Who wins and who loses from state subsidies?

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Abstract

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. We interpret our results in the light of a simple heterogenous firm type model, which highlights the implications of subsidization, in a competitive environment of firms, may potentially harm non-subsidized firms.

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1. Introduction

In recent years, China has run a trade surplus with nearly 80% of the countries in the world.[1] The most striking trade imbalance between the US and China has stirred up the recent trade war between the two countries, giving rise to uncertainties for the global economy and likely losses for both sides. As frequently expressed in public, one of the reasons behind the US trade war against China is the perceived unfair competition in its trade practices induced by the prevailing state subsidies.

Indeed, 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.[2] Underlying this policy 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. This paper provides fresh evidence on this issue using Chinese firm-level data. 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 an unintended consequence.

Economic theory offers contrasting views regarding the merits of firm- or sector-specific subsidies as tools of industrial development policy (see Haley and Haley, 2013a, and references therein). On the one hand, subsidies are seen as an effective way of overcoming market failures such as informational asymmetries in credit markets, or for protection of infant industries, and hence as useful policy instruments for improving firm performance and creating comparative national advantage. This view would thus be in line with the assumption that subsidies give a benefit to Chinese firms. On the other hand, however, subsidies are

[1] According to the WTO's Integrated Data Base (IDB), in 2016, China ran trade surplus with 169 countries among 215 countries that have statistics.

[2] 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).

perceived as distorting the efficient allocation of resources in the economy, which may lead to worsening firm performance and an aggregate welfare loss (Mueller, 2003).

There are several empirical papers 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. Externalities may arise as subsidized firms change the competitive environment, which are likely to affect the strategy, conduct and performance of non-subsidized firms. This means that in addition to estimating the direct impact of subsidies on subsidized firms, for a comprehensive appraisal it is important to evaluate the indirect effects on non-subsidized firms.

However, most empirical studies (including those cited above) on the effect of subsidies do not allow for spillovers to firms that do not receive subsidies. Rather, they focus on estimating the direct effect of the subsidy on the receiving firm. A notable exception is De Mel et al. (2008) who look at the impact on returns to capital of small cash grants to microenterprises in Sri Lanka.[3] Another issue that is generally not considered in the literature 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-subsidies firms.[4]

[3] They 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).

[4] 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

The novel estimation approach employed in this paper allows us to tackle this issue, and hence address an important gap in the literature that debates the role of the state through subsidizing businesses. We exploit observational data on subsidy receipt from a large-scale firm level panel dataset for the Chinese manufacturing sector. We adapt the methodology developed by Girma et al. (2015), which enables us to estimate differing direct or indirect effects depending (possibly non-linearly) on the level of subsidizationsubsidization in a town-cluster. 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. This is why studies use micro-econometric evaluation techniques, such as propensity score matching. However, there is a second selection problem that previous work has overlooked. When modelling the levels of interference, 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 matching techniques at the two levels. Furthermore, given the particular focus on Chinese state-owned enterprises (SOEs) in the subsidy debate, we estimate performance effects separately for private owned firms, SOEs and foreign owned firms.

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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.

Our empirical analysis 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 widely subsidies were given out. 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.

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.

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 Section 5 presents and discusses empirical results. Section 6 then discusses a theoretical framework that fits many aspects of the empirical results. Section 7 concludes.

2. Institutional background and literature

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 et al 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.

Aghion et al. (2015) look at 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.

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. 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.

[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 discussed in the previous sections, 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, existence of political connections, debt (a proxy for access to formal financing channels), 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 spatial 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, highly productive 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 regression results 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.

[Table 4 about here]

This observation motivates our empirical strategy which we discuss in detail below.

4. Estimating the effects of subsidy

The aim of the empirical exercise is to estimate direct and indirect treatment effects of subsidy receipt on productivity. These may potentially differ depending on the level of subsidization in a cluster. As noted in the descriptive analysis in Section 3, firm's selection into subsidy is unlikely to be random, and neither is the selection of town clusters. This motivates the evaluation approach adopted in this study. 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 for each town-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. In both steps, we apply generalized propensity score matching techniques.

