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SUPPLY CHAINS AND THE INTERNALIZATION OF SMEs: EVIDENCE FROM ITALY[1]

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This paper explores the relevance of supply chains participation on firms' probability to internationalize. It studies whether being part of a supply chains and/or of an international network increases the likelihood to enter international markets also for smaller and less productive firms. Our results support the view that belonging to a supply chain increases small firms' probability of exporting as well as the intensive margin of trade. However, supply chain participation does not seem to affect the extensive margin, computed as the number of foreign markets served, coherently with the view that structural limits given by the size matter. The paper also explores the possibly differential effect of the supply chain for subcontractors and firms that produce their own-branded products and shows that the latter benefit more from integration. (JEL F12, F14, F21)

I. INTRODUCTION

International trade models have recently highlighted that firms' heterogeneity often results in self-selection into the foreign market. In such models, the presence of entry costs and imperfect competition allows more productive firms to expand into the foreign market and upgrade, while (initially) lower productivity firms are likely to be confined to the domestic market, since for them internationalization costs are unaffordable. The resulting trade pattern is such that successful exporting firms tend to be relatively few, but larger, more productive and generally

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perform better according to a number of indicators (Melitz, 2003; Bernard et al., 2007; Melitz and Redding, 2013). While a vast empirical literature confirms these predictions (see Wagner, 2012 for a recent review), a natural consequence of this evidence is that empirical studies have mainly focused on large enterprises (LEs), first, because they account for most imports, exports and other multinational activities; second, because of data availability. On the contrary, evidence on the factors fostering the internationalization of small-medium enterprises (SMEs) is still scarce.

A different but related strand of literature has emphasized the importance of international fragmentation of production and of the subsequent specialization in trading "tasks" rather than goods (Grossman and Rossi-Hansberg, 2008). Indeed, the existing evidence suggests that firms find different ways to internationalize, by exploiting higher specialization, involvement in importing activities and participating to global supply chains (Castellani et al., 2010; Baldwin and Lopez-Gonzales, 2013). An active involvement in supply chains, in particular, seems to enhance efficiency, both by allowing firms to specialize in functions better fitting their capacities and due to the many possible external economies arising from linkages along the chain, as well as to opportunities to upgrade in a number of different ways, including through exports and innovation (Humprey and Schimtz, 2002; Gereffi, 1999; Agostino et al., 2011; OECD, 2006). In this context, SMEs, usually disadvantaged in the internationalization process, can play an important role within supply chains, especially as subcontractors and suppliers of intermediate goods. Supply chains, opening new niches for producers of goods and services and allowing SMEs to overcome some of the structural barriers to internationalization (OECD, 2012), can enhance their engagement in international markets (WTO, 2013). In the specific case of SMEs, however, the existing evidence is often restricted to factors hampering internationalization, such as the role of family ownership or lack of human capital and poor access to credit, rather than to factors enhancing firms' capacity to internationalize, including for instance innovation and networking (Higón Añón and Driffield, 2011; OECD, 2012; Cerrato and Piva, 2012; Bricongne et al., 2012).

To our knowledge, these two strands of the literature have not yet been linked and, in particular, (i) the evidence on SMEs' participation to the global market and (ii) the evidence on the effects of supply chain participation on firms' internationalization are still limited. Nonetheless, SMEs are already playing an increasingly important role in global supply chains and empirical research in such direction is very relevant and of policy interest, given that they represent the vast majority of firms, jobs, sales and value-added in most economies (WTO, 2013; UNCTAD 1993).

This paper, exploiting an original dataset based on a survey conducted by MET (Monitoraggio Economia e Territorio) on 25,090 Italian firms, largely SMEs (86.2%), and including direct information on the involvement of firms in supply chains represents an attempt to fill this gap.[2]

Italy is an interesting case for at least two reasons. On the one hand, substantially more than in other European countries, SMEs represent the bulk of productive structure, employment and contribution to the overall export performance (Barba Navaretti et al., 2011). On the other, Italy's sectoral specialization and industrial structure triggered a high division of labour among firms, many of which (especially SMEs) often work as specialized suppliers for other firms. Furthermore, Italian SMEs often engage in formal and informal networking at the local level (Giovannetti et al., 2013), the most successful being industrial districts, involving cooperation among sectorally specialized firms, to achieve collective efficiency and better performance *vis à*

[2] Notable exceptions are Accetturo et al. (2011) and Agostino et al. (2011), which using different samples of Italian firms and a generic status of supplier of intermediate goods as a proxy for participation to the global supply chain, show that belonging to a supply chain increases firms' productivity and performance, especially when firms are able to upgrade.

vis non clustered firms (Becattini, 1990; Brusco and Paba, 1997; Di Giacinto et al. 2012). External economies at cluster level affect the international projection of SMEs and therefore the traditional sources of firms' competitiveness (Crouch et al., 2001; Becchetti et al., 2010; Becchetti and Rossi, 2000).

Our results show that belonging to a supply chain positively affects firms, and especially SMEs, by increasing: (i) a firms' probability of exporting and (ii) the intensive margin (measured as share of total exports on turnover). However, supply chain participation does not seem to affect the extensive margin, computed as the number of foreign markets served by the firm, coherently with the view that structural limits given by the size keep mattering on the scope of the international expansion of SMEs. Additionally, when considering firms' role within the supply chain, we find that the group of SMEs involved in downstream activities emerges as the one with the largest effect of the supply chain on the probability of exporting.

The remaining of the paper is organized as follows. Section 2 presents the data and introduces the relevant definitions. Section 3 contains the econometric analysis on the effect of the supply chain on firms' internationalization through exporting. The analysis is conducted on the probability of exporting, on the intensive and on the extensive margin; and heterogeneous effects due the role of the firm in the production process are investigated. Section 4 concludes.

II. DATA AND DEFINITIONS

Our main source of information is the MET 2011 survey, covering 25,090 Italian firms in the manufacturing sector and services. The survey includes information for the last three years including a large number of questions about employment, inputs, sales, investments, internationalization and innovation. We have merged and matched the MET survey data with balance sheet information from AIDA, a database published by the Bureau van Dijk and collecting the financial information of Italian firms. The final dataset, for which the matching procedure was completed successfully, contains 7,590 firms.[3] A detailed description of the dataset is provided in the appendix.

A number of different definitions have been used so far to identify a supply chain,[4] all however built around the existence of an input-output structure including a range of value-added activities (Gereffi et al., 2001; Baldwin and Lopez-Gonzales, 2013). In this paper, we have the advantage of relying on a direct measure of firms' integration into supply chains, defined as a "*continuative involvement of the firm in the production process of a specific good, provided that this activity constitutes the majority of firm's revenue.*" The information on the supply chain concerns the organization of the production process and is independent from network relationships, included in our database to account for firms' "*relevant and continuative relationships with other firms and institutions*" either at the local, domestic or global level. For consistency of the analysis, our definitions of local, domestic and global networks are mutually exclusive. Hence, while a firm may theoretically be involved in different types of networks simultaneously (e.g. local and domestic, domestic and global or local and global), our definitions are such that the firm is univocally attributed to the wider type of network. For the sake of clarity, FIGURE 1 is drawn according to these definitions.

Descriptive statistics show that being integrated into a supply chain increases the probability of exporting (proxied by the share of exporters) by more than 20p.p. for the whole sample (from 36.9% to 58.3%). In particular, FIGURE 1.a reports the percentage of domestic, local and global

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[3] The loss of information is mainly due to micro and small firms for which balance sheet data is unavailable or inconsistent across the two data sources (*2-digit* sector and/or region do not match).

[4] In this paper we use the term "supply chain" as a more general concept compared to others, equally diffused in the literature, such as Global Value Chain or Global Production Network (see for a recent review, WTO, 2013).

firms involved in a supply chain, as well as that of exporters within each category; while FIGURE 1.b shows the same information for firms not belonging to a supply chain. Belonging to a supply chain increases the probability of exporting for all types of firms, but its effect seems weaker if firms are also integrated into a domestic and global network.[5] This is not surprising considering that 87.4% of all firms integrated into a global network (independently of the whether they are in a supply chain or not) are also exporters: since the share is so high, the fact that belonging to a supply chain still has a positive effect is very relevant. On the other hand, it is interesting to observe that firms into a local network have a lower probability of exporting than firms not in any kind of network. Finally, data show that firms' size matters. In particular, we find evidence of a positive effect of the supply chain on the probability of exporting for all the employment classes, but higher for SMEs (TABLE 1).

