirano and Imbens, 2004; Imai and van Dye, 2004). A key result from this literature is that causal inference can be conducted by conditioning on the generalized propensity score (GPS), which is nothing but the conditional density of the treatment given some pre-treatment covariates.

It is clear that our treatment dosage variable s_r is continuous and bounded between 0 and 1. Accordingly we generate the GPS conditional on pre-treatment cluster level covariates using the fractional logit model due to Papke and Wooldridge (1996). In the empirical implementation, the vector of observable pre-treatment characteristics consists of cluster-specific averages of the firm level covariates discussed in section 3.2 above.

Defining Z to be the vector of cluster level pre-treatment covariates; $\hat{\lambda}$ the vector of estimated coefficients from the fractional logit model and $\omega_i \equiv Z_i'\hat{\lambda}$, for a given level of treatment intensity s, the GPS conditional on Z can be obtained as

$$\hat{G}_r = \left[\frac{e^{\omega_i}}{1+e^{\omega_i}}\right]^{s_r}\left[\frac{1}{1+e^{\omega_i}}\right]^{1-s_r} \tag{3}$$

The expected values of each of the two cluster and firm type level potential outcomes ($\bar{y}_r^d$, d=0, 1) conditional on $\hat{G}_r$ and s_r can then be obtained using quadratic approximation (Hirano and Imbens, 2004) as:

$$E\left[y_r^d | \hat{G}_r, s_r\right] = \beta_0 + \beta_1\hat{G}_r + \beta_2 s_r + \beta_3\hat{G}_r^{\;2} + \beta_4 s_r^{\;2} + \beta_5\hat{G}_r s_r \tag{4}$$

The above polynomial regression is based on ***r*** (number of clusters that are on the common support of the GPS) observations, and the sample average potential outcomes are obtained as follows[11]

$$\bar{y}_r^d = \frac{1}{R}\sum_{r=1}^{R}\hat{\beta}_0 + \hat{\beta}_1\hat{G}_r + \hat{\beta}_2 s_r + \hat{\beta}_3\hat{G}_r^{\;2} + \hat{\beta}_4 s_r^{\;2} + \hat{\beta}_5\hat{G}_r s_r \tag{5}$$

Subsequently we calculate the predicted values $\bar{y}_r^d$ for the two firm level treatments *d* and the continuous cluster-level treatment *s*.

Calculating treatment effects

Using these predicted values as potential outcomes, we can then calculate treatment effects, using insights from the recent statistical literature (e.g. Hudgens and Halloran, 2008). Firstly, we can calculate a *direct treatment effect* $\bar{Y}_{ss}^{10} = \bar{y}_s^1 - \bar{y}_s^0$ as the difference in productivity between subsidized (1) and non-subsidized (0) firms for a given level of the proportion of subsidized firms *s* in a cluster-firm type group.

Secondly, the *indirect treatment effect* is defined as $\bar{Y}_{s0}^{00} = \bar{y}_s^0 - \bar{y}_0^0$, hence, the difference in productivity between non-subsidized firms (0) in a cluster with proportion of subsidized firms *s* and in a cluster without any subsidies.

Based on these two treatment effects we calculate an overall or total treatment effect, described in more detail below, as a weighted sum of the direct and indirect effects.

[11] *In practice we use outlier robust averages.*

5 Main Findings

We firstly estimate the direct and indirect effects separately for any level of subsidization *s* in a cluster as described above. Given that s is between 0 and 100 per cent, the presentation of all treatment effects in a single table is not practical. Instead, we plot all estimated direct and indirect effects among private, state-owned and foreign-owned firms along with their 95% confidence intervals in Figures 3 and 4. An immediate observation from these plots is that the share of subsidized firms in a cluster matters significantly for the magnitude of both the direct and indirect effects among all types of firms, both statistically and economically.[12]

Direct effects: the more, the merrier

We first focus on the direct effects of subsidies. As shown in Figure 3, there is a positive direct effect for all levels of *s* for all firms. This suggests that subsidized firms have higher productivity as a result of receiving a subsidy, which is in line with the idea that subsidies reduce a recipient's marginal cost of production.

Importantly, the strength of the direct effect depends on the level of subsidization in a cluster, and the relationship between the productivity-enhancing effects and the proportion of firms that receive subsidies is nonlinear. Our estimates suggest a positive direct effect of subsidies that for the most part increases in *s*.

The relationship between s and the productivity effect appears fairly similar for private domestic and state-owned firms. For these firms, in a cluster with 5 percent share of subsidized firms, firms that receive a subsidy on average enjoy a productivity increase by 2 percent. In a cluster with 50 percent share of subsidized firms, the direct effect is stronger at around 6 percent for private firms and 8 percent for SOEs, respectively. The direct effect, while always positive, firstly decreases in *s* and then turns to increasing in s from around s = 17 percent.

It is noticeable that the graph for foreign firms is quite different. While these are generally privately owned, they are different from domestic firms in that they are affiliates of foreign-owned multinationals and as such may be expected to behave differently than domestic firms (e.g., Bellak, 2004). There seems to be only limited additional productivity gain for foreign firms from securing government subsidies for levels of *s* lower than about 75 percent. This is not surprising, given that foreign invested firms in China are mostly resource-rich and likely to have received other forms of preferential treatments such as tax reductions or exemptions of utility bills (Klitgaard and Rasmussen, 1983).

Indirect effects: the unintended losers of subsidies

Turning to the indirect effects of subsidy-giving, it is clear that the signs depend on s, the proportion of firms that are subsidized in a town-cluster and firm ownership. As shown in Figure 4, unsubsidized SOEs also experience productivity-reductions due to the state subsidies. The negative effect deteriorates initially but then improves until four-fifths of all firms are subsidized. Then, the indirect effects turn positive towards the end of the distribution.

A similar picture emerges for foreign-owned firms. The indirect effects of subsidies for foreign firms are negative initially, suggesting that subsidies harm unsubsidized firms' productivity. In fact, there is a worsening productivity-reducing effect for unsubsidized foreign firms as more subsidized firms populate, and then that starts to improve as more than 20% of all firms are subsidized. With higher levels of subsidization in a cluster, these turn less negative and eventually positive when 45% or more of all firms are subsidized, similar to the case of indirect effects for SOEs.

However, a very different picture emerges with domestic private firms. The indirect effect on unsubsidized private firms starts being positive. However, this decreases sharply with *s*, until the level

[12] *Note that s in all graphs is calculated for all firms (private, SOE, foreign), so s reflects in all cases the share of all subsidized firms relative to all firms in a cluster.*

of the coverage reaches around 25% of subsidized firms, when the indirect effect of subsidies becomes negative.

Overall effects

The presence of both winners and losers of the state subsidies makes the overall economic impact and interpretation ambiguous. Next, we adopt some "back-of-the-envelope" calculations on the overall effect of subsidies on productivity among treated and non-treated firms. To do this, we follow the standard approach to define a "total treatment effect" as the sum of the direct and indirect treatment effect (Hudgens and Halloran, 2008). As shown above, the strength of the overall effect depends on the relative number of subsidized and non-subsidized firms, i.e., what share of firms experiences the direct and how many the indirect effect. Hence, we calculate an overall effect as a weighted average of the direct and indirect effect, weighted by the relative share of the two groups of firms. These calculations are included in the Appendix Table A2.