First step estimation

In the first step we, start by estimating the relationship between subsidy receipt and productivity separately for each of the 74 town-clusters and 3 firm types (private, SOE, foreign). We define a 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 and firm type. 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 matching.[5]

For each cluster and firm type, this implies that we firstly generate the firm-specific propensity-scores of being treated via a logistic regression with a rich list of pre-treatment covariates subject to balancing conditions being satisfied. The list and precise definition of the pre-treatment covariates can be found in Table 1, and covariate balancing tests results are reported in Appendix Tables A2-A4.

Using the estimated propensity scores we then estimate the following outcome equation (after imposing the common support condition) for each cluster and firm type separately via inverse probability weighted regression,[6]

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

[5] 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.

[6] Treated firms receive a weight of $1/\pi$ and non-treated firms a weight of $1/(1-\pi)$.

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,

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

Second step estimation

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 balancing 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 $\boldsymbol{Z}$ 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 $\boldsymbol{Z}$ can be obtained as

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

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 $\boldsymbol{r}$ (number of clusters that are on the common support of the GPS) observations, and the sample average potential outcomes are obtained as

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

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* $\bar{\gamma}_{ss}^{10} = \bar{y}_s^1 - \bar{y}_s^0$ 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 $\bar{\gamma}_{s0}^{00} = \bar{y}_s^0 - \bar{y}_0^0$, 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.

5. 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.[7] 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.[8]

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,

[7] The calculation of standard errors is complicated by the fact that the potential outcomes are estimated. Hence, we compute bootstrapped standard errors via resampling with replacement, see Girma et al. (2015) for more details.

[8] 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.

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 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.

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, we calculate that the overall effect 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 around 0.07, while the indirect effect is around – 0.12. Hence, the overall negative spillover effect outweighs the positive direct effect. In sum, some subsidies benefit private firms irrespective of whether they are subsidized or not, but too much subsidization 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. Table A4 summarises the calculation.

In our data, the mean value of subsidized firms in a cluster is 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. Theoretical interpretation

In order to make sense of these results, 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.[9] 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

[9] In fact, 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. Results are available upon request.

identification strategy, which relies on the standard conditional independence assumption of the treatment evaluation literature.[10]

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(ω) denotes demand for product ω and the elasticity of substitution σ = 1/(1-α) > 1 is determined by the parameter 0 < α < 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(ω) 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 $0 < \kappa_s < 1$

[10] 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.

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 can be written as $\pi(a) = (p(\omega) - a(\omega))\, d(\omega)$. Firms optimize profits and given their 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. The government gives a subsidy only to firms that are able to enter profitably on their own. 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 without a productivity improvement.[11]

The direct effect where productivity is the outcome variable can be written as:

[11] 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 effecton 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, a competition effect starts to appear. Subsidizing some entrants changes the productivity threshold for entry, and thus makes entry of new firms more difficult. New entrants have to be more productive in a cluster where more firms are subsidized. Hence, this competition effect implies that the set of producing firms becomes on average more

productive given a sufficiently high number of subsidized firms in a cluster (as in Pflüger and Suedekum, 2013), in turn implying that the direct effect increases in the number of subsidized firms.[12]

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 not receiving any 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 $\in [0, s')$ *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.

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 match this result. A strong competition effect within the low range of s,

[12] The competition effect is conditional on the subsidy size not changing too strongly in the share of subsidized firms. Otherwise the competition effect is reversed and the entry of more firms can also reduce the average productivity in the cluster.

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. Again, the empirically found positive and decreasing indirect productivity effect would remain unexplained by the theory.

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 initially negative for a low share of subsidization. For a theory to correspond to this result it needs to be based on a model where subsidization leads in some instances 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).

7. 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.

