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Abstract: We ask whether production related subsidies have a role to play in explaining Chinese firms' export performance. We, firstly, implement an estimation approach that allows for both direct and indirect ("spillover") effects of the subsidy on the probability to export. Secondly, our approach enables us to allow these two effects to differ depending on the share of firms that already receive subsidies in a well-specified cluster. These two issues have, to the best of our knowledge, not been considered in evaluations of subsidies on export performance. Our estimation results provide a sobering assessment of the role of production related subsidies in stimulating export performance.

Keywords: exporting, subsidies, spillovers

JEL Classification: F14, F12, H25

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1 Introduction

According to the WTO's Integrated Data Base (IDB), China ran trade surpluses with 169 countries in 2016. The most striking of these trade imbalances is, of course, between the US and China. This has arguably contributed greatly to the recent trade war between the two countries. One of the reasons for this is the perceived unfair competition due to China's use of state subsidies. Indeed, China is frequently noted for its policy of subsidizing firms in specifically targeted industries, such as electric cars, steel, or solar panels (e.g., Haley and Haley, 2013).[1]

We look at the use of such production-related subsidies and ask whether they have a role to play in explaining Chinese firms' export performance. These subsidies effectively reduce firms' costs, which may enable them to enter into exporting. Building on earlier work that estimated the direct treatment effect of subsidy receipt on the receiving firm's export performance (Girma et al., 2009, Görg et al., 2008) we expand this literature in a number of ways. Firstly, we set out an estimation approach that allows for both direct and indirect ("spillover") effects of the subsidy on the probability to export of both treated and non-treated firms, respectively. Secondly, our approach enables us to allow these two treatment effects to differ depending on the share of firms that already receive subsidies in a well-specified cluster. These two issues have, to the best of our knowledge, not been considered in evaluations of subsidies on export performance.[2]

The estimation of the treatment effects is complicated by the fact that we are likely to have selection at two levels. Firstly, subsidy receipt by a firm is unlikely to be random, as government may target particular firms. Secondly, the distribution of subsidized firms across clusters is also difficult to justify as random, as government policy may favour certain regions and / or industries. We employ the estimation technique developed in Girma et al. (2015) which deals with both types of selection in two steps using propensity score matching methods.

We modify a heterogenous firm model to motivate the expectation that the direct and indirect effects depend on the share of subsidized firms in a cluster. Details of this are in the appendix. In our model, subsidies to a firm reduce their marginal cost of production and go hand in hand with a reduction in the variable cost of exporting. Subsidies are given to firms after they enter the local market but before they decide whether or not to export. In this model set up, there are positive direct treatment effects, since subsidized firms have lower effective marginal cost than non-subsidized firms in a cluster. This means that more subsidized firms will be able to overcome the foreign market entry hurdle, which translates into a higher share

[1] See also 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 27/03/19).

[2] In the theoretical model we work with a combination of a production subsidy and a trade cost (for those same subsidized firms) which depends on the number of subsidized firms in a cluster. The latter is in effect an export promotion activity. Export promotion has been investigated by, e.g., van Biesebroeck et al., 2015 and Martincus and Carballo, 2008, 2010. These studies, also focus on direct effects but neglect spillovers and the possible interaction with the presence of treated firms in a cluster.

of exporters. In addition, the direct subsidy effect depends positively on the share of subsidized firms s in the cluster. This comes from the trade costs for subsidized firms, which decrease in s.

The model also shows that there is a negative indirect treatment effect, which increases in absolute value in s. Subsidising firms increases competition and makes it more difficult for non-subsidized firms in a cluster with subsidies to become exporters. The share of exporting firms among the non-subsidized firms in a cluster with subsidies is therefore lower in comparison to a cluster without subsidies. This effect is aggravated by an increasing share of subsidized firms.

2 Data

We examine these predictions using firm level data from the Chinese manufacturing industry from the Annual Reports of Industrial Enterprise Statistics, compiled by the China National Bureau of Statistics. The dataset covers all firms in China with an annual turnover of more than 5 million Renminbi (about $800,000). These companies account for an estimated 85-90 percent of total output in most industries. For the purpose of this analysis, we have information on more than 170,000 firms for the period 2004-2006.

The dataset provides information on whether or not firms received production-related subsidies. We use this to define our treatment as a firm having received such production subsidies in 2005. The outcome variable is measured as a dummy whether or not a firm exports in 2006. We define clusters based on 245 towns.

Table 1 provides the definition and summary statistics of pre-treatment covariates by treatment status.

[Table 1 here]

Table 2 provides some summary statistics of the cluster level variables. Table 3 shows that the proportion of subsidized firms exhibits significant (unconditional) correlations with most of the cluster level variables, providing suggestive evidence of the importance of controlling for cluster level observables.

[Tables 2 and 3 here]

3 Empirical framework

We briefly outline the estimation framework here, with more details in the appendix and in Girma et al. (2015). To deal with the two levels of selection we proceed in two steps.

In the first step, we estimate the relationship between subsidy receipt and probability to export separately for each cluster, using firm level data. Doing so by cluster allows us to investigate whether the treatment effects differ across clusters, as we would expect from our theoretical model.