Keeping in mind that the direct effect is always positive, the overall effect will certainly be positive as long as the indirect effect is also positive. For private firms, as we can see from Figure 3, this is the case up to a level of s = 25 percent. After this point, the overall effect calculated as a weighted sum of direct and indirect effect is always negative. For example, at s = 30 percent (where 70% of firms do not receive a subsidy), the overall effect is $0.018 \times 0.3 + (-0.016) \times 0.7 = -0.0058$. At s = 50 percent (i.e., the groups of subsidized and non-subsidized firms are equally large), the direct effect is 0.067, while the indirect effect is around – 0.116. Hence, the overall negative spillover effect outweighs the positive direct effect, reaching an overall effect of -0.025. In sum, some subsidies benefit private firms irrespective of whether they are subsidized or not, but more than a quarter of firms being subsidized in the market hurts them.

For SOEs and foreign firms, the overall negative spillover effects on unsubsidized firms outweigh the positive direct effects on subsidized firms, for as long as no more than 45-50% of all firms are subsidized. That gives a largely negative overall weighted total effect for SOEs and foreign firms.

In our data, the mean value of subsidized firms in a cluster is around 15 percent, while the 75th percentile is 24 percent. Hence, for the majority of clusters in our data, the total effect for private firms is still positive, while that for SOEs and foreign firms is negative, which may be contrary to what subsidies were intended for.

6 Sensitivity and extensions

A: Sensitivity to propensity score model specification.

An anonymous referee raised the concern that our results might be driven by the fact that we have included firm-specific past subsidy status and productivity trends in the first-stage propensity score estimations. However, omitting such important variables from the set of the propensity score conditioning covariates will be a source of selection-on-unobservable bias. Nonetheless, we experimented with model specifications where firm-specific values of these covariates are replaced by the corresponding cluster specific averages that leave out the specific firm's values in the first stage estimations. The results from these experiments are reported in Figure 5 and 6, respectively.

As can be seen, the results in Figure 6 (without firm specific productivity trends) are qualitatively similar to our main findings discussed in this section, with one exception: direct effects are much stronger in magnitude for private than for SOEs. Leaving out the firm specific past subsidy status does, however, change results for SOEs who now show negative direct as well as indirect effects. The estimated effects for private and foreign firms are, however, similar to those found before. These small differences in results should perhaps not be surprising because we (deliberately) omitted potentially crucial observable covariates from the analysis.

B. Direct and indirect effects on profitability

Although the main focus of our paper and the theoretical modelling in the next section is on the direct and indirect effects of subsidy receipt on productivity, we also conducted some analysis using an alternative albeit distinct outcome variable, namely profitability defined as returns on assets.

It is necessary to distinguish profitability from productivity, even though they are often deemed closely related in much of the literature perhaps inappropriately (Driffield et al. 2013). This is especially important in context of China and other transitional economies where common institutional factors may lead to different degrees of efficiency-enhancing effect and rent-enhancing effects (Saal and Parker, 2001; De Witte and Saal, 2010). The outcome will be reflected in a divergent effect on firm's productivity and profitability. Hence, profitability can be an ambiguous measure of performance. Driffield et al. (2013) show that competition-enhancing liberalisation measures have more impact on state-owned firms than that for domestic and foreign owned firms. This seems to imply that when competition becomes relaxed, for instance in situation of wider subsidisation, one might expect a more negative effect on SOEs' profitability compared to other firms.

In our case, the profitability model estimates are depicted in Figure 7. The estimated indirect effects mirror those found for productivity in Figure 4: SOEs and foreign firms experience negative spillovers for clusters with low levels of subsidization, but these turn positive when the proportion of subsidized firms grows. Conversely, private firms do only experience negative spillovers in clusters with large numbers of subsidized firms.

The direct effects are also fairly similar to the productivity effects in Figure 3, with one important exception. While private and foreign firms experience positive direct effects in clusters with a medium to high share of subsidization, this is not true for SOEs. For the latter we fail to find any positive direct effect on profitability at all, even though we found positive productivity effects in Figure 3. We interpret this result as the divergence between efficiency-enhancing and rent-seeking given a large number of firms being subsidised. It is another unwanted effect of subsidisation that higher productivity due to wider subsidisation is not translatable into profitability of SOEs, hence collectable tax revenue. It seems a 'lose-lose' situation.

C. Exploring treatment heterogeneity

Our estimations thus far are based on a binary treatment, i.e., subsidy receipt or not. This can be handled by the approach as described in Section 4. An extension to a continuous treatment (amount of subsidy receipt) is far from trivial in this context and would need a modified approach. However, we modified the estimation strategy used in this paper to carry out an exploratory analysis as to whether the level of the subsidy matters as far as the direct and indirect treatment effect estimates are concerned. In particular, we dichotomised subsidised firms into those receiving below and above average (median) subsidies per worker, and then estimate the first stage propensity scores using cluster-specific ordered logit models. The results from this exploratory analysis are summarised in Figure 8. These would appear to suggest that the positive direct effects are observed for both groups (with the exception of SOEs receiving below average subsidies), while increasing and positive indirect effects are only observed among the group of firms receiving above average subsidies.

7 Theoretical interpretation

In order to make sense of the main results reported in Figures 3 and 4, we propose a theoretical framework, where we extend a simple heterogeneous firm type model and show that the treatment effects indeed depend on the proportion of treated firms, i.e. firms that receive a subsidy. The aim is to give some theoretical foundation for why both direct and indirect (spillover) effects may depend on the level of subsidization in a particular cluster. The theoretical predictions on the direct and indirect productivity effects largely match the empirical results.

We utilize a closed economy heterogeneous firm model a la Melitz (2003), where a government subsidizes firms by reducing their marginal cost of production. We make the additional assumption that in clusters with a higher share of subsidized firms, the size of the per-unit subsidy received by a given firm is lower.[13] The subsidy is financed through a lump sum tax and is given to firms randomly after they have entered the local market. We choose this set-up not because we think it is the most realistic – in fact it is well known that governments are likely to select firms to be subsidized on the basis of observables, as we also show in our empirical analysis - but because it is most consistent with our empirical identification strategy, which relies on the standard conditional independence assumption of the treatment evaluation literature.[14]

There is an exogenous number of L workers, there is no unemployment and workers supply their time to firms in exchange for a wage, which is normalized to one. Utility of the individual is represented by a CES utility function

$$U \equiv \left(\int_0^m d(\omega)^{\alpha} d\omega\right)^{\frac{1}{\alpha}},$$

where $d(\omega)$ denotes demand for product ω and the elasticity of substitution $\sigma = 1/(1-\alpha) > 1$ is determined by the parameter $0 < \alpha < 1$. There are infinitely many products ω of mass m, with m being endogenous. Demand for a product equals

$$d(\omega) = \frac{p(\omega)^{-\sigma}}{P^{1-\sigma}} C,$$

where $p(\omega)$ is the price of the product, C is aggregate consumption expenditure, and P is the aggregate price index, defined as

$$P \equiv \left(\int_0^m p(\omega)^{1-\sigma} d\omega\right)^{\frac{1}{1-\sigma}}.$$

Firms develop new products, but in order to do that, each firm has to pay a fixed cost F. The firm then draws marginal cost a from a Pareto distribution with a probability density function $g(a)$ with support $[0, \bar{a}]$ and a cumulative density function

$$G(a) \equiv \int_0^a g(a) da = \left(\frac{a}{\bar{a}}\right)^k.$$

A lump sum tax is given by the government as a subsidy to the marginal cost of randomly chosen firms from the set of entering firms. Suppose the share of subsidized firms is $0 < s < 1$ and the marginal cost of those firms becomes $\kappa_s a$, where $0 < \kappa_s < 1$ determines the size of the per-unit subsidy. We assume that κ_s increases in s, with this assumption the per-unit subsidy received by a given firm decreases in s. A non-subsidized firm stays with marginal cost a.