Taking advantage of the availability of balance sheet information, in order to check the provisions of the literature on heterogeneous firms (Helpman et al., 2004; Melitz, 2003), we are able to compute total factor productivity (TFP).[6] The empirical literature has clearly shown that a hierarchy of firms exists in terms of productivity and other performance indicators, by mode of internationalization (Helpman et al. 2004). Our TFP estimations are in line with the general findings of the heterogeneous firms' literature, showing that firms with different characteristics with respect to the internationalization form present different productivity *premia* (FIGURE 2). Additionally, they show that the productivity *premium* tends to increase with the exported value and that large exporters are generally involved in more complex internationalization forms (e.g.

[5] 21.9p.p. for firms not in any network, 19.9p.p. for firms into a local network, 15.1p.p. for firms into a domestic network and 5.4p.p. for firms into a global network.

[6] The TFP estimation is based on the Solow residuals from an econometric specification derived from a Cobb-Douglas production function. We estimated the TFP at the sectoral level, using the Levinshon and Petrin (2003) methodology, using intermediate inputs as proxies for unobservable productivity shocks. Further details on the estimation methods are provided in the appendix.

FDI). Interestingly, some evidence of heterogeneity emerges if we consider the role of the supply chain. Firms integrated into a supply chain show a level of productivity that can be set between that of non-exporters and exporters (FIGURE 2.a), suggesting that further analysis is needed to disclose the role of supply chains on firms' performance.

III. EMPIRICAL ANALYSIS

Let us start by testing the effect of belonging to a supply chain and firm's size on the probability of exporting. Our dependent variable takes the value of 1 if a firm is an exporter and 0 otherwise.[7] The set of independent variables includes most of the controls adopted in the literature on the determinants of firms' internationalization, such as firms' size, age, group, and innovation (see for instance Barba Navaretti et al., 2011; Giovannetti et al., 2013). We augment this standard model with the inclusion of a variable measuring firm's participation to supply chains. In addition, we separately control for firms' networks participation. Our baseline specification is a standard probit model:

$$\text{(1)} \qquad \Pr(Y=1|X) = \Phi(X'\beta)$$

where $Y=\{0,1\}$ is the export dummy, X is the set of covariates and $\Phi(\bullet)$ is the c.d.f. of the standard normal distribution. TABLE 2 reports the descriptive statistics on the variables included in the empirical analysis.

[7] The construction of this variable is based on one question of the survey, where a firm is asked whether it was involved in international activities over the past three years. Direct and indirect exports have been considered for the purpose of this analysis.

Results, reported in TABLE 3, are consistent across the different samples pointing to an overall stability of the relations.[8] In line with the existing evidence, we confirm that the probability of exporting increases with the age of the firm and with the participation to a group, as well as that innovation is a key driver to internationalization (Grossman and Helpman, 1991; Hallack and Schott, 2008). The introduction of a dummy variable representing small and medium sized enterprises confirms another key finding of the heterogeneous firms' theory, i.e. that larger companies are most likely to internationalize compared to smaller ones (Melitz, 2003; Ottaviano and Mayer, 2007). Participation to different type of networks has heterogeneous effects on the probability of exporting. Firms belonging to local networks are less likely to export, since they might be able to exploit local knowledge and find market niches, while on the contrary reaching stable relations with foreign actors fosters internationalization, reducing transaction costs of exploring far away markets. Belonging to a supply chain has a positive effect on the probability of exporting on aggregate; this result is robust to the introduction different sets of controls.

In model 3 and 4 of TABLE 3, we introduce the lagged level of TFP and its change during the period 2007-2011 as possible determinants of a firms' internationalization. More specifically, we want to test whether firms with higher initial productivity and/or that have increased (or decrease less) their productivity during the period are more likely to export.[9] The 2007-2011period was chosen since it fits the specific question made in survey, as firms were asked to provide information about the last three years for their activities (including internationalization) but also because it covers the beginning and the so far more acute phase of the financial crisis. Testing

[8] Results are consistent also when the model is estimated on the whole sample of 25,090 firms (i.e. not merged with balance sheet data). As a robustness check, all the estimations presented in the paper have been performed also on the whole sample of 25,090 firms (clearly, without controlling for the TFP). Tables available from the authors.

[9] Note that using the initial productivity level and the change in productivity helps also avoiding concerns over a possible simultaneity bias with the dependent variables. Moreover, there is general consensus among trade economists that the direction of causality mainly goes from productivity to export, via self-selection effects *à la* Melitz (2003); on the contrary, evidence on the reverse causality is less sound.

the impact of changes in productivity during the crisis represents in itself an interesting case for the proposition that internationalized firms have been less affected than strictly domestic ones, this being especially true for the group of SMEs. We find that both initial levels of productivity and its subsequent rate of growth exert a positive impact on the probability of exporting. This result is in line with our expectations. First, since firms with higher initial productivity are more likely to be exporters, it perfectly fits heterogeneous trade models (such as Melitz, 2003) in which the firms' self-selection into the foreign market is a key feature. Second, given the initial level of productivity, firms that experienced a higher increase in the TFP are more likely to be exporters, suggesting that they have been less affected by the crisis. Finally, these results do not change the previous findings, and confirm that being integrated into a supply chain has generally a positive effect on the export probability. The evidence above shows that the effect of the supply chain on the export probability is robust to the introduction of the initial level of productivity and its change, as well as to other controls. In particular, our benchmark specification (i.e. estimation 4 of TABLE 3) correctly predicts 72.5% of the observations.[10] Finally, our estimations imply that belonging to a supply chain can increase the probability of exporting by 6.2-8.1p.p. on average.[11]

Supply chain and SMEs' internationalization

In this section we focus on the group of SMEs and apply the previous model to SMEs and LEs separately, so to allow for specificity in each coefficient. Separate regressions produce results that differ from the aggregate estimations for a number of variables (TABLE 3). In the case of SMEs, for instance, we find that neither the participation to a group nor the firms' age have a

[10] The prediction is considered to be correct if the predicted probability is greater than 50% and the firm is indeed exporting or if the probability is below 50% and the firms is not exporting (Hosmer and Lemeshow, 2000).
[11] Average marginal effect and marginal effect at the mean respectively.

direct influence on their exporters' status. Contrary to what found in aggregate, our results show also that what really makes SMEs more viable to enter foreign market is the introduction of new products rather than also of innovative processes. This is not surprising, especially if linked to participation to supply chains, where product innovation is a core strategy to upgrading (Agostino et al., 2011; WTO, 2013). As far as their networking strategy is concerned, in line with previous results, domestic and global networks matter more for SMEs internationalization compared to traditional local linkages. A very interesting result emerges when observing the impact of TFP, given that it shows that it only contributes in a significant way to SMEs' internationalization, this being possibly due to a larger heterogeneity in the distribution of productivity compared to LEs.

More relevant for our research question, belonging to a supply chain has now a clear effect on the SMEs, but not on LEs. This result seems to suggest that the supply chain has heterogeneous effects by firms size. The marginal effects computed from the separate regressions report that belonging to a supply chain can increase the probability of exporting by 6.5-7.9p.p. for SMEs. To have a more detailed picture of how firm's size affects the results, we run two sets of regressions for different size thresholds. In the first set we consider very small firms only (up to 5 employees) and progressively increase the upper bound; in the second set we do the opposite, i.e. start from the largest firms (at least 300 employee) and progressively reduce the lower bound. Clearly, once the upper bound is sufficiently high or the lower bound sufficiently low, regression results converge to the aggregate results. Results for 6 different regressions for small firms (up to 50 employee) and 6 for large firms (from 50 employee) are reported in the appendix.[12] The size of the marginal effects of the supply chain and their confidence interval are instead depicted in

[12] For simplicity, we report here regressions up to 50 employee for SMEs and from 50 employee for large firms. Above 50 employee the two sets of regressions produce very similar results. Regressions for all the different thresholds are available from the authors.

FIGURE 3, which confirms that the positive effect of the supply chain on the probability of exporting is higher in the case SMEs. On the contrary, no significant effect emerges for large firms, considering also that the effect even becomes negative for the largest in the group.

