SUPPLY CHAINS AND THE INTERNALIZATION OF SMEs: EVIDENCE FROM ITALY*

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Abstract *This paper explores the impact of being part of a supply chain on the internationalization of firms. We show that even small and less productive firms, if involved in production chains, can take advantage of reduced costs of entry and economies of scale that enhance their probability to become exporters. The empirical analysis is carried out on an original database, obtained by merging and matching balance sheet data with data from a survey on over 25,000 Italian firms, largely SMEs, which include direct information on the involvement in supply chains. We find a positive and significant impact of being part of a supply chain on the probability to export and on the intensive margin of trade. The number of foreign markets served (the extensive margin), on the other hand, does not seem to be affected. We also investigate whether being in different positions along the chain, i.e. upstream or downstream, matters and we find that downstream producers tend to benefit more. Our results are robust to different specifications, estimation methods, and to the inclusion of the control variables typically used in heterogeneous firm models.*

Keywords Supply Chains, SMEs, Heterogeneous firms, Internationalization

JEL Classification F12, F14, F21

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1 INTRODUCTION

International trade models have recently highlighted that firms' heterogeneity often results in self-selection in foreign markets. The presence of entry costs and imperfect competition allows more productive firms to enter (stay in) foreign markets and upgrade, while (initially) lower productivity firms, given internationalization costs, are likely to be confined to the domestic market. Hence, successful exporting firms tend to be relatively few, but they are larger, more productive and generally better performers according to a number of indicators (Melitz, 2003; Bernard et al., 2007; Melitz and Redding, 2013). A vast empirical literature confirms these predictions (see Wagner, 2012, for a recent review). Most existing studies have focused on large enterprises (LEs), since they account for the bulk of imports, exports and other multinational activities; and because of data availability. Evidence on the factors fostering the internationalization of small and medium enterprises (SMEs), on the other hand, is still relatively scarce.

A different but related strand of the literature, directly focusing on supply chains, has emphasized the importance of international fragmentation of production and specialization in trading "tasks" rather than goods (Grossman and Rossi-Hansberg, 2008). The related evidence suggests that firms find different ways to internationalize, by exploiting their specialization, by being involved in importing activities and by participating in global supply chains (Castellani et al., 2010; Baldwin and Lopez-Gonzales, 2013). In particular, an active involvement in supply chains is likely to enhance efficiency, by allowing firms to specialize in functions better fitting their capacities, thanks to 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 (Humphrey and Schimtz, 2002; Gereffi, 1999; Agostino et al., 2011; OECD, 2006). Furthermore, involvement in supply chains can be seen as a rational choice since it potentially reduces agency and transaction costs and, through formal and informal relations with other firms, allows a more efficient transfer of resources (Wynarczy and Watson, 2005).

To our knowledge, these two strands of the literature have not yet been linked. On the one hand, the literature on heterogeneous firms has highlighted the mechanisms of the internationalization process, especially for large firms; on the other hand, the literature on the supply chain has mainly focused on firms that are already operating at a global level. Moreover, the empirical evidence rarely focuses directly on SMEs. The evidence of the participation of SMEs in the global market as well as that of the effects of supply chain participation on the internationalization of firms is therefore still limited. It is often restricted to factors hampering internationalization, such as the role of family ownership or the lack of human capital and poor access to credit, rather than to factors enhancing the capacity of firms to internationalize, including, for instance, innovation, networking and inter-firm contractual arrangements (Higón Añón and Driffield, 2011; OECD, 2012; Cerrato and Piva, 2012; Bricongne et al., 2012).

SMEs, which represent the vast majority of firms, jobs, sales and value-added in many economies (WTO, 2013), are however playing an increasingly important role in supply chains and are becoming increasingly internationalized. Empirical research highlighting the interaction of heterogeneity benefits with advantages of belonging to a supply chain is therefore not only relevant, but also of immediate policy interest.

Participation in a supply chain may enhance the internationalization of firms through complex and highly interrelated mechanisms. A major one has to do with incomplete contract theory and specialization (Grossman and Helpman, 2002; Grossman and Hart, 1986; Antràs, 2003). In line with Antràs and Helpman (2004), heterogeneous firms deciding whether and how to fragment their production (domestically and/or internationally) are likely to undertake a relationship-specific investment[1] in an incomplete contracts environment. An example of such a situation is the decision on where to position themselves along the supply chain, according to their specialization. Since inputs are often customized to the buyers' needs, trust between agents becomes key.[2] Recognizing the importance of trust has been used to justify the fact that firms could internationalize through vertical FDI. However, fixed costs between firms along the supply chain are likely to be lower *vis à vis* possible vertical integration. Hence, being part of a supply chain (domestic or international) is a strategy that could be chosen by relatively less productive firms, such as SMEs, which may not be able to afford the costs of vertical integration. As a consequence, we maintain that supply chains can enhance SMEs engagement in international markets, by opening new niches, also for services producers, and allowing firms to overcome information costs, incompleteness of contracts and other structural barriers to internationalization.

This paper, exploiting an original dataset based on a survey conducted by MET (Monitoraggio Economia e Territorio) on over twenty-five thousands Italian firms, largely SMEs, which include direct information on their involvement in supply chains, represents an attempt to link the two strands of the literature mentioned above.[3] Italy represents an interesting case for at least two reasons. On the one hand, substantially more than in other European countries, SMEs represent

[1] By «relationship-specific» we mean that the value of assets or investments is higher inside a particular relationship than outside of it.

[2] An interesting example is the value chain certification of the famous Italian brand "Gucci", which has certified its suppliers and subcontractors. The certification involves over 600 firms from Toscany. As a consequence, these firms, improving their reputation have also increased their access to credit (Il Sole 24 ore online, "*Intesa San Paolo e Gucci alleate per favorire l'accesso al credito delle PMI*", January 17, 2013).