The effective marginal cost determines how many labor units the firm needs in order to produce one unit of output. In order to enter the market, each firm also needs to pay a fixed cost F_L. This setup creates a marginal cost threshold a_L for entering the local market, which separates firms that enter from those that are not productive enough and do not enter. The profit of a non-subsidized firm at a point in time can be written as $\pi(a) = (p(\omega) - a(\omega))\, d(\omega)$. Firms optimize profits and given their

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[13] A simple regression of the number of subsidised firms in a cluster on the average subsidy per firm, in our data returns a negative and statistically significant coefficient. It should be noted that total subsidy per cluster is nevertheless positively correlated with the share of subsidized firms. Results are available upon request.

[14] In fact, we use a weaker form of this assumption in that our econometric approach only requires that conditional on observable firm characteristics and time invariant unobservables (since we use panel data), subsidy receipt is as good as random. Nonetheless it is fairly straightforward to write down a model with selection of either the highest or lowest productivity firms receiving subsidies, which would also illustrate the existence of indirect effects.

marginal cost set the price at $p(\omega) = a(\omega)/\alpha$. Profits therefore equal $\pi(a) = \delta(a/P)^{1-\sigma}C$, where for brevity we write $\delta \equiv (\sigma-1)^{\sigma-1}\sigma^{-\sigma}$.

Firms face an exogenous exit probability γ[15]. The government gives a subsidy only to firms that are able to enter profitably on their own[16]. The expected benefit of entry for the threshold firm should therefore equal the fixed cost $\pi(a_L)/\gamma = F_L$. In equilibrium the expected gains from product development, which amount to expected firm value net of the fixed cost of market entry, have to equal the cost of product development F. This equality is expressed in the free entry condition:

$$F = s\int_0^{a_L}\left(\frac{\pi(\kappa_s a)}{\gamma} - F_L\right)g(a)da + (1-s)\int_0^{a_L}\left(\frac{\pi(a)}{\gamma} - F_L\right)g(a)da.$$

We obtain an expression for the marginal cost entry threshold:

$$a_L = \bar{a}\left(\frac{F}{F_L\left(S\frac{k}{k-\sigma+1}-1\right)}\right)^{\frac{1}{k}},$$

where $S \equiv s{\kappa_s}^{1-\sigma} + 1 - s$ and $\frac{\partial S}{\partial s} = {\kappa_s}^{1-\sigma} + (1-\sigma)\kappa_s^{-\sigma}\frac{\partial\kappa_s}{\partial s} - 1.$ We have already stated our assumption that $\frac{\partial\kappa_s}{\partial s} > 0,$ additionally we assume that for low levels of s the derivative $\frac{\partial\kappa_s}{\partial s}$ has a high value and decreases in s, meaning that the second derivative is negative.

Suppose that there is an s' for which in the range $s \in [0, s')$ the derivative $\frac{\partial\kappa_s}{\partial s}$ is large enough so that $\frac{\partial S}{\partial s} < 0$ and for $s \in [s', 1]$ we would have $\frac{\partial S}{\partial s} > 0.$ This implies that in the low range of s between zero and s', increasing the share of subsidized firms $s\uparrow$ would lead to an increase in the marginal cost threshold $a_L\uparrow$ and a decrease in the average firm productivity in the cluster. More subsidies allow the entry of less productive firms and thus makes the market less competitive. In the high range of s however the opposite happens, the average productivity in the cluster increases. More details and the solution to the complete model are provided in the appendix.

We use this model to examine two effects of subsidies, namely, a direct and an indirect effect. As outlined in Section 4, we define the direct effect as the difference, for a given cluster with share s, between the average outcome of the subsidized compared to the non-subsidized firm ($\bar{\gamma}_{ss}^{10} = \bar{y}_s^1 - \bar{y}_s^0$). The indirect treatment effect, ($\bar{\gamma}_{s0}^{00} = \bar{y}_s^0 - \bar{y}_0^0$) is the difference between the outcome of the average non-subsidized firm in a cluster with share of treated firms s compared to the average in a cluster with no subsidized firms. We look at productivity of firms to illustrate these effects within the context of our model.

In order to keep the theory as close as possible to the data we will calculate average productivity of firms based on their effective marginal cost $\kappa_s a$ for subsidized firms and a for non-subsidized firms.[17] The direct effect where productivity is the outcome variable can be written as:

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[15] *Here we follow Melitz (2003). It is important to note that despite an exit rate, which is exogenous and independent of an individual firm's properties, the productivity of operating firms in equilibrium is endogenous. This happens through the endogenous firm entry rate, which leads to a selection of firms based on productivity. Firms with a productivity below a certain threshold do not enter. Naturally, the model can be extend along the lines of the more complex firm exit rate as in Hopenhayn (1992).*

[16] *This assumption should not be seen as contradictory to the finding that the government frequently subsidizes loss-making firms. Negative profits are a development in time, that does not imply that the firm was started as a loss-making enterprise.*

[17] *We should point out that the productivity measure we employ in the empirical analysis is based on observed firm output. If one were to measure productivity in the same way in our theoretical model, output of a subsidized firm would be higher than the one of a non-subsidized firm with the same marginal cost a. The subsidized firm would, hence, appear to have higher productivity.*

$$\bar{\gamma}_{ss}^{10} = \int_0^{a_L} (\kappa_s a)^{1-\sigma} \frac{g(a)}{G(a_L)} da - \int_0^{a_L} a^{1-\sigma} \frac{g(a)}{G(a_L)} da.$$

The parameter *k* of the Pareto distribution has to be larger than σ-1 to make sure that the above integrals converge. The direct effect is positive since ${\kappa_s}^{1-\sigma} > 1$. From the fact that an increase in the share of subsidized firms in the cluster *s* first increases the threshold a_L follows that the average productivity of firms on the market $\int_0^{a_L} a^{1-\sigma} \frac{g(a)}{G(a_L)}$ will decrease in *s*. At the same time κ_s increases in *s* and $\kappa_s^{1-\sigma}$ decreases. The direct effect is positive and decreasing in s. For a large share of subsidized firms in the cluster however the threshold a_L decreases which leads to an average productivity of firms increasing in *s*. To summarize:

The direct productivity effect of a subsidy on the subsidy receiving firm is positive and decreasing in s for $s \in [0, s')$ and positive and increasing in s for $s \in [s', 1]$.

This result corresponds to our empirical results on the direct productivity effect on private firms and SOEs to an increase in the share of subsidization in a cluster. Before moving on, let us spell out the intuition for this a bit more clearly. In the model the non-monotonic response of the positive direct effect to the increase in the share of subsidized firms in the cluster is the result of two forces acting in opposite directions. First there is the assumption that the size of the per-unit-of-production subsidy, and therefore the size of the subsidy given to a firm, decreases with the share of subsidized firms in the cluster. This means that a higher share of subsidized firms decreases the size of the positive direct effect. The lower the subsidy, the lower the positive effect.