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FIGURES

Figure 1

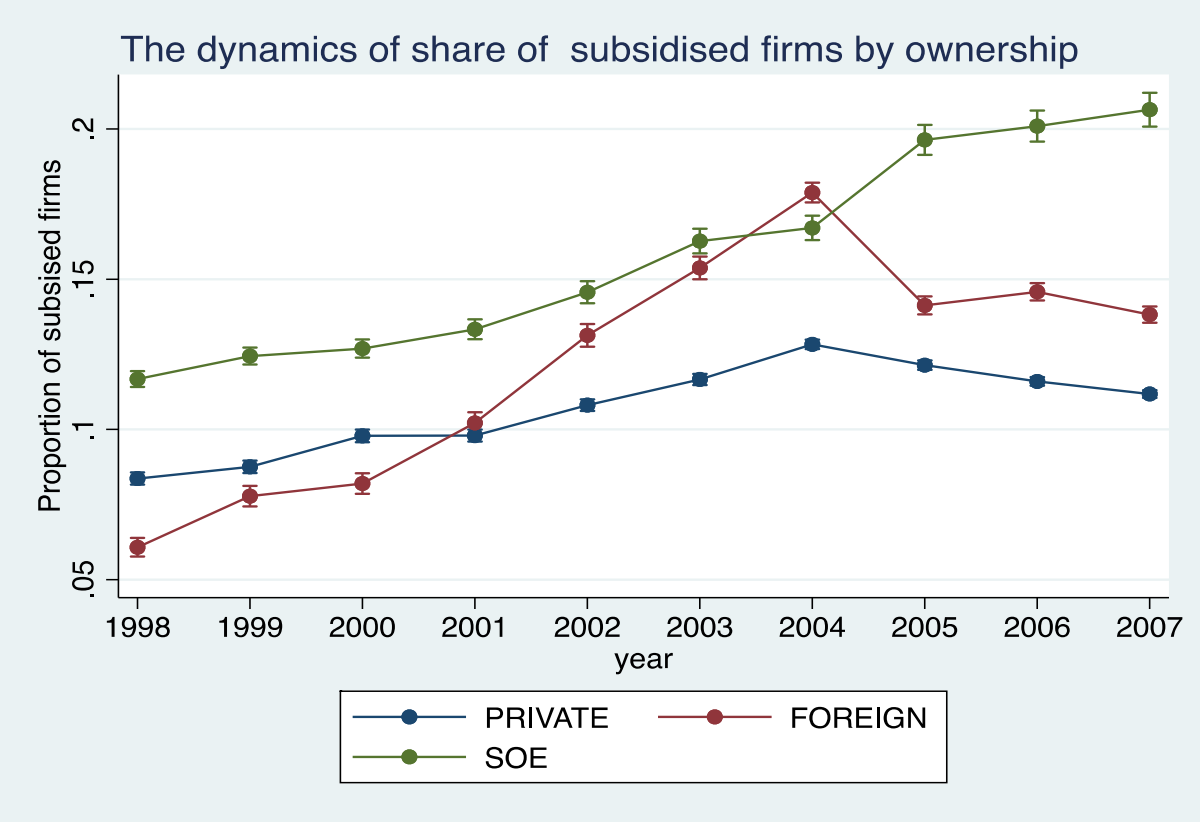


Figure 2

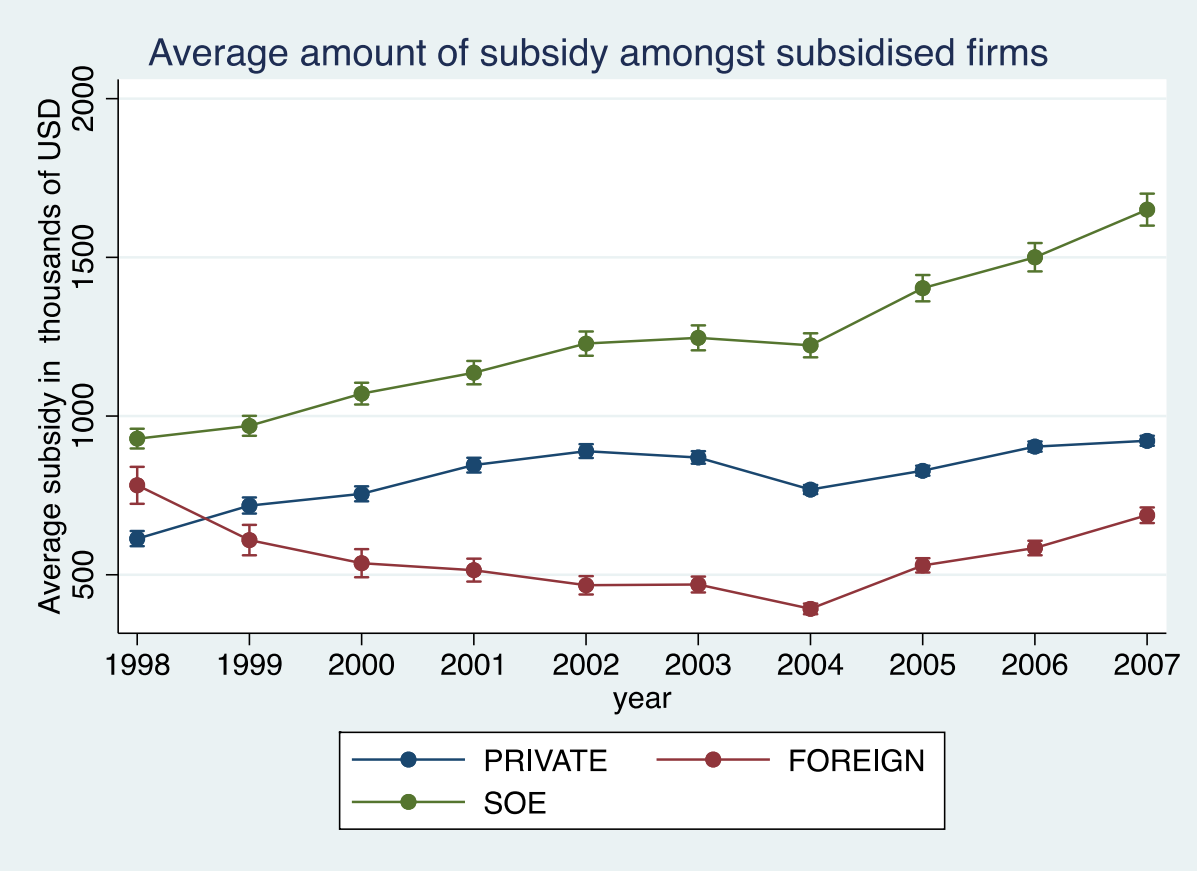

Average amount of subsidy amongst subsidised firms
Average subsidy in thousands of USD
500
1000
1500
2000
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
year
PRIVATE
FOREIGN
SOE

Figure 3:

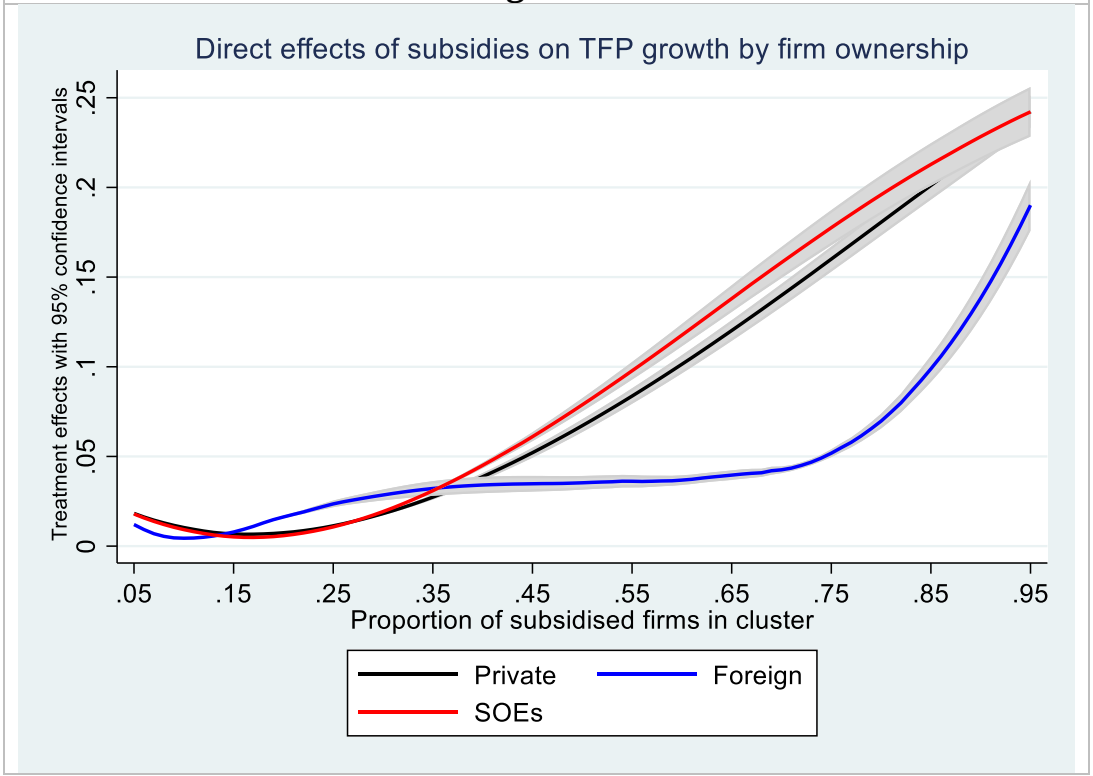
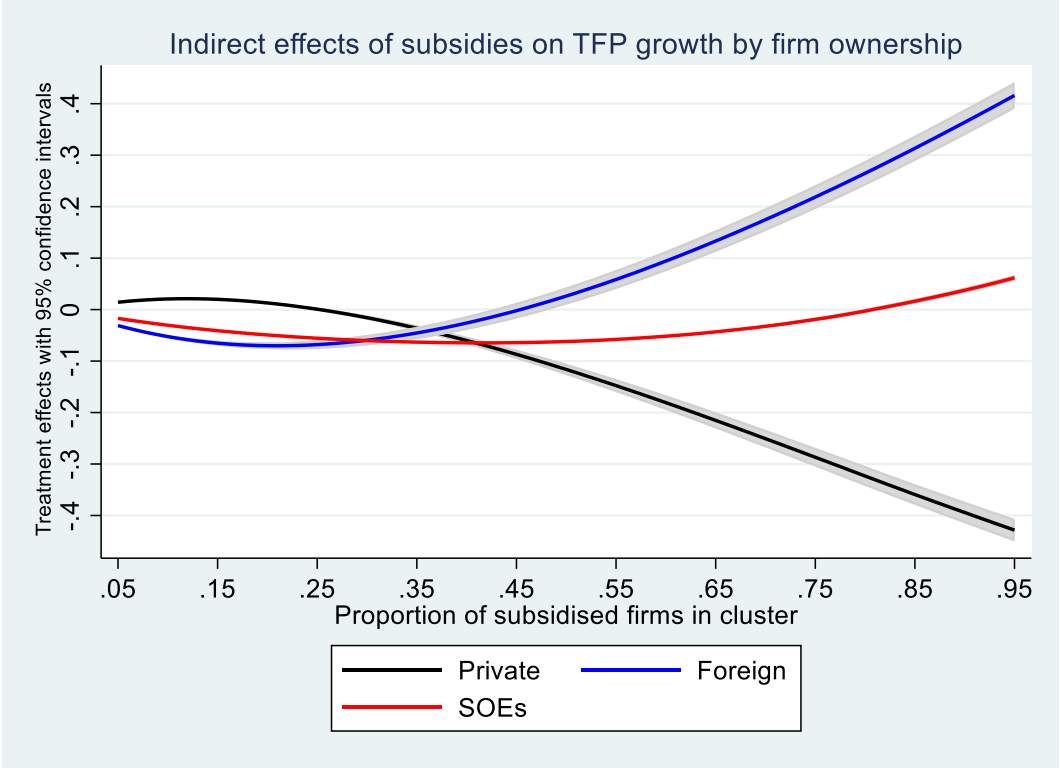