We regress the firm level export dummy in 2006 on the treatment status in 2005. The outcome equation is estimated using inverse propensity score weighted regression to allow for selection of subsidy receipt. The firm level propensity score is generated using a logistic regression of the treatment status on firm level characteristics pre-treatment (i.e., 2004). This is done separately for each cluster.

From these cluster-by-cluster regressions we can calculate predicted values of the probability to export for both treatment statuses (treated and non-treated) for each cluster.

These so-calculated cluster level average potential outcomes are then used as dependent variable in a second step estimation. In this step, the proportion of treated firms in a cluster ($\bar{s}$) is taken as treatment variable. As this treatment variable is continuous and bounded between 0 and 1 we employ a generalised propensity score method to identify the causal effect of the treatment. The propensity score is generated conditional on pre-treatment characteristics of the cluster.[3]

Based on this we can then calculate average potential outcomes for different levels of $\bar{s}$ which are used to estimate the direct and indirect treatment effects parameters, using insights from the recent statistical literature (e.g. Hudgens & Halloran, 2008). Firstly, we can calculate a *direct effect* $\bar{\gamma}_{ss}^{10} = \bar{y}_s^1 - \bar{y}_s^0$ as the difference in the probability to export between subsidized (1) and non-subsidized (0) firms for a given share of subsidized firms s in a cluster. The *indirect effect* is $\bar{\gamma}_{s0}^{00} = \bar{y}_s^0 - \bar{y}_0^0$, hence, the difference in export probability between non-subsidized firms (0) in a cluster s and in a cluster without any subsidized firms (0).

4 Empirical results

The estimated direct and indirect treatment effects are plotted in Figure 1. The graph also shows the associated 95% confidence intervals. The results provide a number of important insights.

[Figure 1 here]

Firstly, as regards the direct treatment effect, we find that this is always positive and differs significantly according to the share of subsidized firms in a cluster. For clusters with low levels of treated firms, the direct effect is positive and increasing in s as predicted by theory. A look at the point estimates shows that for a cluster with five percent treated firms, receipt of a subsidy increases the probability to export by about 6 percent. This effect increases to about 15 percent in a cluster with 30 percent of subsidized firms.

This increase in the positive effects is in line with our theoretical discussion. Trade related subsidies increase in the share of subsidized firms in the cluster, thus making the firms already receiving marginal cost subsidies more likely to export relative to non-subsidized firms.

[3]As we have selection-on-observables in both steps, we of course also perform balancing tests. These are also described in the appendix.

For clusters with more than 30 percent of subsidized firms we find that the direct treatment effect remains positive but decreases with s. While not captured in our model framework, such decreasing positive effect is consistent with the idea that in clusters with high levels of subsidized firms, subsidies can distort the efficient allocation of resources within the subsidized firms and thus lead to a worsening of firm performance. Our results would indicate that this effect only sets in at fairly high levels of subsidy receipt, however. Actually the share of subsidized firms is less than 30 percent in 90 percent of the clusters, in this range the direct effect is monotonic.[4]

Turning to the indirect treatment effect, we find that it is negative and differs depending on the share of treated firms. A negative indirect treatment effect is in line with our theoretical prediction. A cluster with subsidized firms is a more difficult environment for the non-subsidized firms, as a result they are less likely to find it profitable to export. The model also predicts that the negative effect should increase (in absolute terms) with increasing shares of treated firms in a cluster. This is true in our results for clusters of up to 20 percent share of treated firms. For higher levels of treated firms in a cluster, the negative effect decreases in absolute terms but remains negative. The theory could explain such non-monotonicity of the indirect spillover effect if the size of the firm-specific subsidy were to decrease with the number of subsidized firms for $s > 0.2$.[5],[6]

5 Conclusion

Our estimation results put in question the potential role of production related subsidies in stimulating exports. We find that the direct effect of subsidies is always positive, it is increasing for firms in clusters with low levels of subsidisation, but diminishes for high levels of subsidization. Furthermore, subsidising firms has a negative impact on the export propensity of non-subsidized firms. This effect becomes stronger with a higher proportion of subsidized firms in a cluster. For a very large share of subsidized firms the effect decreases but remains negative. Based on these results it is questionable whether such production related subsidies have a large role to play in explaining Chinese firms' export performance.

[4] We assume in the theoretical part that $\frac{\partial \tau}{\partial s}$ is negative and sufficiently small. If for $s > 0.3$ the derivative becomes sufficiently close to zero or positive the theory would generate the non-monotonicity of the direct effect, namely a positive and decreasing spillover effect.

[5] The empirical construction of clusters is not an exact science. One needs to strike a balance between having a large enough number of clusters and sufficient observations per cluster. Also, clusters should be constructed in such a way as to maximize the potential of intra-cluster spillovers, while at the same time minimize possible inter-cluster externalities. Redefining clusters based on four-digit industries instead of towns produces the result depicted in Figure 1b. It also shows positive direct effects and negative indirect effects, both of which differ with the share of subsidized firms in the cluster.

[6] Dai et al. (2017) show that export processors are less productive than ordinary exporters and, more importantly, than non-exporters. They attribute this, at first counter-intuitive finding to the fact that the least productive firms choose to do export processing, as the fixed costs involved and level of production technology employed are relatively low. Using data similar to Dai et al. (2017) we also distinguish export processors and ordinary exporters. Figures 2 and 3 in the appendix show separate results for the two types of firms and we can see that the main results in particular hold for ordinary exporters, and less so for firms engaged in export processing.