Once the subsidy size starts to be less responsive to the share of subsidized firms in a cluster however, a competition effect starts to take over. Subsidizing more firms makes entry of new firms more difficult. The competition effect implies that with more subsidies operating firms become on average more productive (as in Pflüger and Suedekum, 2013) given a sufficiently high number of subsidized firms in a cluster. This in turn implies that the positive direct effect increases in the number of subsidized firms.[18]

The indirect effect, where we compare the average productivity of non-treated firms from a cluster with a share of subsidized firms *s* versus a cluster without any subsidized firms (*s*=0), can be expressed as

$$\bar{\gamma}_{s0}^{00} = \int_0^{a_L} a^{1-\sigma} \frac{g(a)}{G(a_L)} da - \int_0^{a_{nL}} a^{1-\sigma} \frac{g(a)}{G(a_{nL})} da.$$

The threshold a_{nL} is the marginal cost threshold in a cluster where no firms receive subsidies. The indirect effect is first negative, because the firms in a subsidized cluster are on average less productive ($a_L > a_{nL}$). Since a_L is increasing in *s* and a_{nL} remains constant it is easy to show that $\bar{\gamma}_{s0}^{10}$ is first decreasing in *s*. For the high range of s we have $a_L < a_{nL}$ leading to a positive and increasing indirect effect. The indirect effect in this setup depends mainly on the presence of the already mentioned competition effect above. To summarize:

The indirect productivity effect is negative and decreasing in s for $s \in [0, s')$ and positive and increasing in s for $s \in [s', 1]$.

This matches our empirical results for foreign firms and SOEs in the range of high and low shares of subsidization. The theory does not match the part with the middle range of subsidization, where the indirect effect is negative and increasing. Those are results in steady state and the increasing or

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[18] The competition effect is conditional on the subsidy size not changing too strongly in the share of subsidized firms, namely $\frac{\partial \kappa_s}{\partial s} > 0$, but sufficiently small. Otherwise the competition effect is reversed and the entry of more firms can also reduce the average productivity in the cluster.

decreasing TFP effect comes from small changes in s around a steady state level of subsidization. The negative and increasing indirect effect can be generate in transitional dynamics however. Suppose we are in a steady state with $s_{old} \in [0, s')$, this implies $a_{L,old} > a_{nL}$. Jumping to $s_{new} \in [s', 1]$, or following a gradual increase in subsidization with values of $s_{new} > s'$, would result in a gradual decrease in a_L eventually surpassing and becoming lower than a_{nL} for sufficiently high values of s_{new}. This would lead to a negative and increasing and for high values of s_{new} positive and increasing indirect effect.

Turning to private firms, in the empirical results the indirect effect for them is a mirror image to the one for foreign firms and SOEs. A heterogeneous firm model where the average per-firm subsidy decreases slowly for low values of s and then rapidly for high values of s would generate this result. A strong competition effect within the low range of s, where only more productive firms on average are able to enter a market, would ensure the initial positive and increasing indirect effect. For a high range of s the competition effect wanes off and on average less productive firms enter a cluster, then the indirect effect would turn negative and decreasing.

In a standard heterogeneous firm model with subsidies as in Pflüger and Suedekum (2013) the average firm productivity in a cluster increases as a result of subsidization. In the data clearly the indirect effect is in many if not most instances negative. For a theory to correspond to this result it needs to be based on a model where subsidization can lead to lower average firm productivity in a cluster. We make in our model the assumption that the size of the per-unit subsidy decreases with the number of subsidized firms. There are also other theoretical approaches that can generate this result. In a model with soft budget constraints for instance a firm's expectation to receive subsidies may reduce its managerial effort to maximize profits, reduce costs or invest in innovation, hence leading to a worsening of firm performance relative to a firm that does not expect to be subsidized (see Kornai et al., 2003). A similar argument could be made in a model with x-inefficiency among firms (e.g., Leibenstein and Maital, 1994).

We extend the current model and check the results also for an open economy version as in Helpman et al. (2014). All domestic firms in the model would correspond to the private firms in the data. The affiliates of foreign FDI firms would correspond to the foreign firms in the data. Subsidization in the model is bilateral and symmetric and we again assume that the per-unit subsidy decreases in the share of subsidized firms s.

Since the subsidy is randomly assigned, no group of firms (domestic, exporters or FDI) has an advantage over another group. The marginal cost cutoffs separating the firm types move in the same direction as a result of subsidization. The direct effect is positive and decreasing for low levels of subsidization and positive and increasing for high levels of s. The indirect effect is also the same as in the closed economy, first negative and decreasing and then positive and increasing. The results hold for both private and foreign firms.

8 Conclusion

In this paper, we implement an approach that allows for the joint estimation of direct and indirect effects of subsidies on subsidized and non-subsidized firms. In line with much of the existing literature, we find that firms that receive subsidies experience a boost to productivity. Looking at it from this angle would then suggest that such a policy "works". However, our approach highlights the importance of indirect effects, which are generally not considered in the literature. We find that, in general but not always, non-subsidized firms experience reductions in their productivity growth if they operate in a cluster where other firms are subsidized. These negative externalities, and also the positive direct effects, depend on the share of firms that receive subsidies in a cluster. We interpret our results with a simple heterogeneous firm type model, which highlights the implications of subsidization for the competitive environment of firms. Subsidies may potentially harm non-subsidized firms.

Our paper demonstrates the importance of considering indirect effects in evaluation studies. Not only from a technical perspective (as this improves upon the accuracy of the results) but, importantly, also from a policy perspective. Taking the effects on non-subsidized firms into account may significantly change the conclusion as to whether or not the subsidization policy was beneficial, in terms of improving overall productivity growth in a local economy. Specifically, our findings, contrasting with advocates of state capitalism, provide empirical evidence that highlights the potential cost of state intervention through subsidization, in terms of negative externalities. Overall, our estimation approach allows us to provide a much richer analysis on the relationship between subsidies and firm performance than the literature thus far.

Of course, the use of subsidisation (or industrial policy more generally) by the domestic economy – in our case China – may also have implications for other countries. In particular, Chinese subsidisation policy may be expected to have beggar-thy-neighbour implications for its trade partners. Indeed, this is frequently cited as one of the reasons for the US – China trade dispute, or misgivings in EU – China relations.[19] While this is undoubtedly an important and relevant issue it has to be left for future research, as this would necessitate information about detailed trade relationships which is well beyond the scope of this paper.

[19] *See https://www.theguardian.com/us-news/2019/aug/23/trump-china-economic-war-why-reasons; Bickenbach and Liu (2021).*

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Xu, C. (2011). The Fundamental Institutions of China's Reforms and Development. *Journal of Economic Literature*, 49(4): 1076–1151.