Direct effects of subsidies on TFP growth by firm ownership
Treatment effects with 95% confidence intervals
0
.05
.1
.15
.2
.25
.05
.15
.25
.35
.45
.55
.65
.75
.85
.95
Proportion of subsidised firms in cluster
Private
Foreign
SOEs

Figure 4:


Indirect effects of subsidies on TFP growth by firm ownership
Treatment effects with 95% confidence intervals
-.4
-.3
-.2
-.1
0
.1
.2
.3
.4
.05
.15
.25
.35
.45
.55
.65
.75
.85
.95
Proportion of subsidised firms in cluster
Private
Foreign
SOEs

TABLES

Table 1: Definition of variables used in the analysis

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.
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
Spatial variables	**All defined as spatial averages within the town the firm is located in (the cluster) but excluding one's own value. The prefix S_ is used to indicate spatial averages.**
S_Past Subsidy; S_Employment; S_Age; S_Loss; S_TFP; S_TFP trend; S_Debt; S_POL	
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	
S_subsidy	Proportion of subsidized firms (excluding one' own value) in the firm's town.

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

	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**	
	(N=800103)		*(N=144655)*	
	Mean	**Std. dev**	**Mean**	**Std. dev**
TFP growth	0.014	0.423	0.006	0.359
Past Subsidy	0.064	0.245	0.619	0.486
Employment	4.880	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	1.228	184.465	1.393	121.249
Debt	0.057	0.140	0.060	0.125
POL	0.478	0.500	0.528	0.499
S_Past subsidy	0.127	0.069	0.168	0.077
S_Employment	4.827	0.247	4.780	0.234
S_Age	1.993	0.212	1.984	0.196
S_Loss	0.218	0.098	0.215	0.103
S_TFP	0.828	0.107	0.826	0.103
S_TFP trend	1.180	6.472	1.098	6.180
S_Debt	0.056	0.032	0.051	0.031
S_POL	0.461	0.284	0.438	0.279
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	0.098	0.297	0.111	0.314

Table 4: The conditional probability of subsidy:
log odds ratios from spatial logistic regression:

	Log odds ratio	Robust standard errors
Past Subsidy	2.915***	(0.00914)
Employment	0.287***	(0.00370)
Age	-0.0542***	(0.00531)
Loss making	0.141***	(0.00889)
TFP	0.0639***	(0.00828)
TFP growth trend	0.0000159	(0.0000185)
Debt	0.0603*	(0.0268)
Political connection	0.178***	(0.00937)
S_past Subsidy	4.656***	(0.0201)
S_employment	-0.303***	(0.0296)
S_Age	-0.110***	(0.0623)
S_Loss making	-0.218***	(0.0609)
S_TFP	-0.847***	(0.000510)
S_TFP growth trend	-0.000943	(0.238)
S_Debt	-1.949***	(0.0328)
S_ POL	-0.268***	
FOREIGN	-0.0127	(0.00973)
SOE	0.112***	(0.0117)
Medium low-tech industries	0.183***	(0.00931)
Medium high-tech industries	0.147***	(0.0105)
High-tech industries	0.196***	(0.0130)
Observations	944758	
Log likelihood	-283030.6	
Pseudo R-squared	0.300	

Notes:

(i) Private firms and low-tech industries form their respective base group.

(ii) All regressions include year effects.