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A Appendix

Table 1
Variable definition and summary statistics of pre-treatment and outcome variables

		Non-subsidized firms		Subsidized firms	
Pre-treatment control variables (2004)	Definition	Mean	S.D	Mean	S.D
Previous subsidy status	Dummy variable subsidy status in 2004	0.45	0.50	0.47	0.52
Size	Log of total assets	8.25	1.59	9.00	1.80
Log age	Log of years since establishment +1	1.91	0.89	2.07	0.86
Productivity	Estimated using the Levinsohn and Petrin (2003) methodology	5.33	1.00	5.43	1.00
Debt	Long term liability divided by total assets	0.16	2.08	0.35	19.72
State-ownership	Dummy variable for majority state ownership	0.04	0.19	0.06	0.22
Returns on assets	Net income divided by total assets	0.03	0.21	0.04	0.74
Outcome variables (measured in 2006)					
Export markets participation	A dummy variable indicating any type of exports	0.33	0.47	0.36	0.48
Processing exports participation	A dummy variable indicating firms' involvement in exports processing	0.12	0.32	0.16	0.36
Final product exports participation	A dummy variable indicating exports of final products	0.28	0.45	0.31	0.46
Total export intensity	Total exports divided by sales	0.21	0.37	0.23	0.38
Processing exports intensity	Exports processing divided by sales	0.06	0.20	0.06	0.20
Final product exports intensity	Final products l exports divided by sales	0.16	0.32	0.17	0.33
Number of firms		130201		36495	

Note: The original number of total observations was 171578. This is reduced to 166695 after imposing the common support condition in the first step estimations.

Table 2
Summary statistics of cluster level variables

	Mean	Median	Standard deviation	Min	Max
Current proportion of subsidized firms	0.220	0.199	0.109	0.054	0.614
Control variables (all in pre-treatment year)					
Log number of subsidized firms in previous period	4.715	4.554	1.356	0.693	8.444
Size	10.137	10.115	0.624	8.737	12.262
Log age	2.432	2.409	0.281	1.276	3.266
Productivity	5.207	5.229	0.321	4.132	6.137
Debt	0.227	0.176	0.403	0.001	6.139
Log number of SOEs	3.125	3.135	1.140	0.000	6.444
Returns on assets	0.017	0.021	0.044	-0.438	0.094
Number of clusters	245				

Notes: Size, age, productivity, returns on assets and debt are defined as the cluster-level average values. Out of the original 245 clusters, 41 were lost because of common support conditions (see Appendix A4 for detail).

Table 3: Correlation matrix of cluster level variables:

	1.	2.	3.	4.	5.	6.	7.	8.
1. Proportion of subsidized firms	1							
2. subsidized firms in previous period	-0.267***	1						
3. Size	0.231***	-0.248***	1					
4. Log age	0.0697	-0.338***	0.422***	1				
5. Productivity	-0.120*	0.339***	-0.0732	-0.447***	1			
6. Debt	-0.00369	-0.0830	0.0409	0.128**	0.0316	1		
7. SOEs	-0.226***	0.666***	0.121*	0.224***	0.0483	-0.00929	1	
8. Return on assets	-0.101	0.185***	-0.180***	-0.327***	0.320***	-0.0107	-0.0876	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.1 Model details

We develop an open economy model with heterogeneous firms, where a government subsidizes firms by reducing their marginal cost of market entry. The subsidy is financed through a lump sum tax and is given to firms randomly after they have entered the local market but before they have made the decision on whether to export. The number of workers is normalized to one and the wage is the numeraire. Utility of the individual is represented by the standard CES preferences $U \equiv \left(\int_0^m d(\omega)^\alpha d\omega\right)^{\frac{1}{\alpha}}$. Demand for product ω is $d(\omega)$ and the elasticity of substitution between products $\sigma = 1/(1-\alpha) > 1$ is defined by $0 < \alpha < 1$. Solving the consumers' problem yields the usual demand $d(\omega) = \frac{p(\omega)^{-\sigma}}{P^{1-\sigma}}C$, with $p(\omega)$ being the price of the product, C being consumption expenditure, and $P \equiv \left(\int_0^m p(\omega)^{1-\sigma} d\omega\right)^{\frac{1}{1-\sigma}}$ the aggregate price index.

To develop a new product firms pay a fixed cost F, following which they draw marginal cost a from a Pareto distribution with a probability density function $g(a)$ with support $[0, \overline{a}]$ and a cumulative density function $G(a) \equiv \int_0^a g(a)da = (a/\overline{a})^k$, where $k > \sigma - 1$. In order to enter their home market firms need to pay another fixed cost F_L. This naturally creates a marginal cost threshold a_L, which separates firms that enter and produce from those that do not.