FIGURES

Figure 1: The dynamics of share of subsidized firms by ownership

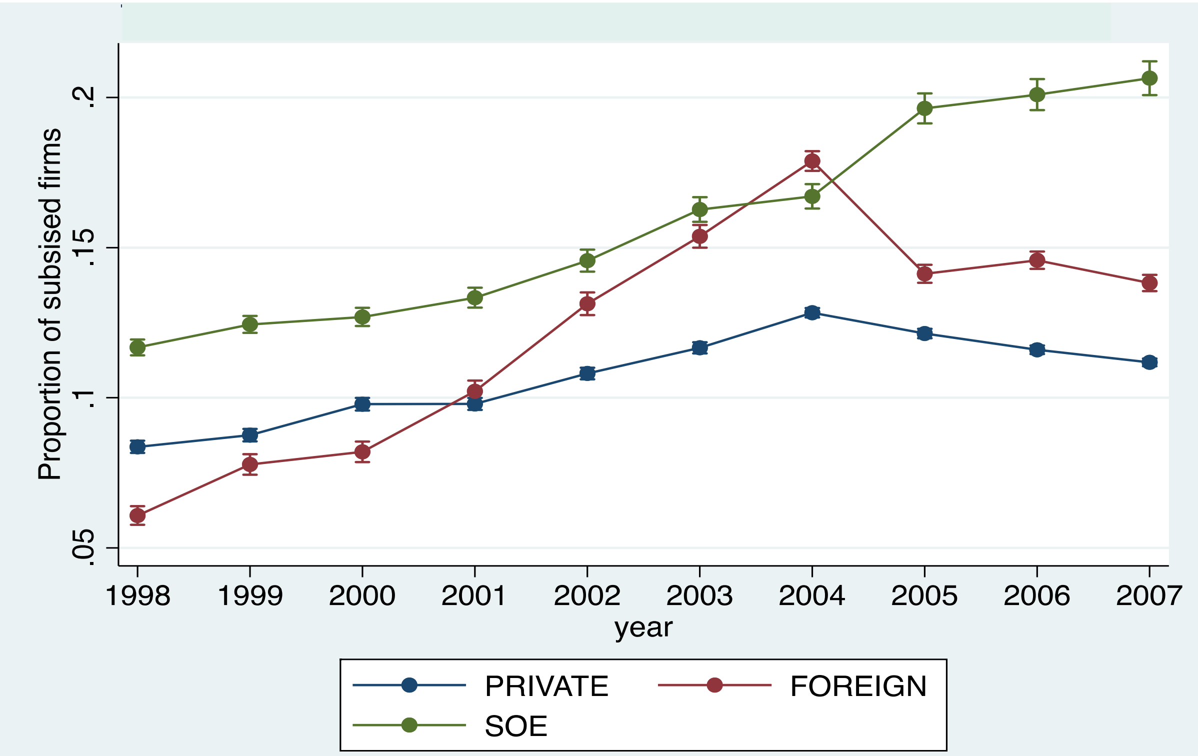


Figure 2: **Average amount of subsidy amongst subsidised firms**

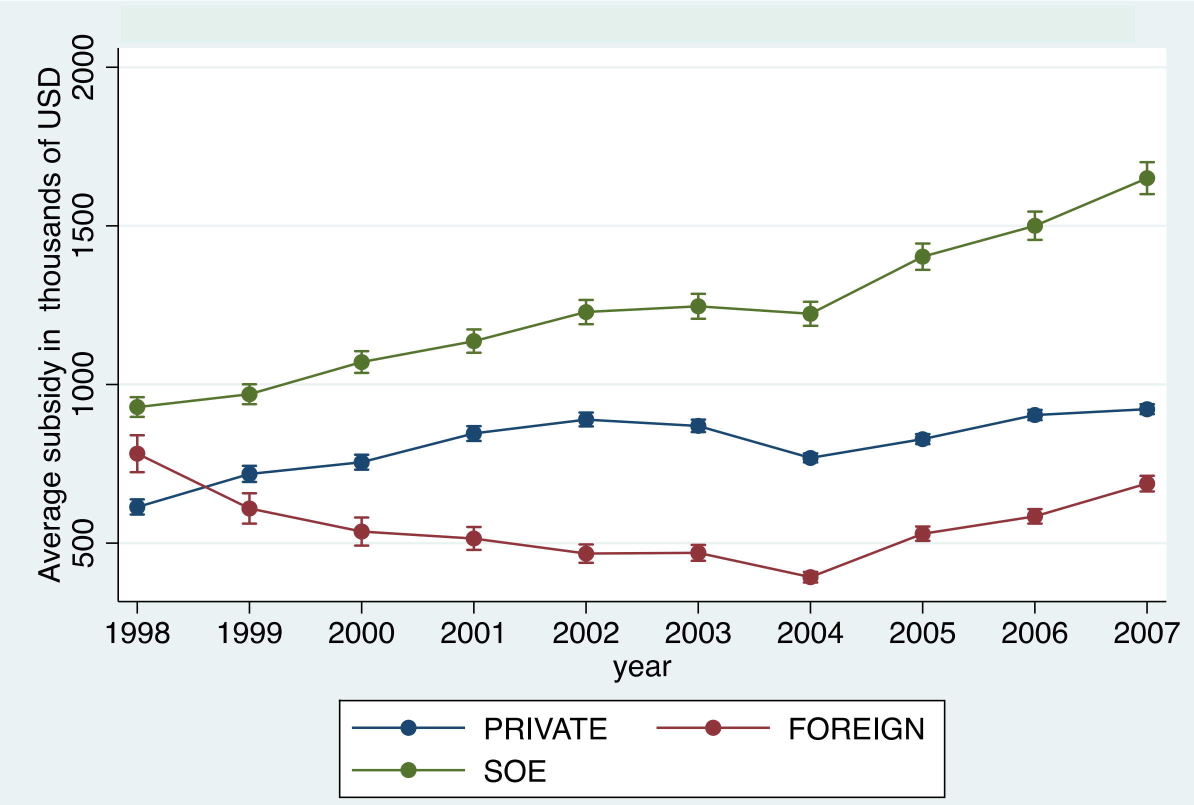


Figure 3: **Direct effects of subsidies on TFP growth by firm ownership**

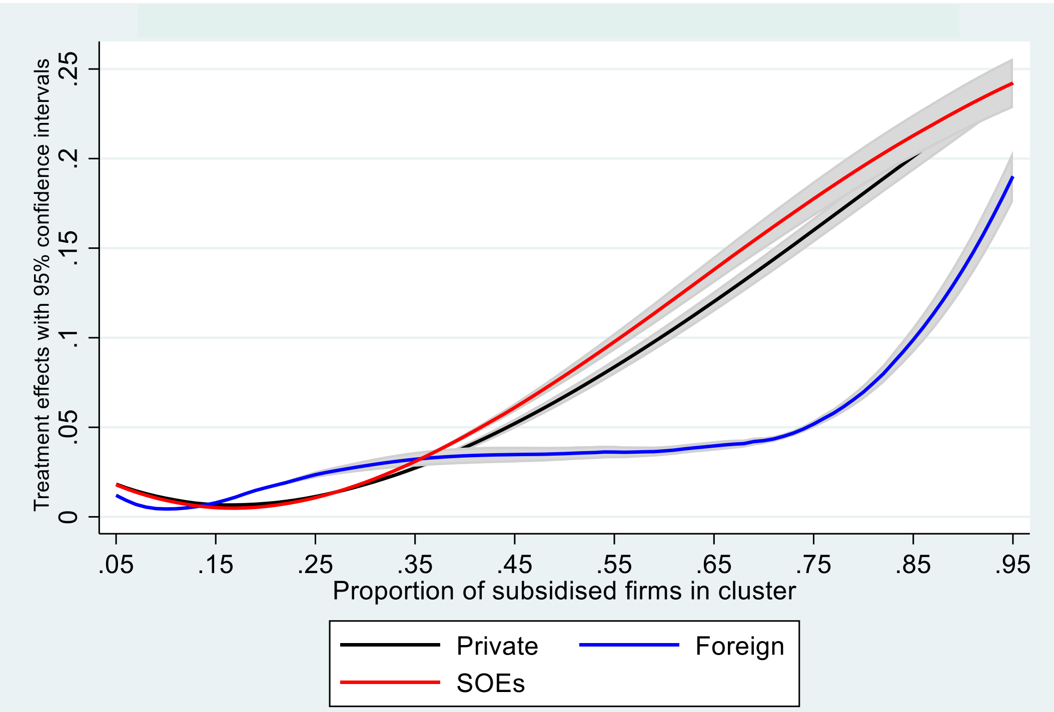