(iii) * p<0.1, ** p<0.05, *** p<0.01

Appendix

Table A1: The conditional probability of subsidy:
log odds ratios from spatial logistic regression: by ownership

	Private		Foreign		SOEs	
	Log odds ratio	Robust s/e	Log odds ratio	Robust s/e	Log odds ratio	Robust s/e
TFP growth	3.090***	(0.0124)	2.369***	(0.0177)	2.974***	(0.0208)
Past Subsidy	0.289***	(0.00539)	0.242***	(0.00750)	0.316***	(0.00720)
Employment	-0.0492***	(0.00706)	-0.155***	(0.0148)	-0.0457***	(0.0102)
Age	0.237***	(0.0128)	-0.130***	(0.0183)	0.112***	(0.0172)
Loss	0.122***	(0.0118)	-0.0363*	(0.0171)	0.0631***	(0.0157)
TFP	0.0000130	(0.0000278)	-0.0000293	(0.0000411)	0.0000495	(0.0000298)
TFP trend	-0.0351	(0.0391)	0.265***	(0.0737)	0.0894	(0.0469)
Debt	0.236***	(0.0120)	0.0173	(0.0192)	0.0228	(0.0279)
POL	5.093***	(0.0803)	4.854***	(0.131)	2.730***	(0.128)
S_Past subsidy	-0.222***	(0.0299)	-0.538***	(0.0498)	-0.0857*	(0.0359)
S_Employment	-0.187***	(0.0402)	-0.111	(0.0789)	-0.132*	(0.0596)
S_Age	0.209*	(0.0872)	-0.690***	(0.161)	0.252*	(0.124)
S_Loss	-0.675***	(0.0851)	-1.894***	(0.165)	-0.164	(0.118)
S_TFP	-0.00200	(0.00103)	0.00332	(0.00209)	-0.000873	(0.000633)
S_TFP trend	-4.224***	(0.352)	0.543	(0.741)	-0.116	(0.387)
S_Debt	-0.0994*	(0.0444)	-0.344***	(0.0756)	-0.436***	(0.0769)
S_POL	0.211***	(0.0125)	0.0938***	(0.0196)	0.160***	(0.0214)
Medium high-tech	0.151***	(0.0142)	0.153***	(0.0214)	0.112***	(0.0242)
High-tech	0.211***	(0.0181)	0.182***	(0.0256)	0.139***	(0.0280)
Observations	568323		209071			167364
Log likelihood	-157174.7		-69499.5			-54360.3
Pseudo R-squared	0.325		0.232			0.322

Notes:

(i) Low tech industries used as the base group

(ii) * p<0.1, ** p<0.05, *** p<0.01

Table A2:
Covariate balance tests based on standardized differences and variance ratios: Private firms

	Standardised differences		Variance ratio	
	Raw data	**Weighted data**	Raw data	**Weighted Data**
Pre-treatment covariates				
TFP growth	152.24%	0.85%	4.452	1.017
Past Subsidy	33.12%	4.31%	1.260	1.096
Employment	11.54%	-1.64%	0.985	0.971
Age	23.72%	2.36%	1.465	1.044
Loss	3.17%	-0.48%	1.055	1.007
TFP	-0.03%	0.26%	0.446	0.507
TFP trend	-1.16%	0.25%	0.779	0.915
Debt	12.07%	-0.89%	1.030	0.997
POL	64.53%	8.38%	1.151	0.888
S_Past subsidy	-22.38%	-0.69%	0.882	0.995
S_Employment	-4.00%	-0.17%	0.747	0.957
S_Age	-3.54%	2.27%	1.077	1.034
S_Loss	1.23%	-2.23%	0.893	1.060
S_TFP	-3.11%	-0.72%	0.950	1.081
S_TFP trend	-23.97%	-0.55%	0.816	1.021
S_Debt	-9.82%	-0.33%	0.954	0.984
S_POL	2.30%	-2.85%	1.013	0.982
Medium high tech	6.99%	0.41%	1.096	1.006
High tech	4.52%	2.06%	1.133	1.059
Year=2001	-5.73%	1.81%	0.813	1.063
Year=2002	-2.36%	-1.99%	0.925	0.936
Year=2003	-1.04%	-2.05%	0.973	0.946
Year=2004	10.87%	0.88%	1.322	1.025
Year=2005	6.20%	1.72%	1.146	1.039
Year=2006	-1.37%	-0.29%	0.982	0.996
Year=2007	-1.97%	-0.87%	0.976	0.990