<u>The intensive and the extensive margins</u>

A significant correlation is found between a firm's participation to supply chains and its probability of exporting. To gather additional evidence, we check whether the same relation applies to other measures measuring the international exposure of firms. To do this, and taking into account the limitations of the data, we computed two rough indicators for the intensive and extensive margins at the firm's level. The former is calculated as the share of exports over total turnover, while the latter has been constructed as an index including the number of different geographic destinations served by the firm.

In order to measure the impact of the supply chain on the intensive margins, we employ a standard Tobit model with left censoring at 0. Results, displayed in TABLE 4, are consistently in line with those discussed before, showing that the same variables that affect the probability of exporting do contribute to the intensity of exports. Also in such case, a significant difference emerges between firms at different sizes. We find that not only participation to supply chains foster SMEs' internationalization, but that their high levels of specialization and the likely linkages with production chains make this subgroup of firms more dependent on foreign rather than local markets.

Conversely, we do not find evidence of positive spillovers arising from being part of supply chains in the level of geographic diversification of SMEs. Results reported in the second part of TABLE 4, obtained by means of a negative binomial estimator, shows in fact that the geographic scope of SMEs does not significantly improve when they are in supply chains. Interestingly, we show that LEs in supply chains seem to take advantage of it having a significant probability of operating at the same time in different markets, independently on their distance. This last finding clearly show that size still needs to be accounted as a structural barrier to the international expansion of SMEs, and that being part of a supply chain cannot substitute for other characteristics.

Firms' role within the supply chain

The evidence above shows that SMEs, while generally less likely to internationalize, may partly overcome their intrinsic weakness by an active involvement in a supply chain. However, it must be noted that SMEs represent a very heterogeneous group and that different firms involved in the production of the same final good may take different roles, thus having a differentiated degree of decisional power and of proximity to the final market. In this context, ignoring such differences among firms may be misleading, even when firms have similar size and are similar on other dimensions. The Italian productive structure in particular is historically renowned for its industrial districts, with a strong division of labour and a large diffusion of subcontracting practices among firms (Accetturo et al., 2011). Moreover, for structural reasons, Italian firms are relatively more outsourcing, either domestically or internationally, oriented than integration oriented, with respect to other countries (Federico, 2012). This evidence is in line with theoretical models showing that smaller, less productive firms are more likely to outsource and hence being part of production networks (Antràs and Helpman, 2004). However, while the above evidence seems suited to explain, among other factors, why Italian SMEs may find convenient to be involved in supply chains as outsourcing firms, little has been said on the their role as subcontractors. The (scant) existing evidence, including on Italian firms (Razzolini and Vannoni, 2011), points to a consistent *subcontracting discount,* reporting a marginal role of subcontractors in terms of performance, when compared to final producers. Even in this case, however, Accetturo et al. (2011) and Agostino et al. (2011) find a good degree of heterogeneity even within the group of subcontractors.

In order to take into account such heterogeneity, we introduce a set of additional variables. In our database, we know for each respondent the share of total sales by type of product (final vs. intermediate) and to which extent it operates for other firms or on their own. In light of this, we distinguish three different kind of firms: 1) *final-good producer*, a firm whose sales are entirely constituted by final consumption and final industrial goods; 2) *subcontractor,* a firm which works only on subcontracts; and 3) *own-branded firm*, if it only sells own-designed proprietary products (i.e. a firm that designs its own products, final or not, and retains the industrial property, either with or without patents).[13] Given this definitions, we introduce the new variables into our baseline model (TABLE 5). Regressions are robust to the inclusion of the new dummy variables: all coefficients have the same sign and their numerical value is similar to previous results.[14] While the supply chain keeps its explanatory power, final-good producers strongly emerge as those with the highest probability of exporting, while, consistently with other works, we find evidence of a subcontracting discount. We then restrict the sample only to subcontractors, own-branded firms and final-good producers, respectively. Belonging to a supply chain strongly increases the probability of exporting of final-good producers as well as of own-branded firms. While the supply chain coefficient is still positive for the group of subcontractors, it shows no statistical significance. Our results suggest that not only final-good producers are more likely to export than other firms, but also they benefit more from being involved into a supply chain. On

[13] In our case, the definition of binary variables is preferable to the use of the actual shares of total sales. In fact, the latter is likely to contain measurement errors, i.e. the observed shares are only indicative and extreme values are indeed prevalent in the sample.

[14] Results are also robust to the inclusion of each variable separately.

the contrary, while own-branded firms do not seem to be more likely to export than others, they are still able to benefit from the supply chain. This finding suggests that firms having some decisional power within the supply chain are the most likely to export. In order to test for this hypothesis, we further restrict the analysis to the subgroup of own-branded and final firms. While all the coefficients are in line with the previous models, the coefficient of the supply chain further increases, thus confirming our hypothesis. Finally, we test whether the result holds and is driven by SMEs, as we would expect. Indeed, SMEs represent the vast majority of the own-branded/final group (69%) and the results hold even when we exclude LEs.

Evidence on the causal effect of the supply chain on SMEs' internationalization

The econometric analysis shows that belonging to a supply chain is positively correlated with the probability of exporting. This finding is robust to different specifications. However, from a statistical point of view, not much can be said on the direction of causality, particularly due to the cross-sectional limitation of the data. A typical problem is self-selection; for instance, if firms with an *ex-ante* higher probability of exporting also choose to produce within a supply chain, then the observed correlation might be overestimating the causal effect of the supply chain. Such a problem is difficult to overcome, unless one has panel data and/or has a good instrument. Alternatively, matching procedures may be employed. There are two main advantages of the matching procedures over the regression analyses: (i) first, matching, under the common support condition, focuses on comparable subjects only; (ii) second, it is a non-parametric technique, thus avoiding potential misspecification of the conditional mean. In this section, we match firms with the same observable characteristics but their participation to supply chain (and exclude from the analysis firms that do not match) by performing a propensity score matching. Since the two matched groups are similar conditioning on controls (and in particular they have the same probability of belonging to a supply chain), the second group acts as a counterfactual allowing us to obtain more reasonable estimates of the causal effect of the supply chain on the probability of exporting. More formally, the parameter of interest is the “average treatment effect on the treated” (ATT), which in our case represents an estimate of the difference in the average probability of exporting for firms belonging to a supply chain, had they not belonged to the supply chain (the counterfactual). The ATT is defined as:

$$(2) \qquad \tau_{ATT} = E(\tau|D=1) = E[Y(1)|D=1] - E[Y(0)|D=1]$$

where D={0,1} is the treatment (the supply chain) and Y(D) is the potential outcome (the probability of exporting). Since the counterfactual E[Y(0)|D=1] cannot be observed, a control group is selected through the matching procedure so that it can reasonably mimic treated units had they not be treated. In particular, the propensity score matching estimator can generally be written as:

$$(3) \qquad \tau_{PSM} = E_{P(X)|D=1}\{E[Y(1)|D=1,P(X)] - E[Y(0)|D=0,P(X)]\}$$

where P(X) is the propensity score, that is the probability of receiving the treatment.[15]

As regarding to the conditions for the application of the propensity score matching, Heckman-Ichimura-Todd (1998) show that in observational studies it is desirable (i) that the same questionnaire has been submitted to the treated and the control group and (ii) that the two groups can be extracted from the same local market. Our dataset allows us to satisfy both requirements.

It should be noted that the matching procedure may not guarantee, nor allow testing, that the so called unconfoundedness assumption holds, that is the requirement that the treatment is

[15] We refer to the literature for a more detailed discussion of the methodology (Caliendo, 2005; Becker-Ichino, 2002; Dehejia-Wahba, 1999; Heckman-Ichimura-Todd, 1998; Rosenbaum-Rubin, 1983).

exogenous or independent of the potential outcomes (Imbens-Wooldrige, 2009; Becker-Caliendo, 2007).[16] This is typically a problem with non experimental data, where unconfoundedness might not hold exactly for the same reason why regression results might not capture the true causal effect; in our case, because the choice of belonging to a supply chain may be endogenous. Indeed, two otherwise identical firms may take different decisions about the integration into a supply chain, if the decision depends on some unobserved factors. Importantly, however, it can be shown that if such unobserved factors are unrelated to the probability of exporting or more in general unrelated to the access to the foreign market, then the unconfoundedness assumption may not be violated (Imbens-Wooldrige, 2009; Becker-Caliendo, 2007). For instance, the decision of belonging to a supply chain could be driven, among other things, by some unobserved factors not directly related to the likelihood of being an exporter: not controlling for such factors does not introduce any bias in the analysis. The literature clearly points out that one must control only for the variables that simultaneously affect both the treatment and the outcome; but few other indications are provided on which covariates to include in the propensity score model (Imbens-Wooldridge, 2009; Caliendo, 2005).