Figure 4: **Indirect effects of subsidies on TFP growth by firm ownership**

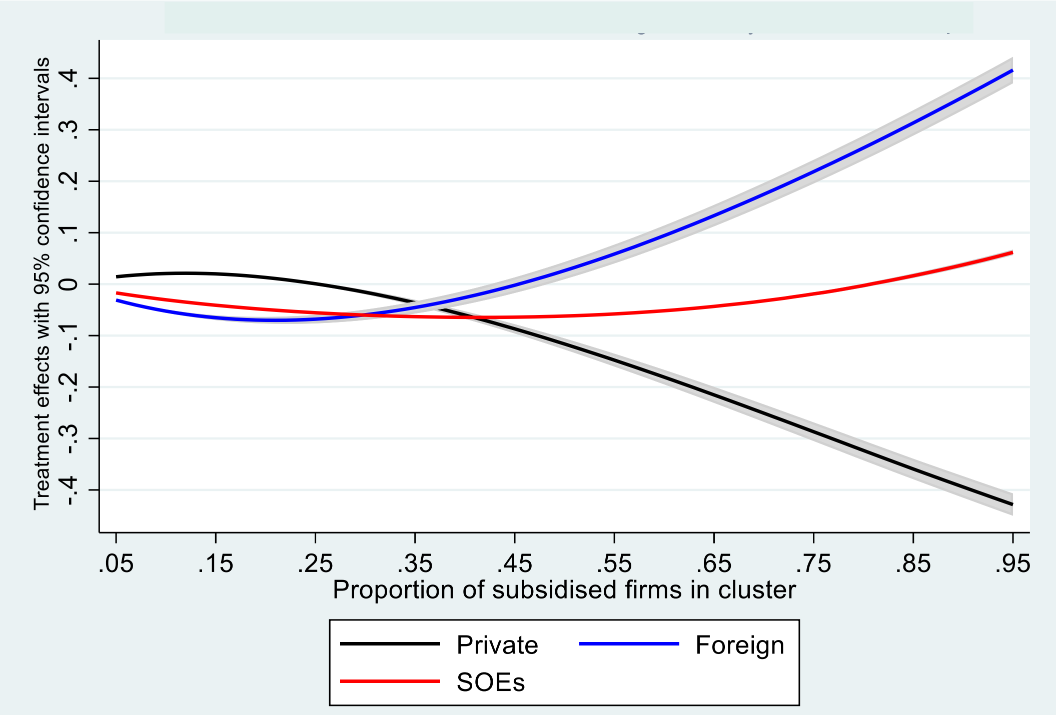


Figure 5: **Estimation without firm-specific past subsidy status in first-stage propensity score model**

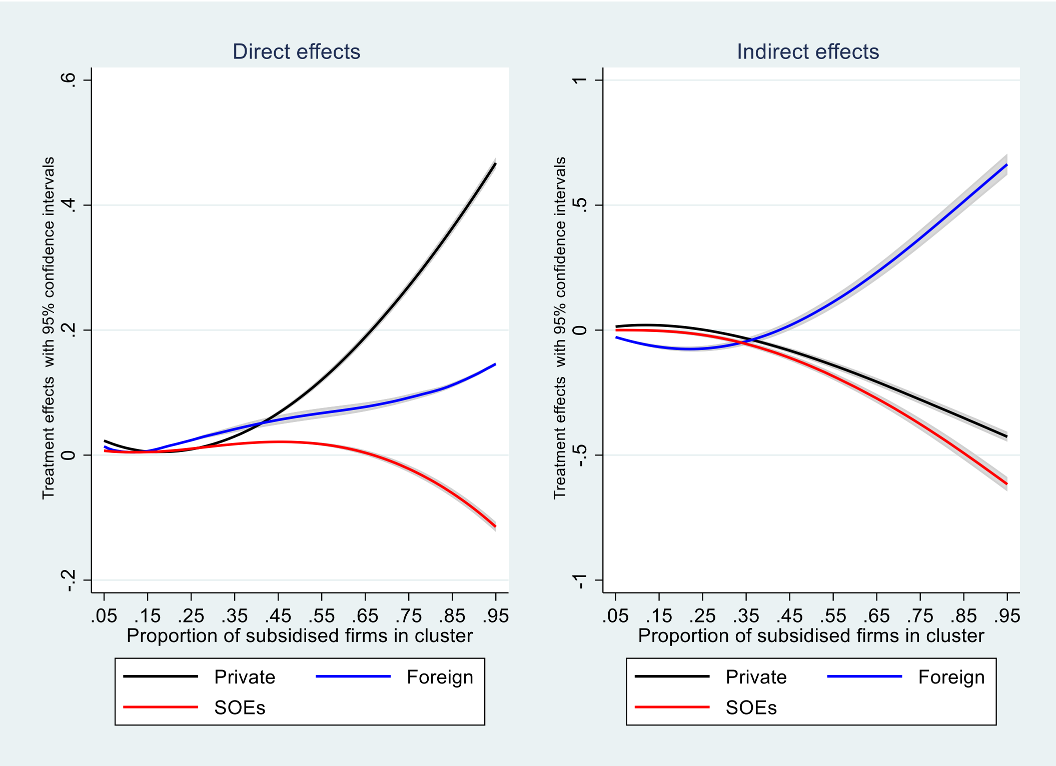


Figure 6: **Estimation without firm-specific productivity trends in first-stage propensity score models**