Table A3:
Covariate balance tests based on standardized differences and variance ratios: Foreign firms

	Standardised differences		Variance ratio	
	Raw data	**Weighted data**	Raw data	**Weighted Data**
Pre-treatment covariates				
TFP growth	115.557%	0.841%	3.388	1.016
Past Subsidy	23.000%	-0.802%	0.990	0.970
Employment	-5.869%	-0.730%	1.093	1.066
Age	-10.693%	0.762%	0.859	1.010
Loss	-0.851%	0.976%	0.951	1.140
TFP	0.006%	-0.199%	0.405	0.411
TFP trend	2.254%	0.967%	0.658	0.585
Debt	-4.601%	-1.536%	0.968	0.990
POL	63.286%	4.081%	1.229	0.919
S_Past subsidy	-41.155%	-3.164%	0.727	0.895
S_Employment	-11.094%	-1.543%	0.888	1.029
S_Age	-27.415%	0.817%	1.048	0.999
S_Loss	-6.079%	1.159%	0.823	1.043
S_TFP	3.238%	1.299%	1.085	0.977
S_TFP trend	-21.087%	-1.571%	0.879	1.000
S_Debt	-13.146%	-1.105%	0.936	0.992
S_POL	-4.967%	-1.331%	0.943	0.985
Medium high tech	5.920%	0.244%	1.076	1.003
High tech	3.397%	-0.409%	1.090	0.989
Year=2001	-10.187%	-1.848%	0.707	0.943
Year=2002	-2.827%	-1.756%	0.919	0.949
Year=2003	3.334%	1.284%	1.088	1.033
Year=2004	16.915%	-0.208%	1.463	0.995
Year=2005	1.551%	6.454%	1.034	1.142
Year=2006	1.253%	-0.520%	1.019	0.992
Year=2007	-1.212%	-3.458%	0.983	0.950

Table A4:
Covariate balance tests based on standardized differences and variance ratios: SOEs

	Standardised differences		Variance ratio	
	Raw data	**Weighted data**	Raw data	**Weighted Data**
Pre-treatment covariates				
TFP growth	155.445%	0.948%	3.117	1.015
Past Subsidy	58.520%	3.910%	1.034	1.072
Employment	7.462%	-3.632%	1.094	1.058
Age	15.172%	-1.225%	1.033	0.996
Loss	4.474%	0.786%	0.989	1.035
TFP	0.313%	0.081%	0.380	0.494
TFP trend	4.207%	-0.636%	0.771	0.829
Debt	-0.094%	-2.699%	1.002	1.070
POL	34.659%	4.343%	1.446	0.890
S_Past subsidy	-1.931%	3.267%	0.912	0.965
S_Employment	-15.184%	-0.496%	0.998	1.039
S_Age	-3.948%	1.803%	1.107	1.055
S_Loss	7.578%	-1.129%	0.988	1.020
S_TFP	-1.370%	0.497%	0.731	0.661
S_TFP trend	-11.115%	0.927%	0.960	1.038
S_Debt	-19.083%	0.096%	1.063	1.009
S_POL	9.675%	-0.449%	1.079	0.996
Medium high tech	5.997%	-0.162%	1.079	0.998
High tech	2.377%	0.490%	1.055	1.011
Year=2001	-9.103%	0.096%	0.833	1.002
Year=2002	-4.494%	-1.202%	0.909	0.975
Year=2003	-1.389%	-0.638%	0.970	0.986
Year=2004	7.074%	-0.044%	1.199	0.999
Year=2005	8.228%	-0.937%	1.243	0.974
Year=2006	8.643%	-0.632%	1.239	0.983
Year=2007	8.269%	1.614%	1.252	1.046

Table A5:
Direct, indirect and (weighted) total treatment effects

Private firms

	Direct effects	Indirect effects	Weighted total effects
% 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
% 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
% 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