Firms have the option to enter the foreign market as exporters. Before they decide on that however they learn whether they will be receiving a subsidy or not. The effective marginal cost of subsidized firms is $a' \equiv \kappa a$, where $0 < \kappa < 1$ is the parameter which determines the size of the per-unit subsidy $a - \kappa a$. In order to enter the foreign market a firm needs to pay a fixed cost $F_E > F_L$, which creates two more marginal cost cutoffs a_{ES} dividing exporting from non-exporting subsidized firms and a_{EN} dividing exporting from non-exporting, non-subsidized firms. In addition to paying a fixed cost to enter the foreign market firms have to pay an iceberg trade cost $\tau_n > 1$, if they are not subsidized, or $\tau_s > 1$ if they are subsidized. We assume that the iceberg trade cost for subsidized firms $\tau_s < \tau_n$ is lower than the one for non-subsidized firms and also that τ_s decreases with the share of subsidized firms in a cluster $\frac{\partial \tau_s}{\partial s} < 0$, where $0 < s < 1$. We simplify our analysis and look at the lower iceberg trade cost for subsidized firms as lower red tape that they face when exporting. There is no transfer of resources in that instance and the lower τ_s is not present in the government budget condition.

The profit of a producing firm from selling at home can be written as $\pi_h(a) = (p_h(\omega) - a(\omega))d_h(w)$ if not subsidized and $\pi_h(\kappa a) = (p_{sh}(\omega) - \kappa a(\omega))d_h(w)$ if subsidized. Firms optimize profits and given their marginal cost set the price at $p_h(\omega) = \frac{a(\omega)}{\alpha}$ or $p_{sh}(\omega) = \frac{\kappa a(\omega)}{\alpha}$. Profits therefore equal $\pi_h(a) = \delta \left(\frac{a(\omega)}{P}\right)^{1-\sigma} C$ or $\pi_h(\kappa a) = \delta \left(\frac{\kappa a(\omega)}{P}\right)^{1-\sigma} C$, where for brevity $\delta \equiv (\sigma-1)^{\sigma-1}\sigma^{-\sigma}$. The profit of a producing firm from selling abroad can be written as $\pi_f(a) = (p_f(\omega) - \tau_n a(\omega))d_f(w)$ if not subsidized and $\pi_f(\kappa a) = (p_{sf}(\omega) - \tau_s \kappa a(\omega))d_f(w)$ if subsidized. Firms optimize profits and given their marginal cost set the price abroad at $p_f(\omega) = \frac{\tau_n a(\omega)}{\alpha}$ or $p_{sf}(\omega) = \frac{\tau_s \kappa a(\omega)}{\alpha}$

The standard exogenous exit probability is denoted by γ. The value of a firm from entering the home market and after knowing its marginal cost equals $v(a) = s\pi_h(\kappa a)/\gamma + (1-s)\pi_h(a)/\gamma$. To find the threshold marginal cost a_L, the value of the marginal firm must equal the fixed cost of local market entry $v(a_L) = F_L$. One can therefore find

$$a_L = \left(s\kappa^{1-\sigma} + 1 - s\right)^{-\frac{1}{1-\sigma}} P \left(\frac{F_L\gamma}{C\delta}\right)^{1/(1-\sigma)}.$$

The threshold separating exporting from non-exporting subsidized firms can be found from $\pi_f(\kappa a_{ES})/\gamma = F_E$:

$$a_{ES} = \frac{P}{\kappa\tau_s}\left(\frac{F_E\gamma}{C\delta}\right)^{1/(1-\sigma)}.$$

The threshold separating exporting from non-exporting non-subsidized firms can be found from $\pi_f(a_{EN})/\gamma = F_E$:

$$a_{EN} = \frac{P}{\tau_n}\left(\frac{F_E\gamma}{C\delta}\right)^{1/(1-\sigma)}.$$

With those marginal cost thresholds we can find the share of exporting firms within the groups of subsidized and non-subsidized firms. The direct effect in our estimations is the share of exporters within the group of subsidized firms minus the share of exporters within the group of non-subsidized firms, both from the same cluster:

$$\overline{\gamma}_{pp}^{10} = \frac{G(a_{ES})}{G(a_L)} - \frac{G(a_{EN})}{G(a_L)}.$$

Substituting for the cumulative distribution function of the Pareto distribution and the threshold marginal costs we obtain

$$\overline{\gamma}_{pp}^{10} = \left(\frac{F_E^{1/(1-\sigma)}}{\left(s\kappa^{1-\sigma}+1-s\right)^{-\frac{1}{1-\sigma}} F_L^{1/(1-\sigma)}}\right)^{k} \tau_n^{-k}\left(\left(\kappa\frac{\tau_s}{\tau_n}\right)^{-k} - 1\right).$$

Notice that the direct effect does not depend on consumption expenditure or the aggregate price index. It is always positive, since $\left(\kappa\frac{\tau_s}{\tau_n}\right)^{-k} - 1 > 0$ and increases in s if the following holds:

$$-\frac{\partial\tau_s}{\partial s}\frac{1}{\tau_s}\left(\frac{\kappa\tau_s}{\tau_n}\right)^{-k} - \left(\left(\frac{\kappa\tau_s}{\tau_n}\right)^{-k} - 1\right)\frac{1}{\sigma-1}\frac{\kappa^{1-\sigma}-1}{s\kappa^{1-\sigma}+1-s} > 0.$$

We assume that the above inequality holds, which implies that $\frac{\partial\tau_s}{\partial s}$ is sufficiently low.

Intuitively, more firms are able to become exporters within the subsidized group as their expected profits from selling abroad are on average higher than those of non-exporters. More subsidized firms will find it optimal to pay the foreign market entry fixed cost. This is why the likelihood for a subsidized firm to be an exporter is greater (the positive direct effect).