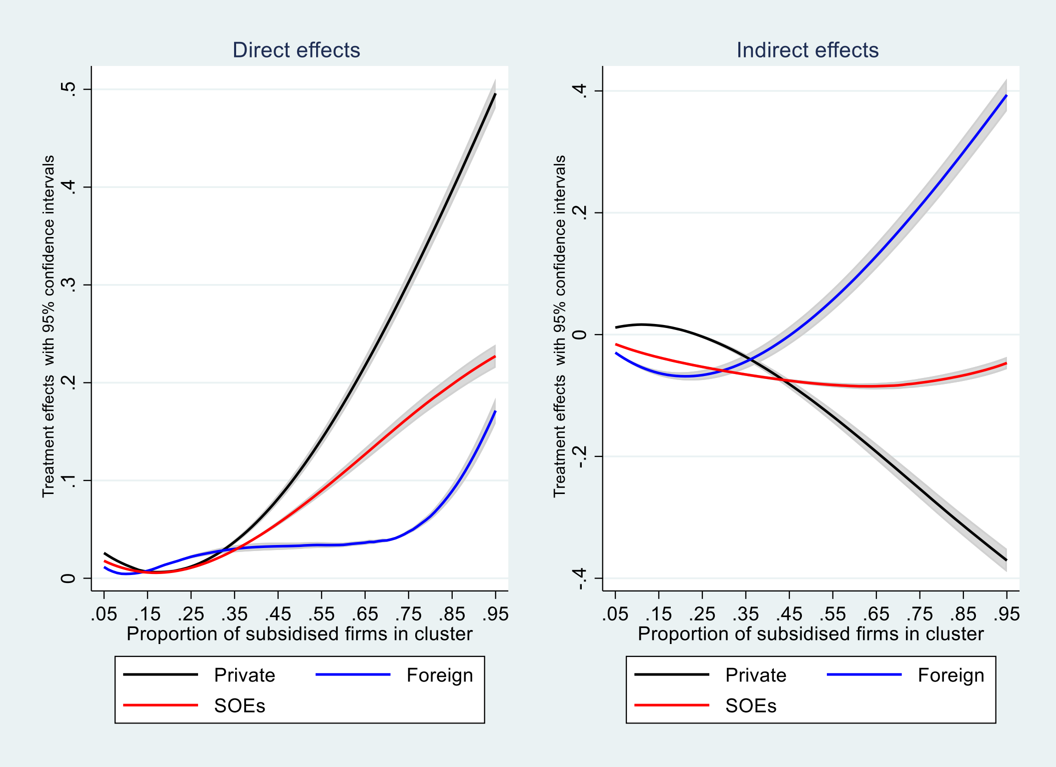


Figure 7: **Effects on profiability**

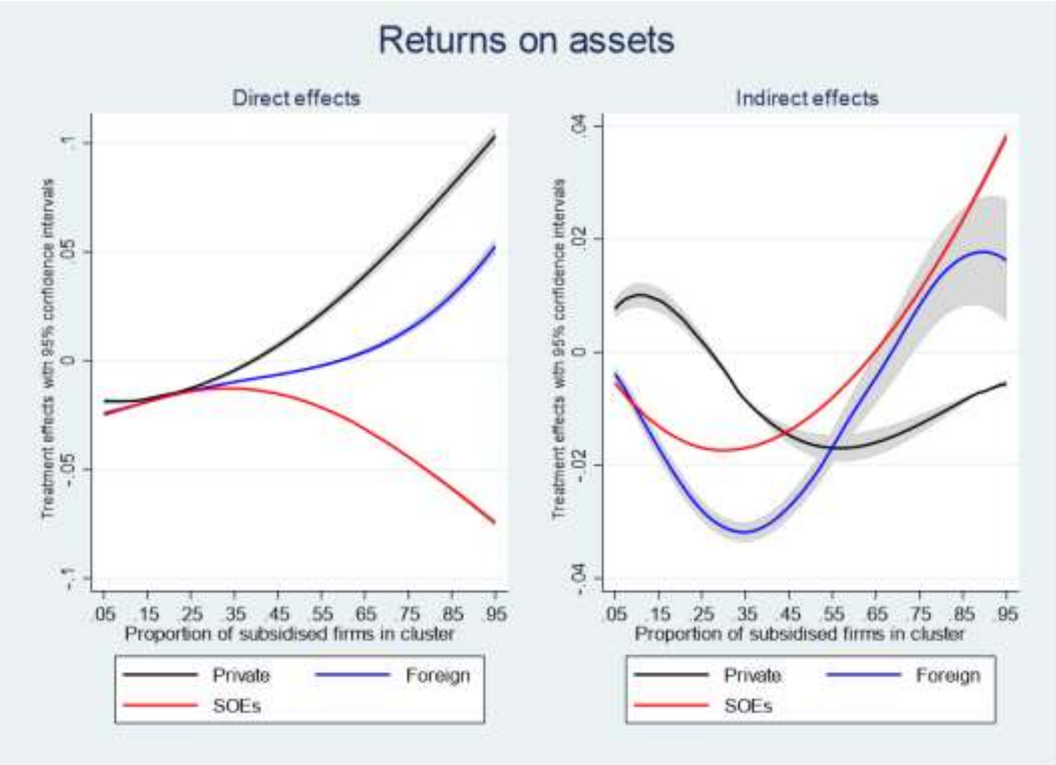
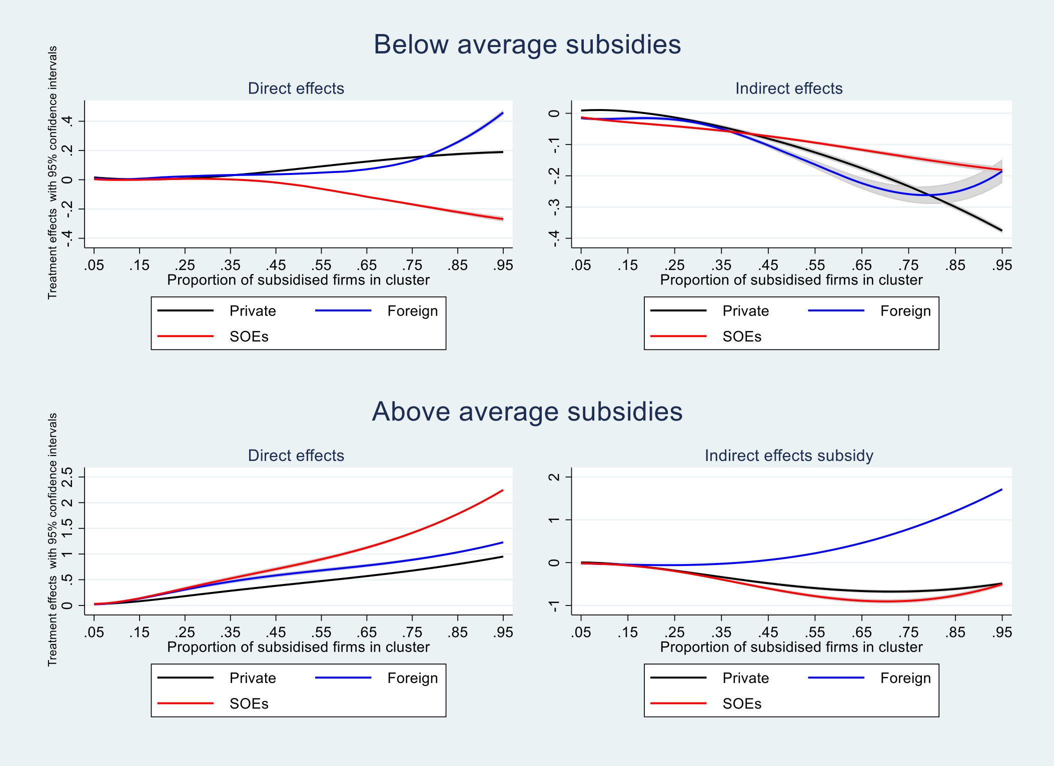


Figure 8: **The causal effects of subsidy on productivity by the level of subsidy**



TABLES

Table 1: **Definition of variables used in the analysis (Table_Head)**

Variables	Definition
Pre-treatment covariates	
Past Subsidy	Dummy variable indication whether the firm received subsidy in the past two years
Employment	Log of number of employees employment
Age	Log of firm age
Loss	Dummy variable indicating whether the firms was a loss making one in the past two years
TFP	Total factor productivity calculated using Ackerberg, Caves and Frazer (2015) correction, with the amount of subsidies included in the production function as a state variable. Production functions are estimated by sector.
TFP trend	Firms TFP growth relative to industry median trend
Debt	Total liability of total assets
POL	Dummy variable indicating whether the firm enjoys political affiliation with local and central governments
Dummy variables with private firms, low tech used as base groups.	
Foreign	Dummy variable indicating whether a firm is foreign owned
SOE	Dummy variable indicating whether a firm is a state-owned enterprise
Medium low tech	Dummy variable indicating whether a firm operates in a medium low tech industry, using OECD classification scheme, see http://www.oecd.org/sti/ind/48350231.pdf.
Medium high tech	Dummy variable indicating whether a firm operates in a medium high tech industry.
High tech	Dummy variable indicating whether a firm operates in a high tech industry.
Outcome variable	
TFP change	TFP change after receipt of subsidy relative to the pre-treatment period, Baseline regressions conducted with respect to changes one year after the treatment period. This approaches allows for a difference-in-differences type approach to control for time-invariant unobservables.
Treatment variables	
Subsidy	Dummy variable indication whether the firm received subsidy in the current period
Indirect effects capturing variable	
Cluster level subsidy	Proportion of subsidized firms per cluster

Table 2: **Total subsidies in Billions of USD and the number of of subsidized firms by ownership**[20]

	Private firms		Foreign firms		SOEs	
Year	SUBSIDY	# of firms	SUBSIDY	# of firms	SUBSIDY	# of firms
1998	3.618	5897	1.070	1369	6.118	6588
1999	4.482	6244	1.099	1805	6.311	6514
2000	5.666	7509	1.093	2038	6.291	5878
2001	7.314	8654	1.458	2836	6.118	5384
2002	9.562	10751	1.896	4064	6.458	5259
2003	11.617	13364	2.541	5419	6.250	5015
2004	17.073	22229	3.698	9421	6.671	5457
2005	17.413	21049	3.892	7354	6.779	4833
2006	20.776	22994	4.815	8240	6.952	4635
2007	23.662	25673	5.887	8565	6.727	4077