In what follows, we focus on SMEs only and present estimates of the average treatment effects on the treated for different propensity score matching specifications. We start from a basic specification which includes sectoral and regional dummies only and then turn to more complete specifications including different set of covariates. In particular, we estimate 5 models. The outcome variable is the probability of exporting and the treatment is the supply chain. For all five models, the matching procedure uses the common support condition and the balancing property of the propensity scores is satisfied both according to the stratification t-test procedure and to the

[16] The unconfoundedness assumption, sometimes in a weaker form, is also referred in the literature as "selection on observables", "exogeneity", "conditional independence."

standardized percentage bias.[17] The ATT are estimated with the nearest neighbor matching both according to the Becker-Ichino (2002) and the Leuven-Sianesi (2003) algorithm, with indistinguishable results.[18] The estimated ATT indicate that SMEs belonging to a supply chain are at least 7.7p.p. more likely to export on average (TABLE 6). These numbers are largely consistent with the marginal effects from the previous regression analysis (i.e. 6.5-7.9p.p from model 5 in TABLE 3). Finally, the propensity score matching analysis confirms our previous results showing that they are robust and provides some evidence on the causal effect of the supply chain on the probability of exporting for SMEs.

IV. CONCLUSION

Belonging to a supply chain is found to have a positive effect on the probability of exporting, being particularly helpful for SMEs. On average, SMEs into a supply chain are at least 6.5-7.9p.p. more likely to export by with respect to firms outside a supply chain, even after controlling for a number of variables such as different kind of networks and productivity. On the contrary, the effect of the supply chain for LEs, though positive, is statistically insignificant and its numerical value is about half that for SMEs. Results are robust to different specifications and to the introduction of different controls. Moreover, a similar result holds when, instead of probability of exporting, we consider the export intensive margin at the firm level. Conversely, participation to a supply chain does not seem to affect SMEs' extensive margin and geographical differentiation, while having a positive effect on LEs. Such general findings on the effect of the supply chain on SMEs internationalization being robust, we further investigate firms' role within

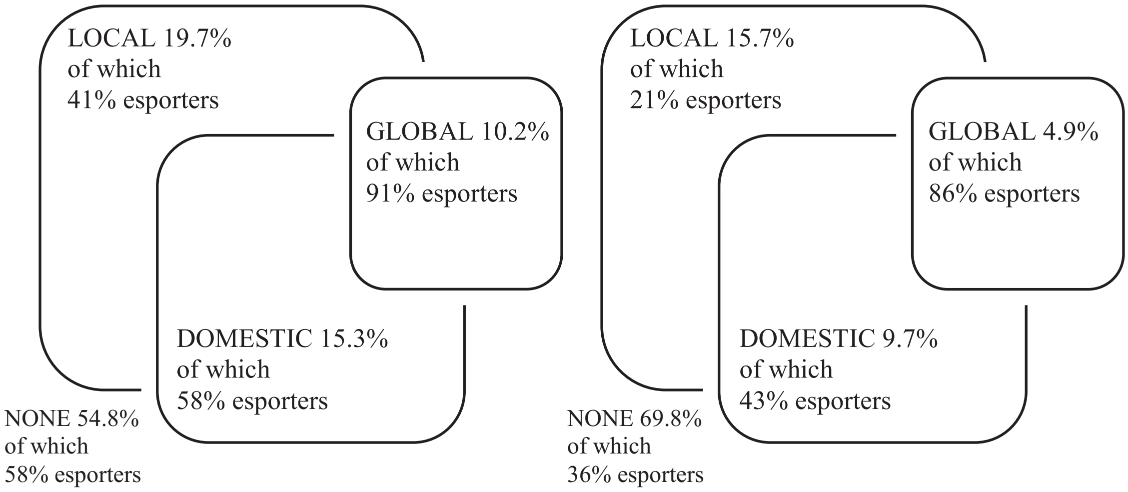
[17] Aggregate tests are reported in the appendix.
[18] The propensity score matching models and the ATTs estimations have been performed also on the whole survey as a robustness check. Estimated ATTs are similar (slightly higher) to those reported in the paper, but the matching procedure was more problematic. Details are available from the authors.

the supply chain as a potential source of heterogeneity, particularly among SMEs. Indeed, the distinction between subcontractors, final-good producers, and own-branded firms is found to be relevant. On the one hand, in line with existing evidence, subcontractors tend to be less internationalized and to gain less, in terms of internationalization, from the supply chain participation. On the other hand, firms producing final goods are both more internationalized and more likely to be positively affected by involvement in the supply chain and this result is particularly strong when the final-good producer is also an own-branded firm designing its own products.

TABLES AND FIGURES

FIGURE 1

Firms' and exporters by supply chain and type of network.



(a) FIRMS IN SUPPLY CHAIN
15.7% of total

(b) FIRMS NOT IN SUPPLY CHAIN
84.3% of total

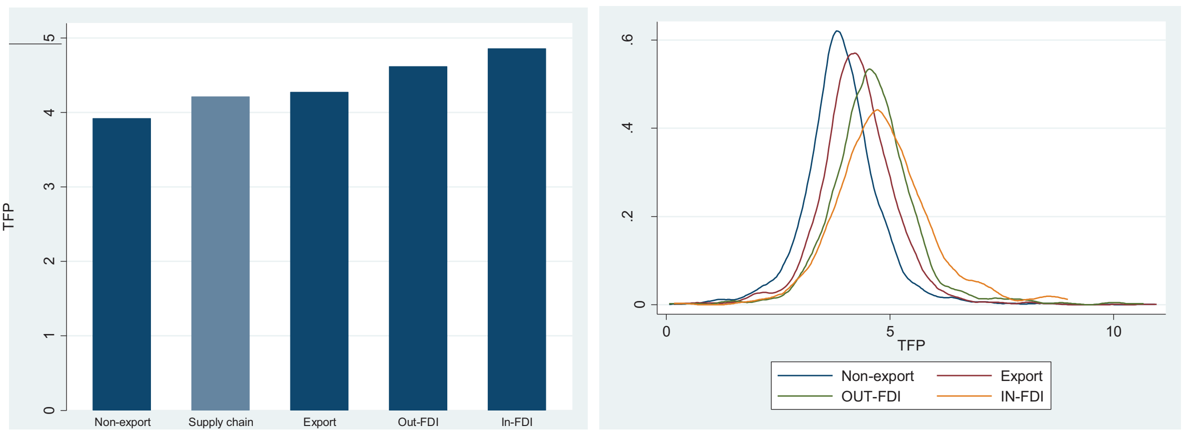
TABLE 1

Probability of exporting by class of employment.

	Probability of exporting		
Class of employment	Supply chain	Others	Odds
1-9	0.36	0.18	1.98
10-49	0.57	0.42	1.34
50-249	0.73	0.54	1.34
≥250	0.75	0.60	1.25
Total	0.58	0.37	1.58

FIGURE 2

Total factor productivity by mode of internationalization.



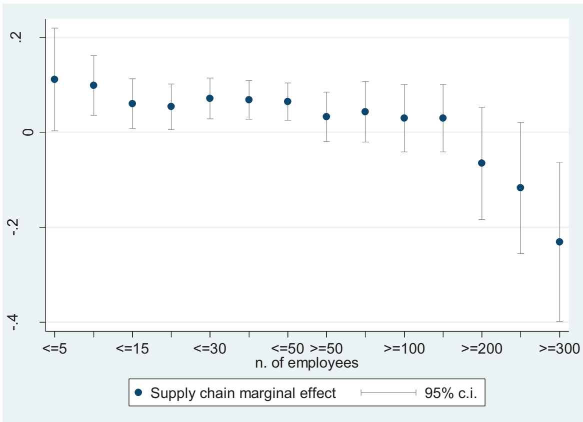
(a) Average TFP by mode of internationalization.

(b) TFP distribution by mode of internationalization.