Further, when more firms within a cluster are subsidized, the firm-specific iceberg trade cost of subsidized firms is lower (our assumption that τ_s decreases in s), more firms enter the foreign market relative to the number of firms that enter only the home market. The relative share of subsidized exporters increases, which leads to the direct effect increasing in s.

The indirect effect is the share of non-subsidized exporting firms in all non-subsidized firms within a cluster with subsidies minus the share of exporters in all firms within a cluster without subsidies.

$$\overline{\gamma}_{p0}^{00} = \frac{G(a_{EN})}{G(a_L)} - \frac{G(a_{nEN})}{G(a_{nL})}.$$

We again substitute for the cumulative distribution function and the threshold marginal costs and arrive at

$$\overline{\gamma}_{p0}^{00} = \left(\frac{F_E^{1/(1-\sigma)}}{(s\kappa^{1-\sigma} + 1 - s)^{-\frac{1}{1-\sigma}} \tau_n F_L^{1/(1-\sigma)}} \right)^k - \left(\frac{F_E^{1/(1-\sigma)}}{\tau_n F_L^{1/(1-\sigma)}} \right)^k,$$

where a_{nL} is the marginal cost threshold separating entering from non-entering firms in a cluster without subsidies, a_{nEN} is the threshold separating exporters from non-exporters and τ_n is the iceberg trade cost in the same cluster. The above is negative because $\left(\frac{1}{(s\kappa^{1-\sigma}+1-s)^{-\frac{1}{1-\sigma}}} \right)^k < 1$ and decreasing in s.

The theoretical discussion thus provides a basis for our empirical analysis. We expect to find a positive and increasing in s direct effect and a negative and decreasing in s indirect treatment effects.

A.2 First step estimation

We first estimate the average potential outcomes $\bar{y}_s^1$ and $\bar{y}_s^0$ corresponding to the two treatment states (subsidized and non-subsidized) for *each cluster*. We identify the expected individual outcomes for the two treatment states per cluster by regressing a firm level export dummy on the treatment status. 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, a so-called doubly-robust estimator (Bang and Robins, 2005, Hirano et al., 2003).[7]

For each cluster, this implies that we firstly generate the firm-specific propensity-scores (p) of being treated via a logistic regression with a rich list of pre-treatment covariates X subject to balancing conditions being satisfied. The list and precise definition of the pre-treatment covariates can be found in Table 1. Results are reported in Table 4. As we have 245 propensity

[7]The estimator is doubly robust as it provides two opportunities to adjust for selection on observables by combining inverse probability reweighing with regression covariates adjustment. Our identifying assumption is, of course, selection on observables. To the extent that there are unobservables that are correlated with both the treatment conditional on observables and the export dummy, this would potentially bias our results.

score estimations, we report summary statistics for the estimated coefficients. The last column of Table 4 also shows that propensity score conditioning has done a remarkably good job at balancing firm level observable covariates across the two groups of firms.

Using the obtained propensity scores we then estimate the following outcome equation by cluster via inverse probability weighted regression. We impose the common support condition to ensure that the propensity score is balanced across treated and non-treated firms:

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

where y is a firm level export dummy and $F(.)$ represents a function of pre-treatment covariates vector X. In the inverse probability weighting, treated firms receive a weight of $1/p$ and non-treated firms $1/(1-p)$. From the regression we can then calculate the cluster specific potential outcomes for the average treated (1) and non-treated (0) firm in a cluster with foreign presence s as

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

The average difference between the two potential outcomes in the above equation would be an estimate of the average treatment effect in the absence of externalities, i.e., if the cluster-specific level of treated firms did not matter.

In order to investigate whether there is a causal relationship between the cluster specific treatment intensities s and the cluster specific potential outcomes, we implement a second step estimation. This allows us to generate the direct and indirect treatment effects as described in Section 3.

Table 4

Summary statistics from the first stage cluster-specific logit regressions and balancing tests.

	Marginal effects from cluster-specific logit regressions							**Balancing tests**:
Pre-treatment covariates	Mean	S.D	Min	Lower quartile	Median	Upper quartile	Max	% of balanced clusters
Previous subsidy status	0.074	0.099	-0.304	0.013	0.067	0.133	0.411	100%
Size	0.052	0.028	-0.027	0.033	0.048	0.066	0.151	100%
Log age	0.020	0.045	-0.147	-0.001	0.021	0.044	0.194	100%
Productivity	0.009	0.041	-0.092	-0.014	0.006	0.028	0.194	100%
Debt	-0.037	0.218	-2.334	-0.034	-0.000	0.022	0.168	99.2%
State-ownership	0.023	0.235	-2.291	-0.038	0.027	0.091	1.342	95.1%
Returns on assets	0.089	0.401	-2.057	-0.039	0.071	0.274	1.698	100%

Notes: (i) As explained in the text, the determinants of subsidy receipt are estimated separately for each of the 245 clusters. (ii) The last column gives the results from the covariate balancing test which consists of testing (at 10% level or lower) for difference in the means of the covariates in treatment and control groups, conditional on the estimated propensity score.