Table 3: **Summary statistics by subsidy status**

	Non-Subsidized		Subsidized	
	Mean	Std. dev	Mean	Std. dev
TFP growth	0.0139	0.423	0.00563	0.359
Past Subsidy	0.0644	0.245	0.619	0.486
Employment	4.881	1.077	5.312	1.186
Age	2.187	0.772	2.272	0.800
Loss	0.209	0.406	0.279	0.448
TFP	0.826	0.472	0.834	0.480
TFP trend	1.229	184.5	1.393	121.3
Debt	0.0566	0.140	0.0598	0.125
POL	0.478	0.500	0.528	0.499
Private firms	0.609	0.488	0.561	0.496
Foreign firms	0.221	0.415	0.225	0.418
SOEs	0.170	0.376	0.214	0.410
Low-tech	0.362	0.481	0.314	0.464
Medium low-tech	0.325	0.468	0.332	0.471
Medium tech	0.215	0.411	0.243	0.429
High-tech	0.0976	0.297	0.111	0.314
Observations	*799805*		*144610*	

[20] *Table 2 (and Figures 1 and 2) are based on the master file containing all available firms in the database. The econometric analysis is based on a subset of this file which satisfies various data availability conditions (e.g. at least 3 years per firm and full availability of the conditioning and outcome variables).*

Table 4: **The determinants of subsidy: Some exploratory regressions:**

	Firm level logistic regression		Firm level logistic regression with additional cluster level variables	
	Log odds ratio	Robust standard errors	Average marginal effects	Robust standard errors
Past Subsidy	21.92***	(0.159)	18.39***	(0.137)
Employment	1.270***	(0.00419)	1.336***	(0.00461)
Age	0.947***	(0.00472)	0.945***	(0.00482)
Loss making	1.093***	(0.00923)	1.153***	(0.00995)
TFP	1.013	(0.00808)	1.067***	(0.00873)
TFP growth trend	1.000	(0.0000175)	1.000	(0.0000185)
Debt	0.907***	(0.0238)	1.060*	(0.0273)
Political connection	1.119***	(0.00966)	1.203***	(0.0111)
FOREIGN	0.955***	(0.00893)	0.991	(0.00972)
SOE	1.022*	(0.0106)	1.121***	(0.0120)
Medium low-tech industries	1.149***	(0.00989)	1.203***	(0.0106)
Medium high-tech industries	1.199***	(0.0119)	1.157***	(0.0117)
High-tech industries	1.203***	(0.0151)	1.216***	(0.0154)
With additional cluster level variables				
Share of subsidised firms			59.83***	(3.308)
Average employment			0.661***	(0.0143)
Average age			0.997	(0.0387)
Share of loss making firms			0.942	(0.0572)
Average TFP			0.473***	(0.0290)
Average growth trend			1.000	(0.000606)
Average debt			0.200***	(0.0476)
Share of politically connected firms			0.764***	(0.0276)
Observations	944415		944415	
Pseudo R-squared	0.2849		0.3007	

Notes:

i. All conditioning variables are lagged by one year (prior to the treatment period)/

ii. In the firm level regressions, private firms and low-tech industries form their respective base group.

iii. All regressions include year effects.

$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX

***Table A1*: A summary of balancing statistic in raw and propensity score weighted data**

	Lower quartile				Upper quartile			
	Standardised difference		Variance ratio		Standardised difference		Variance ratio	
	Raw data	Weighted data	Raw data	Weighted data	Raw data	Weighted data	Raw data	Weighted data
Past Subsidy	125.63%	0.45%	2.73	0.99	150%	2%	5.07	1.02
Employment	30.06%	2.25%	1.09	0.97	59%	10%	1.37	1.16
Age	6.84%	1.58%	0.98	0.95	27%	8%	1.18	1.06
Loss making	12.32%	0.71%	1.04	0.98	36%	7%	1.29	1.02
TFP	4.26%	1.57%	0.80	0.75	15%	7%	1.28	1.15
TFP growth trend	4.39%	1.23%	0.70	0.68	13%	7%	1.04	0.99
Debt	5.97%	1.42%	0.89	0.99	26%	7%	1.03	1.02
Political connection	1.07%	0.70%	0.26	0.18	5%	3%	1.86	0.89
FOREIGN	4.43%	2.22%	0.93	0.98	19.69%	10.26%	1.53	1.18
SOE	6.52%	1.71%	1.00	0.99	30.96%	6.22%	1.33	1.04
Medium low-tech industries	5.81%	1.59%	0.98	0.96	19.02%	6.78%	1.10	1.00
Medium high-tech industries	4.72%	1.37%	0.81	0.92	14.15%	7.70%	1.15	1.04
High-tech industries	3.02%	1.08%	0.96	0.96	14.53%	5.11%	1.31	1.09
Year=2001	4.90%	1.92%	0.68	0.93	13.95%	7.13%	1.03	1.11
Year=2002	3.16%	1.16%	0.74	0.89	11.60%	6.75%	1.05	1.05
Year=2003	1.95%	1.09%	0.84	0.92	10.02%	4.85%	1.06	1.05
Year=2004	4.21%	0.87%	1.08	0.93	14.65%	5.18%	1.44	1.06
Year=2005	4.25%	1.23%	1.05	0.93	13.41%	5.39%	1.34	1.05
Year=2006	3.27%	2.04%	0.94	0.92	12.61%	5.32%	1.21	1.03
Year=2007	3.64%	1.44%	0.94	0.94	14.65%	4.69%	1.23	1.04

Notes:

i. For ease of presentation we only report the interquartile range of the balancing statistics for each of the 18 covariates across the 74 clusters. The full data are available upon request.

ii. By convention, standardized differences in the weighted data of less than 20% and a variance ratios of between 0.5 and 2 are deemed satisfactory in terms of balancing the covariates between the treated and untreated groups.

***Table A2*: Direct, indirect and (weighted) total treatment effects**

Private firms	Direct effects	Indirect effects	Weighted total effects
share of subsidized			
0.05	0.018	0.014	0.014
0.10	0.010	0.021	0.020
0.15	0.007	0.020	0.018
0.20	0.007	0.013	0.012
0.25	0.011	0.001	0.004
0.30	0.018	-0.016	-0.006
0.35	0.027	-0.036	-0.014
0.40	0.039	-0.060	-0.020
0.45	0.052	-0.087	-0.024
0.50	0.067	-0.116	-0.025
SOEs	Direct effects	Indirect effects	Weighted total effects
share of subsidized			
0.05	0.018	-0.017	-0.015
0.10	0.009	-0.030	-0.026
0.15	0.005	-0.041	-0.034
0.20	0.006	-0.049	-0.038
0.25	0.011	-0.056	-0.039
0.30	0.019	-0.060	-0.036
0.35	0.031	-0.063	-0.030
0.40	0.045	-0.065	-0.021
0.45	0.061	-0.064	-0.008
0.50	0.079	-0.062	0.009
Foreign firms	Direct effects	Indirect effects	Weighted total effects
share of subsidized			
0.05	0.012	-0.031	-0.029
0.10	0.004	-0.052	-0.046
0.15	0.008	-0.065	-0.054
0.20	0.016	-0.070	-0.053
0.25	0.024	-0.068	-0.045
0.30	0.029	-0.060	-0.033
0.35	0.032	-0.045	-0.018
0.40	0.034	-0.026	-0.002
0.45	0.035	-0.002	0.015
0.50	0.035	0.026	0.031