TABLE 2
Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Export dummy	7590	0.40	0.49	0	1
Export share	7590	14.18	23.99	0	100
N. foreing markets	7590	0.83	1.49	0	8
Supply chain	7590	0.16	0.36	0	1
SMEs	7590	0.75	0.43	0	1
Age (ln)	7560	3.07	0.59	0.69	5.20
Group dummy	7590	0.17	0.38	0	1
Local network	7590	0.16	0.37	0	1
Domestic network	7590	0.11	0.31	0	1
Foreign network	7590	0.06	0.23	0	1
Product innovation dummy	7590	0.11	0.32	0	1
Process innovation dummy	7590	0.09	0.29	0	1
TFP (ln)	7590	4.06	0.94	-2.60	10.96
TFP change (Δln)	5396	-0.13	0.54	-5.97	4.16
Subcontractor	7590	0.29	0.45	0	1
Own-branded firm	7590	0.55	0.50	0	1
Final-good producer	7590	0.44	0.50	0	1

FIGURE 3
Supply chain coefficients for different firm's sizes.



Note: the bars represents the confidence intervals at 95% of the supply chain coefficients in the probability to export regression, by firms' size.

TABLE 3
Probability of exporting and belonging to a supply chain.

	Final dataset		Controlling for TFP		SMEs	LEs
Dep. export dummy	(1)	(2)	(3)	(4)	(5)	(6)
Supply chain	0.399***	0.217***	0.352***	0.204***	0.206**	0.122
	(9.24)	(4.69)	(7.19)	(3.88)	(3.24)	(1.24)
SME	-0.458***	-0.501***	-0.378***	-0.424***		
	(-11.94)	(-11.84)	(-8.64)	(-8.47)		
Age	0.181***	0.05	0.147***	0.0382	0.0453	0.0236
	(6.73)	(1.67)	(4.56)	(1.07)	(1.06)	(0.34)
Group	0.276***	0.258***	0.177***	0.165**	0.124	0.253**
	(6.35)	(5.56)	(3.65)	(3.17)	(1.73)	(3.07)
Local network	-0.459***	-0.405***	-0.478***	-0.430***	-0.436***	-0.367***
	(-10.23)	(-8.46)	(-8.88)	(-7.49)	(-6.20)	(-3.46)
Domestic network	0.0709	0.0904	0.0855	0.118	0.168*	-0.0232
	(1.42)	(1.72)	(1.49)	(1.95)	(2.34)	(-0.19)
Foreign network	1.312***	1.348***	1.295***	1.320***	1.301***	1.438***
	(15.90)	(15.02)	(13.66)	(12.75)	(11.44)	(4.98)
Product innovation	0.783***	0.677***	0.761***	0.655***	0.646***	0.663***
	(14.00)	(11.42)	(11.92)	(9.68)	(7.56)	(5.64)
Process innovation	0.148*	0.211**	0.151*	0.195**	0.107	0.297*
	(2.40)	(3.24)	(2.16)	(2.62)	(1.09)	(2.44)
Initial TFP			0.122***	0.210***	0.249***	0.139
			(5.41)	(5.57)	(5.32)	(1.80)
TFP change			0.0684*	0.130***	0.155***	0.0636
			(1.98)	(3.35)	(3.42)	(0.76)
Constant	-0.679***	0.104	-1.006***	-0.735**	-1.363***	-0.157
	(-7.28)	(0.72)	(-7.01)	(-2.93)	(-4.86)	(-0.29)
Sector and Region f.e.	no	yes	no	yes	yes	yes
Observations	7560	7549	5383	5357	3755	1561
Pseudo R-squared	0.14	0.227	0.135	0.221	0.181	0.27

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

TABLE 4

Intensive and extensive margins and belonging to a supply chain.

	Intensive margin			Extensive margin		
	all	SMEs	LEs	all	SMEs	LEs
	(1)	(2)	(3)	(4)	(5)	(6)
Supply chain	4.842**	5.944**	1.004	0.125**	0.0848	0.145*
	(3.05)	(2.76)	(0.44)	(2.68)	(1.32)	(2.13)
SME	-11.83***			-0.472***		
	(-7.64)			(-10.19)		
Age	0.476	0.533	0.266	0.0432	0.0439	0.0538
	(0.42)	(0.35)	(0.16)	(1.24)	(0.94)	(1.03)
Group	6.735***	6.786**	6.704***	0.154**	0.156*	0.164**
	(4.25)	(2.78)	(3.34)	(3.28)	(2.14)	(2.70)
Local network	-16.19***	-17.83***	-12.81***	-0.506***	-0.639***	-0.335***
	(-8.34)	(-6.81)	(-4.42)	(-7.98)	(-7.25)	(-3.61)
Domestic network	1.232	2.624	-0.821	0.082	0.0809	0.0614
	(0.64)	(1.03)	(-0.28)	(1.39)	(1.04)	(0.68)
Foreign network	26.90***	31.83***	16.83***	0.786***	0.875***	0.551***
	(11.98)	(10.86)	(4.83)	(12.83)	(11.11)	(5.73)
Product innovation	16.58***	20.66***	10.97***	0.436***	0.496***	0.342***
	(8.73)	(7.62)	(4.30)	(7.96)	(6.38)	(4.53)
Process innovation	2.779	1.668	3.701	0.0258	0.0586	-0.0135
	(1.30)	(0.52)	(1.36)	(0.41)	(0.61)	(-0.16)
Initial TFP	8.182***	8.918***	7.970***	0.264***	0.244***	0.310***
	(6.65)	(5.30)	(4.07)	(6.81)	(4.61)	(5.01)
TFP change	4.915***	6.340***	2.472	0.126**	0.152**	0.0932
	(3.88)	(3.87)	(1.18)	(3.12)	(2.94)	(1.39)
Constant	-29.71***	-45.86***	-26.82*	-1.087***	-1.409***	-1.424***
	(-3.65)	(-4.53)	(-2.05)	(-4.27)	(-4.45)	(-3.49)
sigma / ln_alpha	38.37***	40.67***	33.69***	-0.500***	-0.427***	-0.748***
	(64.81)	(49.60)	(42.00)	(-8.53)	(-5.31)	(-8.26)
Sector and Region f.e.	yes	yes	yes	yes	yes	yes
Observations	5383	3786	1597	5383	3786	1597
Pseudo R-squared	0.055	0.05	0.056	0.106	0.1	0.102

t statistics in parentheses

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

TABLE 5
Firms' role within the supply chain and export.

					own-branded and final		
	all	subcon.	own-branded	final	all	SMEs	SMEs
Dep. export dummy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Supply chain	0.242***	0.132	0.245**	0.365***	0.413***	0.319*	0.345**
	(4.56)	(1.32)	(3.29)	(4.39)	(3.71)	(2.45)	(2.67)
SMEs	-0.418***	-0.478***	-0.486***	-0.454***	-0.471***		
	(-8.29)	(-4.94)	(-7.02)	(-5.80)	(-4.58)		
Subcontractor	-0.142*						
	(-2.35)						
Own-branded firm	0.00372						
	(0.07)						
Final-good producer	0.299***						
	(7.19)						
Age	0.0306	0.00623	0.00700	0.0146	0.0454	-0.00251	
	(0.85)	(0.09)	(0.14)	(0.27)	(0.64)	(-0.03)	
Group	0.169**	0.0976	0.194**	0.149	0.0714	0.182	
	(3.23)	(0.97)	(2.67)	(1.83)	(0.67)	(1.20)	
Local network	-0.411***	-0.553***	-0.403***	-0.375***	-0.352**	-0.378*	-0.389**
	(-7.11)	(-5.07)	(-4.93)	(-4.15)	(-2.86)	(-2.49)	(-2.59)
Domestic network	0.133*	0.197	0.0469	-0.00953	0.0637	0.158	
	(2.19)	(1.74)	(0.53)	(-0.10)	(0.48)	(0.98)	
Foreign network	1.312***	1.275***	1.240***	1.430***	1.323***	1.258***	1.257***
	(12.60)	(6.12)	(9.35)	(8.44)	(6.72)	(6.02)	(6.05)
Product innovation	0.624***	0.591***	0.726***	0.678***	0.678***	0.594***	0.585***
	(9.16)	(3.74)	(7.90)	(6.97)	(5.37)	(3.82)	(4.10)
Process innovation	0.180*	0.304	0.0891	0.0645	-0.0784	-0.0286	
	(2.41)	(1.94)	(0.89)	(0.59)	(-0.57)	(-0.16)	
Initial TFP	0.218***	0.222**	0.231***	0.281***	0.301***	0.382***	0.377***
	(5.73)	(2.81)	(4.61)	(4.94)	(4.12)	(4.15)	(4.35)
TFP change	0.135***	0.162*	0.0763	0.0527	0.0273	0.0347	
	(3.48)	(2.20)	(1.46)	(0.92)	(0.37)	(0.40)	
Constant	-0.987***	-0.774	-0.677*	-0.902*	-1.169*	-1.864***	-1.838***
	(-3.82)	(-1.47)	(-2.03)	(-2.44)	(-2.46)	(-3.54)	(-4.15)
Sector and Region f.e.	yes	yes	yes	yes	yes	yes	yes
Observations	5357	1498	2948	2450	1474	1018	1019
Pseudo R-squared	0.230	0.195	0.251	0.218	0.227	0.197	0.196