A.3 Second step estimation

In the second step of the analysis we follow Hudgens and Halloran (2008) and treat $\bar{y}_s^1$ and $\bar{y}_s^0$ estimated in the first step as the "outcome" variables. The share of firms receiving a subsidy in the cluster is taken to be the "treatment" variable which in this case is continuous between 0 and 1. In order to control for selection at the cluster level, we employ the causal inference approach for continuous treatments (Hirano and Imbens, 2004). A key result from this literature is that causal inference can be conducted by conditioning on the generalized propensity score (GPS), which is essentially the conditional density of the treatment given some pre-treatment balancing covariates.

As we have a dosage variable s_r that is continuous and bounded between 0 and 1, we generate the GPS conditional on pre-treatment cluster level covariates, say $\hat{G}_r$, using the fractional logit model (Papke and Wooldridge, 1996). A full list of these cluster level variables can be found in Table 2. Marginal effects from the fractional logit model and the accompanying covariate balancing tests are reported in Table 5. We also report results from covariate balancing test in this second step estimation in the final two columns.[8]

[8] In order to check for covariate balancing conditional on generalized propensity scores (GPS), we adopt the blocking approach proposed by Hirano and Imbens (2004). Accordingly we first divide clusters into 3 discrete groups defined by treatment intensity (i.e., employment share of foreign firms), and then create 5 blocks within each such group based on the estimated GPS quintiles. Within each block, we carry out difference-in-means

We show the average p-values from these tests (null hypothesis: there is covariate balancing), and it is reassuring to see that conditioning on GPS has done a very good job at covariate balancing. What remains then is to calculate cluster level potential outcomes conditional on $\hat{G}_r$ and s_r using polynomial approximation (Hirano and Imbens, 2004). In this paper we use the following quadratic approximation[9]

$$\mathbb{E}[y_r^d|\hat{G}_r, s_r] = \beta_0 + \beta_1\hat{G}_r + \beta_2 s_r + \beta_3\hat{G}_r s_r + \beta_4\hat{G}_r^2 + \beta_5 s_r^2 \tag{3}$$

with sample counterpart over R clusters obtained as

$$\bar{y}_r^d = \frac{1}{R}\sum_{r=1}^{R}(\hat{\beta}_0 + \hat{\beta}_1\hat{G}_r + \hat{\beta}_2 s_r + \hat{\beta}_3\hat{G}_r s_r + \hat{\beta}_4\hat{G}_r^2 + \hat{\beta}_5 s_r^2) \tag{4}$$

The so calculated potential outcomes allow us to generate sample-counterparts of the direct and indirect treatment effects parameters described in Section 3.

Since the treatment variable in our second stage estimation is continuous, we gauge the extent to which the balancing property of the covariate s in supported by the data, we follow the "blocking on GPS" approach advocated by Hirano and Imbens (2004). Our operational scheme to test for can be summarized as follows:

- We divided the observations into four groups by treatment quartiles,
- Within each quartile we compute the GPS at the median value of the treatment variable, and we then further divide the sample into "blocks" based the quartiles of the this GPS
- For each covariate and treatment intensity quartile, we test for the mean difference between clusters that belong the treatment quartile in question and treatment quartiles that belong to the same GPS "block".

Thus for each of our 7 covariates, we conduct 16 mean difference tests, the p-values of which are summarized in table 6 below, shows that the balancing property is well supported by the data.

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tests between a treatment intensity group and the other two groups combined by conditioning on the GPS. This process is repeated for each of the 3 treatment intensity groups and 9 covariates, entailing a total of 135 balancing tests.

[9] Note that individual parameters from such polynomial approximations do not have any behavioral interpretation (Hirano and Imbens, 2004).

Table 5
Estimated coefficients and average marginal effects from cluster-level fractional logit model:
Dependent variable: proportion of subsidized firms in cluster

	Estimated coefficients	Marginal effects
Number of subsidized firms in previous period	0.0150	0.0025
Size	(0.0863)	(0.0141)
	0.3568***	0.0583***
Log age	(0.0977)	(0.0164)
	-0.1418	-0.0232
Productivity	(0.2080)	(0.0340)
	-0.1773	-0.0290
Debt	(0.1738)	(0.0285)
	-0.0189	-0.0031
Number of SOEs	(0.1955)	(0.0319)
	-0.2245**	-0.0367**
Returns on assets	(0.0947)	(0.0158)
	-3.7312**	-0.6096**
	(1.7570)	(0.2868)
Observations	245	

Notes:
(i) Standard errors are given in parenthesis
(ii) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
(iii) Based on the generalized propensity score estimated from the above regression, 44 clusters are subsequently lost due to common support conditions (see below for detail)

Table 6

p-values from balancing tests second stage estimation

Covariate	Mean	Median	Lower quartile	Upper quartile
Debt	0.448	0.457	0.177	0.694
Productivity	0.288	0.127	0.057	0.583
Returns on assets	0.401	0.395	0.040	0.643
Number of subsidized firms in previous period	0.464	0.425	0.245	0.716
Log age	0.471	0.468	0.173	0.793
Size	0.462	0.452	0.220	0.703
Number of SOEs	0.596	0.751	0.234	0.903

Note: Since the treatment is continuous we divided the observations into four groups by treatment quintiles and conditional on the generalised propensity score, we tested for equality of means of each of the covariates across all quartiles (using robust regression and Quintile 1 as the base group). We did not reject the null hypothesis of equality of means in any of the tests whose p-value are reported above.