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

TABLE 6

Supply chain and probability of exporting: average treatment effects on the treated (SMEs).

model	ATT	std. err.	t	n. treated	n. controls	common support	balancing property
(1)	0.130	0.020	6.674	786	4916	[.021, .278]	yes/yes
(2)	0.129	0.020	6.540	786	4377	[.017, .326]	yes/yes
(3)	0.099	0.026	3.794	785	1057	[.010, .629]	yes/yes
(4)	0.093	0.020	4.654	786	4717	[.013, .537]	yes/yes
(5)	0.077	0.021	3.595	786	3914	[.010, .543]	yes/yes

Note: ATT estimated using the nearest neighbor matching according to the Becker-Ichino (2002) algorithm. Indistinguishable results are obtained with the Leuven-Sianesi (2003) algorithm. The balancing property is tested using both the propensity score stratification t-test procedure and the standardised percentage bias.

Listed models use the following variables: (1) 1-digit sector and macro-region f.e.; (2) 1-digit sector and region f.e.; (3) variable that affect the treatment, i.e. age, group dummy, size class, final producer, network dummies and product innovation; (4) variables with the stronger effect on the treatment, i.e. network dummies and product innovation; (5) variables that affect both the treatment and the outcome, i.e. size class, final producer, network dummies and product innovation. Models 3-5 also use 1-digit sector and macro-region f.e.

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APPENDIX

Data and variables description

The main source of information is a survey conducted by the MET (Monitoraggio Economia e Territorio s.r.l.). The survey contains information on 25,090 Italian firms for the year 2011, with some information also referring to the period 2009-2011. The firms' sample is built using a stratification procedure by firm's size, sector and region in order to ensure representativeness at the national level. Firms in the dataset belong to different sectors of manufacturing and services and are located in all the Italian regions. The information contained in the survey is mostly qualitative and ranges from employment to investments, innovation and internationalization. In order to add more quantitative information (particularly for the TFP estimation), the final dataset we employ in this paper is the result of a merging and matching procedure between the MET survey and the balance sheet information from AIDA (Bureau Van Dijk). After matching the information for each firm from the survey with the balance sheet data and checking the consistency of a number of firm identifiers (mainly the 2-digit sector and the region) we are left with 10,459 firms for which the matching procedure has been successful. Finally, the data allow estimation of the TFP for 7,590 firms, which represent our final dataset. The main variables we employ are described in TABLE A1.

TABLE A1
Main variables description.

Variable	Source	Description
Export dummy	MET	1 if direct or indirect export in the last three years
Export share	MET	Export as a share of total turnover
N. foreing markets	MET	Number of export markets (EU, EXTRA-EU, NA, China, India, rest of Asia, SA, other)
Supply chain	MET	1 if firm is steadily involved in the production process of a specific good and this activity constitutes its major source of revenue.
SMEs	MET	1 if firms has up to 50 employees
Age (ln)	MET	Number of years of the firm
Group dummy	MET	1 if firm belongs to a group
Local network	MET	1 if firm has relevant and continuative relationships with local firms
Domestic network	MET	1 if firm has relevant and continuative relationships with domestic firms
Foreign network	MET	1 if firm has relevant and continuative relationships with foreign firms
Product innovation dummy	MET	1 if product innovation in the last three years
Process innovation dummy	MET	1 if process innovation in the last three years
TFP (ln)	calculations on AIDA data	Productivity of the firm in 2007
TFP change	calculations on AIDA data	Change in productivity 2007-2011 (%)
Subcontractor	MET	1 if firm sales come 100% from subcontracts
Own-branded firm	MET	1 if firm sales come 100% from own designed products, final or not, and the firm retains the industrial property
Final-good producer	MET	1 if firm output is 100% final products

Total factor productivity estimation

The TFP estimation is generally based on the Solow residuals from an econometric specification derived from a Cobb-Douglas production function. This measure of the TFP, strictly related to the economic theory and rooted on clear assumptions, triggers a number of empirical issues, mainly due to the endogeneity of the observed data (del Gatto et al., 2011; van Beveren, 2012). As a robustness check, we estimate the TFP in three different ways using a fixed effects estimation (FE), the general method of moments (GMM) and the Levinsohn-Petrin (2003) approach (LP). Exploiting information from our merged database we build a panel of indicators to estimate TFP on data covering the period 2007-2011. Overall, the three TFP estimates are robust and show a good degree of overlap (TABLE A). In the paper, however, we only present the results based on the LP estimates, more appropriate for our analysis, since they explicitly take into account firms' intermediate inputs.

TABLE A2

Estimates of the total factor productivity.

	Summary statistics				Correlations		
	Mean	Std. Dev.	Min	Max	FE	GMM	LP
			ln(TFP) in 2011				
FE	5.16	1.19	-1.73	13.59	1		
GMM	3.93	1.08	-2.77	9.10	0.55	1	
LP	4.06	0.94	-2.60	10.96	0.73	0.53	1
			Δln(TFP) 2007-2011				
FE	-0.11	0.52	-6.01	4.18	1		
GMM	-0.13	0.54	-5.96	3.94	0.92	1	
LP	-0.13	0.54	-5.97	4.16	0.91	0.93	1

Tables and figures

TABLE A3
The effect of the supply chain for small firms.

	(1) ≤5 empl.	(2) ≤10 empl.	(3) ≤15 empl.	(4) ≤20 empl.	(5) ≤30 empl.	(6) ≤40 empl.
Supply chain	0.502*	0.390**	0.212*	0.179*	0.232**	0.218**
	(2.00)	(3.04)	(2.26)	(2.21)	(3.24)	(3.29)
Age	-0.0339	-0.127	-0.0630	-0.0568	-0.0259	0.0576
	(-0.22)	(-1.56)	(-1.01)	(-1.04)	(-0.53)	(1.28)
Group	0.612*	0.284	0.133	0.107	0.112	0.135
	(2.20)	(1.86)	(1.17)	(1.10)	(1.31)	(1.74)
Local network	0.0196	-0.234	-0.327***	-0.302***	-0.366***	-0.428***
	(0.09)	(-1.89)	(-3.30)	(-3.55)	(-4.76)	(-5.89)
Domestic network	0.222	0.238	0.189	0.230*	0.213**	0.176*
	(0.79)	(1.61)	(1.75)	(2.43)	(2.60)	(2.31)
Foreign network	1.138**	1.298***	1.326***	1.328***	1.356***	1.285***
	(3.28)	(6.36)	(8.43)	(9.24)	(10.50)	(10.74)
Product innovation	1.021**	0.774***	0.513***	0.520***	0.607***	0.637***
	(3.14)	(4.08)	(3.73)	(4.47)	(6.20)	(6.99)
Process innovation	0.191	0.214	0.0171	0.0724	0.0893	0.0868
	(0.45)	(0.90)	(0.10)	(0.53)	(0.78)	(0.82)
Initial TFP	-0.0700	0.00281	0.0962	0.156**	0.158**	0.199***
	(-0.56)	(0.04)	(1.54)	(2.76)	(3.03)	(4.09)
TFP change	-0.189	-0.0467	0.0326	0.0803	0.0999*	0.129**
	(-1.61)	(-0.70)	(0.59)	(1.57)	(2.05)	(2.77)
Constant	-1.054	-0.339	-0.654	-0.897**	-0.929**	-1.277***
	(-1.24)	(-0.71)	(-1.73)	(-2.64)	(-2.98)	(-4.38)
Sector and Region f.e.	yes	yes	yes	yes	yes	yes
Observations	494	1325	2041	2510	3048	3468
Pseudo R-squared	0.186	0.178	0.158	0.154	0.166	0.174

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

TABLE A4

The effect of the supply chain for large firms.

	(1) ≥75 empl.	(2) ≥100 empl.	(3) ≥150 empl.	(4) ≥200 empl.	(5) ≥250 empl.	(6) ≥300 empl.
Supply chain	0.168	0.124	-0.0107	-0.257	-0.482	-0.985**
	(1.33)	(0.82)	(-0.05)	(-1.08)	(-1.65)	(-2.59)
Age	-0.0121	0.0216	-0.102	0.0399	-0.0500	0.00990
	(-0.14)	(0.22)	(-0.80)	(0.26)	(-0.26)	(0.04)
Group	0.272**	0.192	0.0839	-0.0297	0.150	-0.181
	(2.71)	(1.63)	(0.54)	(-0.15)	(0.66)	(-0.64)
Local network	-0.392**	-0.507***	-0.711***	-0.527*	-0.558	-0.474
	(-3.06)	(-3.30)	(-3.44)	(-2.21)	(-1.93)	(-1.33)
Domestic network	0.0674	0.0683	0.183	-0.0396	-0.151	0.0328
	(0.44)	(0.37)	(0.73)	(-0.14)	(-0.47)	(0.08)
Foreign network	1.386***	1.415***	1.232*	.	.	.
	(4.02)	(3.58)	(2.47)			
Product innovation	0.602***	0.670***	0.569*	0.882**	0.958**	1.010*
	(4.18)	(3.77)	(2.55)	(3.24)	(3.13)	(2.47)
Process innovation	0.471**	0.607***	0.630**	0.351	0.476	0.294
	(3.20)	(3.58)	(2.82)	(1.33)	(1.62)	(0.78)
Initial TFP	0.194*	0.303**	0.162	0.145	0.154	0.232
	(1.99)	(2.64)	(1.17)	(0.89)	(0.74)	(0.92)
TFP change	0.144	0.135	0.128	-0.0526	-0.353	-0.383
	(1.27)	(1.05)	(0.84)	(-0.31)	(-1.42)	(-1.37)
Constant	-0.494	-1.185	0.502	0.245	0.600	0.0273
	(-0.72)	(-1.48)	(0.50)	(0.21)	(0.40)	(0.01)
Sector and Region f.e.	Yes	yes	yes	yes	yes	yes
Observations	1069	826	534	345	264	202
Pseudo R-squared	0.298	0.350	0.375	0.337	0.355	0.387

t statistics in parentheses

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

TABLE A5

Aggregate tests for the balancing property (SMEs).

model	sample	pseudo R2	LR chi2	p-val	mean bias	med bias
(1)	Raw	0.063	287.160	0.000	15.000	9.400
	Matched	0.000	0.000	1.000	0.000	0.000
(2)	Raw	0.069	313.770	0.000	7.900	5.100
	Matched	0.000	0.000	1.000	0.000	0.000
(3)	Raw	0.101	462.190	0.000	17.500	17.800
	Matched	0.006	13.660	0.691	3.300	2.100
(4)	Raw	0.087	397.470	0.000	16.200	17.800
	Matched	0.000	0.130	1.000	0.400	0.300
(5)	Raw	0.095	436.420	0.000	16.600	17.800
	Matched	0.000	0.840	1.000	0.900	0.600

Listed models use the following variables: (1) 1-digit sector and macro-region f.e.; (2) 1-digit sector and region f.e.; (3) variable that affect the treatment, i.e. age, group dummy, size class, final producer, network dummies and product innovation; (4) variables with the stronger effect on the treatment, i.e. network dummies and product innovation; (5) variables that affect both the treatment and the outcome, i.e. size class, final producer, network dummies and product innovation. Models 3-5 also use 1-digit sector and macro-region f.e.

ADDITIONAL APPENDIX

Total factor productivity estimation (detailed)

Our TFP estimation procedure follows a vast literature on the topic. The theoretical basis for the estimation lies in the assumption of a Cobb-Douglas production function for the firm:

(A1) $$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \qquad \beta_l, \beta_k > 0$$

where *i* and *t* are firms and year subscripts respectively; Y is output (value added); L is labor; K is capital and A is a Hicksian neutral technology multiplier (unobservable). One of the advantages of the econometric approach is that the production function is not required to exhibit constant returns to scale (i.e. $\beta_l + \beta_k = 1$), as it is often necessary under non-econometric approaches. However, in order to perform the estimation, we must assume that firms share the same technology, except than for the neutral parameter A, that is β_l and β_k are the same for all firms, otherwise we may get biased estimates. Taking the logarithm (denoted by small case letters), the baseline econometric specification takes the following form:

(A2) $$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \varepsilon_{it}$$

In the above equation, the sum of the constant and the error term gives the Hicksian technology:

(A3) $$a_{it} = \beta_0 + \varepsilon_{it}$$

Theoretically, we can further model the unobservable firm-level error term so to decompose it into a predictable and an unpredictable component such that $\varepsilon_{it} = v_{it} + u_{it}$. Since both terms are unobservable, additional assumptions need to be made on the v_{it} terms; while the u_{it} terms are usually assumed to be i.i.d. and uncorrelated with inputs choices, being due to measurement errors and other unpredictable factors. After the estimation of the production function parameters, the estimated productivity can be calculated as:

(A4) $\hat{a}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}$

The above equation (A4) represents the objective of the TFP estimation. We now discuss the empirical approaches that we employ. First, note that applying the above model directly or performing an OLS estimation gives biased estimates for several reasons, mainly due to the endogeneity of labor and capital and to the fact that we cannot disentangle the predictable and unpredictable component of the error term without additional data and/or assumptions (Arnold, 2005; del Gatto et al., 2009; van Beveren, 2010). For this reasons, we perform three different non-OLS estimations of the TFP: fixed effects (FE), general method of moments (GMM) and Levinsohn-Petrin (2003, LP). In the empirical specification, the GDP deflator is used for output and capital, while for intermediate inputs we use the producer price index at the 2-digit sectoral level; moreover, we perform all the estimations at the sectoral level. The FE estimation assumes that the predictable component of the error term is time-invariant so that it can be estimated by adding firm-level fixed effects. In the GMM, lagged first-differences of the variables are used as instruments (Blundell and Bond, 2000; Benfratello and Sembenelli, 2006). The LP estimation uses intermediate inputs as an instrument for unobservable productivity shocks. In particular, the LP estimation assumes that the firm demand for intermediate inputs depends on firms state variables, namely capital and the predictable component of the error term, $m_{it} = m(k_{it}, v_{it})$. Under the assumption of monotonicity, the latter function can be inverted and we can write $v_{it} = v(k_{it}, m_{it})$, so that the unobservable productivity is a function of two observable variables. However, the functional form is unknown. Following Olley-Pakes (1996), LP take a semiparametric approach by approximating the function $\varphi(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + v(k_{it}, m_{it})$ with a third-order polynomial. The production function to be estimated can now be written as:

(A5) $\quad y_{it} = \beta_l l_{it} + \varphi(k_{it}, m_{it}) + u_{it}$

The first stage of the LP estimation involves estimating the above equation (A5) so to get $\hat{\beta}_l$, while $\hat{\beta}_k$ is obtained in the second stage under some additional assumptions about the v_{it} terms, e.g. that they follow a first order Markov process. For further details we refer to LP (2003).

Tables and figures (robustness checks on the whole survey)

TABLE B1
Probability of exporting and the supply chain (whole survey; see TABLE 3).

	whole survey		SMEs	Les
Dep. export dummy	(1)	(2)	(3)	(4)
Supply chain	0.405***	0.281***	0.289***	0.174*
	(14.26)	(8.92)	(8.07)	(2.49)
SME	-0.689***	-0.613***		
	(-25.10)	(-20.03)		
Age	0.213***	0.153***	0.157***	0.0410
	(17.18)	(10.24)	(9.72)	(0.93)
Group	0.402***	0.352***	0.359***	0.320***
	(13.44)	(10.77)	(8.47)	(5.90)
Local network	-0.278***	-0.275***	-0.270***	-0.259***
	(-9.90)	(-8.98)	(-7.86)	(-3.62)
Domestic network	0.206***	0.178***	0.225***	-0.0379
	(6.33)	(5.07)	(5.74)	(-0.46)
Foreign network	1.354***	1.317***	1.362***	1.068***
	(26.45)	(23.07)	(21.69)	(7.67)
Product innovation	0.768***	0.694***	0.695***	0.677***
	(21.23)	(17.49)	(15.02)	(8.32)
Process innovation	0.205***	0.228***	0.173**	0.398***
	(5.10)	(5.19)	(3.24)	(4.80)
Constant	-0.901***	3.349	2.542	-0.663
	(-19.13)	(0.03)	(0.02)	(-1.28)
Sector and Region f.e.	no	yes	yes	yes
Observations	23797	20414	17189	3186
Pseudo R-squared	0.173	0.225	0.165	0.270

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

TABLE B2

Intensive and extensive margins and the supply chain (whole survey; see TABLE 4).