A.4 Detail on common support conditions

We were careful to impose that the common support condition are satisfied at both the first stage (i.e. cluster-specific) and second stage (i.e. cluster level) of the estimation in order to comply with the requirements of propensity score based estimators.

1. Imposing common support at the first stage is quite straightforward since the treatment variable is a binary variable. Thus after estimating the logistic regression and generating the propensity-score, all control group firms with estimated propensity score below the minimum value and above the maximum value of the propensity score variable for the subsidized firms are removed from the analysis. This process is carried out for each of the 245 clusters, and in the final analysis 5883 out of the original 172579 firms are found to lie outside the propensity score support leaving us with 166696 (130201 control and 36495 treated) observations.

2. The treatment variable at second stage analysis is continuous as it is defined as the proportion of subsidized firms in a cluster. While imposing common support in such cases is not straightforward, the statistical and econometrics literature have made some strides towards this end (e.g.Flores et al., 2012). In the spirit of this literature, we determine the generalised propensity score common support or overlap region across clusters as follows:

- Divide the cluster level sample (N=245) into four based on treatment intensity (i.e. proportion of subsidized firms) quartiles.
- For each quartile, evaluate the genearlized propensity score (GPS) at the median level

of the treatment in that quartile. This is done for all units whether they belong to that particular quartile or not.

- The overlap region with respect to a particular quartile is defined as consisting of all observation from the other three quartile whose GPS is no more than 5% outside the minimum or maximum GPS of that quartile.

- The above procedure is repeated for all quartiles, dropping firms whose GPS is outside the overlap region of the quartile in question. This has resulted in the loss of 44 clusters, restricting our estimating sample to 204 clusters that are comparable.

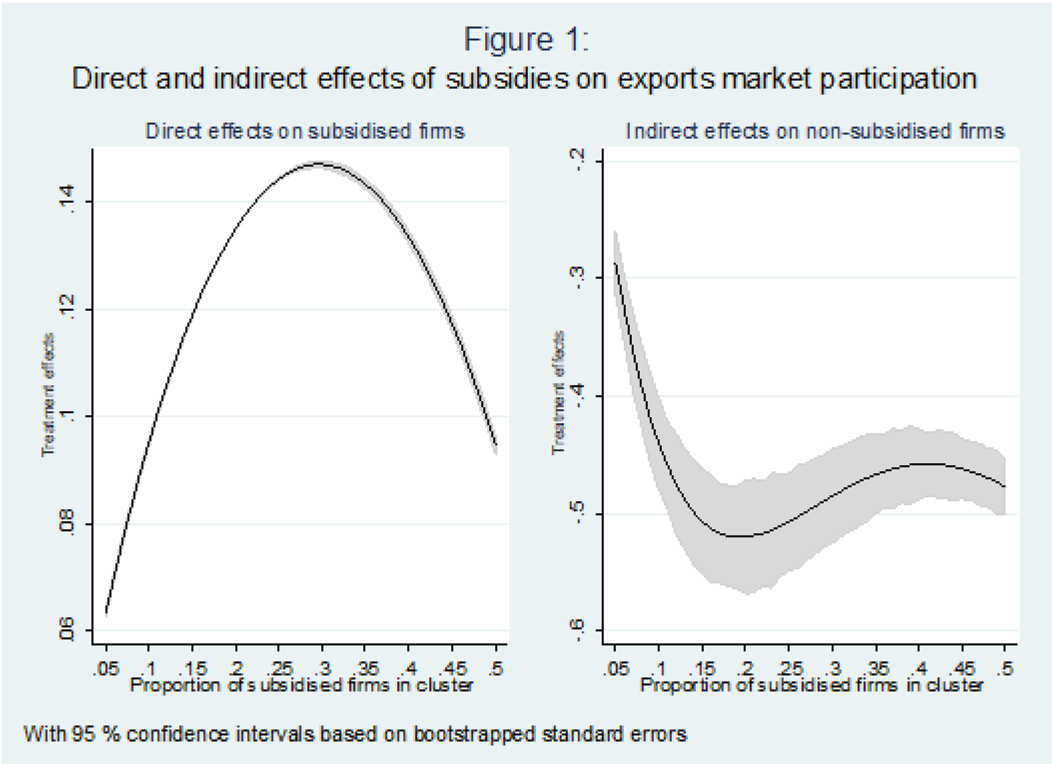
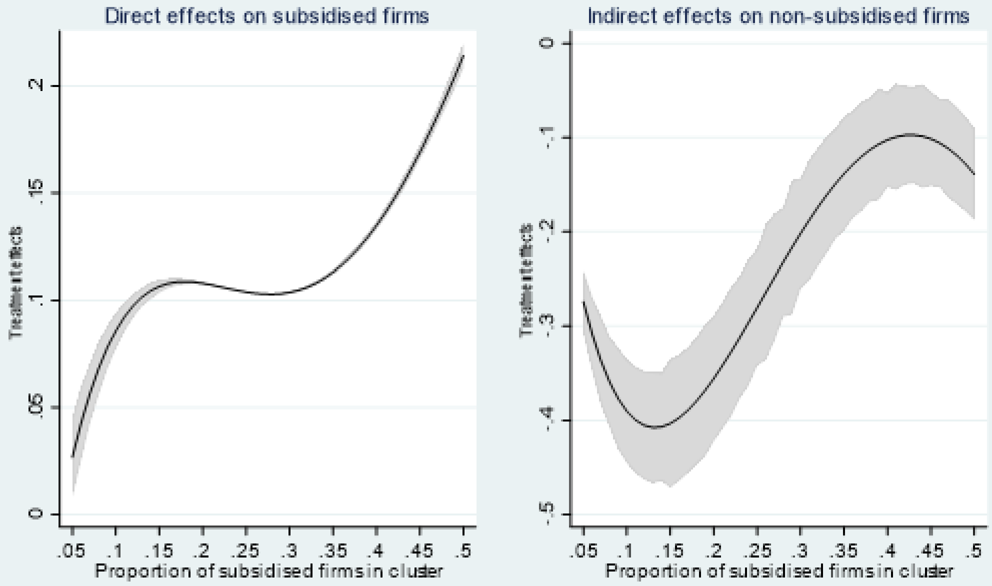