	Intensive margin			Extensive margin		
	all	SMEs	LEs	all	SMEs	LEs
	(1)	(2)	(3)	(4)	(5)	(6)
Supply chain	9.081***	11.31***	2.535	0.284***	0.315***	0.156**
	(8.03)	(7.77)	(1.46)	(7.83)	(6.53)	(3.07)
SME	-21.91***			-0.708***		
	(-20.00)			(-20.68)		
Age	5.683***	6.513***	0.342	0.230***	0.252***	0.103**
	(9.88)	(9.45)	(0.29)	(11.56)	(10.43)	(2.89)
Group	13.86***	15.79***	10.94***	0.340***	0.428***	0.253***
	(11.98)	(9.28)	(7.70)	(9.23)	(7.56)	(5.83)
Local network	-11.72***	-12.80***	-9.099***	-0.360***	-0.392***	-0.271***
	(-9.83)	(-8.62)	(-4.47)	(-8.74)	(-7.51)	(-4.15)
Domestic network	4.393***	6.229***	-1.456	0.262***	0.329***	0.0837
	(3.33)	(3.79)	(-0.66)	(6.12)	(6.05)	(1.28)
Foreign network	36.45***	45.06***	18.31***	1.058***	1.257***	0.593***
	(22.37)	(21.35)	(7.54)	(21.33)	(18.88)	(8.88)
Product innovation	21.00***	25.09***	13.20***	0.574***	0.693***	0.354***
	(15.45)	(13.77)	(7.00)	(13.34)	(11.53)	(6.41)
Process innovation	5.508***	5.534**	6.431**	0.120*	0.164*	0.0774
	(3.61)	(2.59)	(3.24)	(2.42)	(2.27)	(1.29)
Constant	-21.16	-55.94	-8.010	-1.075	-2.113	-0.586
	(-0.50)	(-1.22)	(-0.50)	(-0.74)	(-1.34)	(-1.09)
sigma / ln_alpha	42.51***	45.55***	34.87***	0.0823*	0.389***	-0.662***
	(95.66)	(77.33)	(57.18)	(2.40)	(9.53)	(-10.14)
Sector and Region f.e.	yes	yes	yes	yes	yes	yes
Observations	20452	17236	3216	20452	17236	3216
Pseudo R-squared	0.073	0.058	0.059	0.119	0.093	0.103

t statistics in parentheses

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

TABLE B3

Firms' role within the supply chain and export (whole survey; see TABLE 5).

					own-branded and final		
	all	subcon.	own-branded	final	all	SMEs	SMEs
Dep. export dummy	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Supply chain	0.300***	0.167**	0.384***	0.314***	0.455***	0.437***	0.521***
	(9.48)	(2.86)	(8.49)	(6.47)	(6.91)	(5.96)	(7.27)
SMEs	-0.607***	-0.601***	-0.652***	-0.702***	-0.750***		
	(-19.77)	(-10.48)	(-15.56)	(-14.38)	(-11.47)		
Subcontractor	-0.229***						
	(-7.01)						
Own-branded firm	-0.0854**						
	(-2.85)						
Final-good producer	0.233***						
	(10.47)						
Age	0.148***	0.144***	0.161***	0.163***	0.196***	0.205***	
	(9.85)	(5.51)	(7.61)	(7.37)	(6.57)	(6.41)	
Group	0.348***	0.363***	0.355***	0.325***	0.281***	0.383***	
	(10.64)	(6.00)	(7.90)	(6.28)	(4.10)	(4.37)	
Local network	-0.269***	-0.395***	-0.213***	-0.267***	-0.247***	-0.248***	-0.262***
	(-8.74)	(-7.10)	(-4.91)	(-5.62)	(-3.81)	(-3.43)	(-3.72)
Domestic network	0.175***	0.193**	0.158**	0.145**	0.120	0.185*	
	(4.96)	(3.01)	(3.15)	(2.70)	(1.64)	(2.27)	
Foreign network	1.299***	1.298***	1.295***	1.311***	1.299***	1.334***	1.370***
	(22.71)	(12.30)	(16.91)	(15.51)	(12.06)	(11.38)	(11.92)
Product innovation	0.656***	0.726***	0.627***	0.668***	0.547***	0.492***	0.550***
	(16.43)	(8.27)	(11.73)	(11.78)	(7.39)	(5.80)	(7.23)
Process innovation	0.224***	0.230*	0.216***	0.151*	0.126	0.111	
	(5.09)	(2.55)	(3.63)	(2.29)	(1.49)	(1.11)	
Constant	3.447	-1.580***	3.341	-1.212***	-1.212**	-2.212***	-1.604**
	(0.03)	(-3.98)	(0.02)	(-3.43)	(-2.74)	(-4.35)	(-3.20)
Sector and Region f.e.	yes	yes	yes	yes	yes	yes	yes
Observations	20413	6579	10708	8247	4756	3955	4196
Pseudo R-squared	0.232	0.192	0.244	0.238	0.257	0.199	0.189

t statistics in parentheses

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

TABLE B4

Average treatment effects on the treated (SMEs from the whole survey; see TABLE 6).

model	ATT	std. err.	t	n. treated	n. controls	common support	balancing property
(1)	0.142	0.011	12.894	2094	19527	[.022, .207]	yes/yes
(2)	0.138	0.011	12.509	2094	18633	[.014, .242]	no/yes
(3)	0.082	0.014	6.072	2061	5236	[.011, .591]	no/yes
(4)	0.103	0.011	9.254	2094	19307	[.015, .474]	no/yes
(5)	0.081	0.012	7.067	2094	17910	[.010, .500]	no/yes

Note: ATT estimated using the nearest neighbor matching according to the Becker-Ichino (2002) algorithm. Indistinguishable results are obtained with the Leuven-Sianesi (2003) algorithm. The balancing property is tested using both the propensity score stratification t-test procedure and the standardised percentage bias.

Listed models use the following variables: (1) 1-digit sector and macro-region f.e.; (2) 1-digit sector and region f.e.; (3) variable that affect the treatment, i.e. age, group dummy, size class, final producer, network dummies and product innovation; (4) variables with the stronger effect on the treatment, i.e. network dummies and product innovation; (5) variables that affect both the treatment and the outcome, i.e. size class, final producer, network dummies and product innovation. Models 3-5 also use 1-digit sector and macro-region f.e.

TABLE B5

Aggregate tests for the balancing property (SMEs from the whole survey; see TABLE A5).

model	sample	pseudo R2	LR chi2	p-val	mean bias	med bias
(1)	Raw	0.053	728.380	0.000	16.800	17.800
	Matched	0.000	0.000	1.000	0.000	0.000
(2)	Raw	0.059	807.710	0.000	9.700	6.000
	Matched	0.000	0.000	1.000	0.000	0.000
(3)	Raw	0.089	1183.150	0.000	18.900	20.100
	Matched	0.003	18.430	0.427	2.000	1.000
(4)	Raw	0.078	1079.700	0.000	17.900	20.100
	Matched	0.000	0.000	1.000	0.000	0.000
(5)	Raw	0.088	1215.230	0.000	19.000	20.100
	Matched	0.000	0.590	1.000	0.300	0.200

Listed models use the following variables: (1) 1-digit sector and macro-region f.e.; (2) 1-digit sector and region f.e.; (3) variable that affect the treatment, i.e. age, group dummy, size class, final producer, network dummies and product innovation; (4) variables with the stronger effect on the treatment, i.e. network dummies and product innovation; (5) variables that affect both the treatment and the outcome, i.e. size class, final producer, network dummies and product innovation. Models 3-5 also use 1-digit sector and macro-region f.e.