Figure 1b: Subsidies and exports markets participation

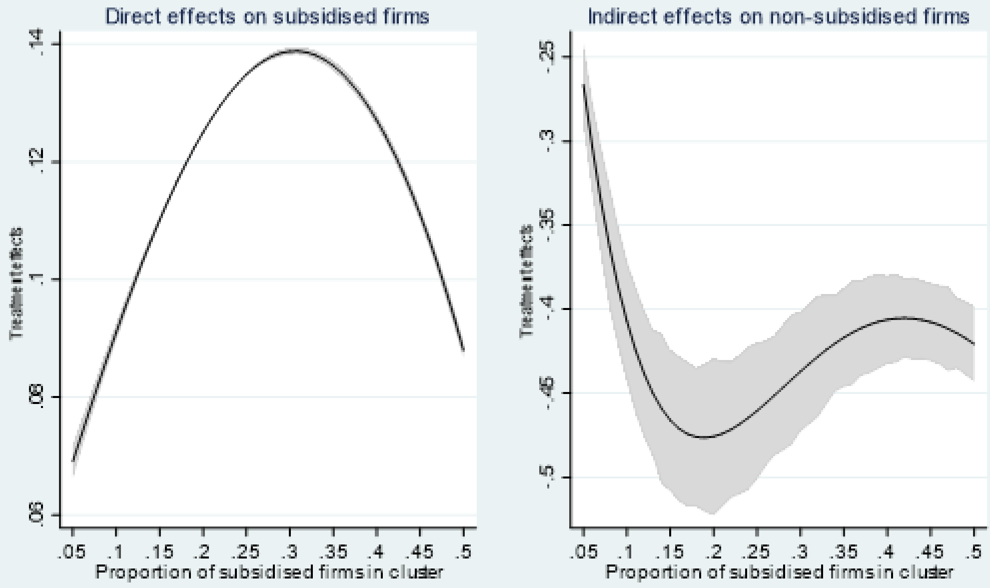
Clusters based on four-digit industries



With 95 % confidence intervals based on bootstrapped standard errors

Figure 2

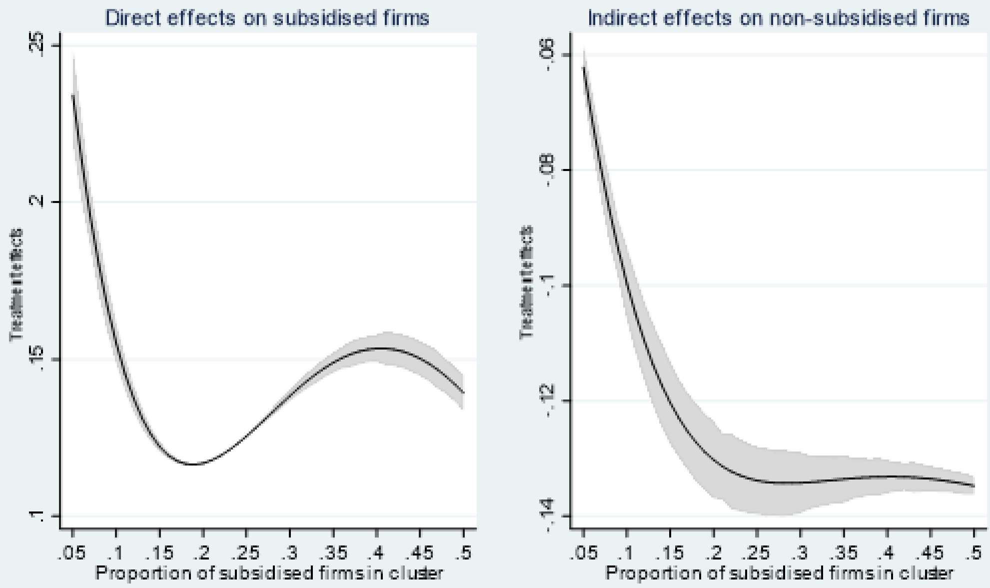
Direct and indirect effects of subsidies on final product exports participation



With 95 % confidence intervals based on bootstrapped standard errors

Figure 3

Direct and indirect effects of subsidies on exports processing participation



With 95 % confidence intervals based on bootstrapped standard errors