[3] In particular, we exploit the answers to an explicit question in the survey about the involvement of firms in supply chains. Related papers, such as Accetturo et al. (2011), Agostino et al. (2011) and Wynarczy and Watson (2005), rely on the status of subcontractor or supplier of intermediate goods as a proxy for participation in global supply chains.

the bulk of the productive structure, employment and contribution to the overall export performance (Barba Navaretti et al., 2011). On the other hand, Italy's sectoral specialization and industrial structure triggered a high division of labor among firms, many of which (especially SMEs) often work as specialized suppliers. Furthermore, Italian SMEs often engage in formal and informal networking at the local level (Giovannetti et al., 2013), involving cooperation among specialized firms, to achieve collective efficiency and better performance compared to firms outside industrial districts (Becattini, 1990; Brusco and Paba, 1997; Di Giacinto et al. 2012). External economies at the cluster level affect (also) the international projection of SMEs and therefore the traditional sources of firms' competitiveness (Crouch et al., 2001; Becchetti and Rossi, 2000).

Our results show that belonging to a supply chain enhances (i) SMEs' probability of exporting and (ii) the intensive margin of exports (measured as share of total exports on turnover). However, supply chain participation does not seem to affect the extensive margin, measured as the number of foreign markets served by the firm, coherently with the view that structural limits linked to the size matter for international expansion of SMEs. Furthermore, we find that if SMEs are involved in downstream activities, belonging to the supply chain has the largest effect on the probability of exporting.

The remainder of the paper is organized as follows: Section 2 describes the data and introduces the relevant definitions. Results from of the econometric exercise estimating the effect of the supply chain on the internationalization of firms according to different methodologies are presented in Sections 3. Section 4 concludes.

2 DATA AND DESCRIPTIVE STATISTICS

Our main source of information is the MET 2011 survey, covering 25,090 Italian firms belonging to manufacturing and service sectors. The survey consists of detailed information on employment, input, sales, investments, internationalization modes, innovation, and possible belonging and position along the supply chain over the period 2009-2011. In order to estimate the total factor productivity (TFP), we merged the MET survey data with the balance sheet information from AIDA, a database published by the Bureau van Dijk, providing financial information on Italian firms. This merged dataset contains 7,590 firms[4] and its characteristics are in line with those of the most recent census for Italy (ISTAT, 2013). A detailed description of the dataset is in the appendix.

In the existing literature, supply chains are defined in a number of different ways, all built around the existence of an input-output structure including a range of value-added activities (WTO, 2013; Baldwin and Lopez-Gonzales, 2013; Gereffi et al., 2001).

In this paper, we take advantage of a direct measure of the involvement of firms in supply chains, defined in the survey as a "*participation in a specific supply chain, implying a continuative contribution of the firm to the production process of a specific good, provided that this activity constitutes the majority of the firm's turnover*."

According to this definition, firms belonging to a supply chain are 15.7 percent of our total sample, a majority of which (82.3 percent) are manufacturers. The share of exporters (40.3 percent) rises to 58.3 percent for firms in a supply chain. In TABLE 1 we report the share of exporters by employment class, also separated for firms in supply chains; the comparison of the

[4] 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). After the merge, the share of firms below 50 employee decreases to 75.3 percent from 86.2 percent. Moreover, we lose a large number of firms in services: the share of manufacturing increases to almost two-thirds after the merge from about one-half before the merge.

two columns suggests that belonging to a supply chain increases the share of exporters for all the employment classes, but particularly for SMEs.

TABLE 1 HERE

The survey also provides direct information on the involvement of firms in network activities. Networks are defined as *"relevant and continuative relationships with other firms and institutions"* (including for instance authorities, research centers and Universities). In order to avoid confusion, it is worth noting that such network relationships consist of a range of many different – and not mutually exclusive – activities that are independent from the type of production relationships within the supply chain. Indeed, we can observe firms in supply chains that do not entertain any of the relationships categorized as "network" in the survey (54.8 percent of supply chain firms) as well as firms in networks that do not operate within a supply chain (78.1 percent of network firms). The surveys allows us to distinguish local, domestic (national) or foreign networks. TABLE 2 reports the share of firms involved in different activities (buying, selling, design, marketing etc) by type of network and supply chains.

TABLE 2 HERE

The empirical literature on heterogeneous firms has shown the existence of a hierarchy of firms in terms of productivity and other performance indicators, by mode of internationalization (Helpman et al. 2004). Exploiting the information on FDI activities of Italian firms from the ICE-Reprint database after merging it with MET and Aida data, we compute total factor productivity for Italian firms and check the existence of such a hierarchy.[5] Our TFP estimates are in line with the findings of the literature, and show that productivity *premia* are different for different internationalization modes (FIGURE 1). On average, the productivity *premium* tends to increase with the exported value and large exporters are generally involved in more complex internationalization forms, such as FDIs. 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 in-between that of non-exporters and exporters (FIGURE 1.a), suggesting that participation in a supply chain should definitely be further analyzed. This is in line with Antràs and Yeaple (2013), who, concentrating on Spanish firms, find an organizational sorting in which outsourcing, either domestic or global, is performed by the least productive firms, while the most productive firms are more likely to choose integration at home or abroad.[6] If this is the case, we might observe that the firms participating in supply chains are on average less productive than exporters (which in turn are less productive than multinationals, as in the standard heterogeneous firms model).

FIGURE 1 HERE

3 EMPIRICAL ANALYSIS

[5] 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, with intermediate inputs as proxies for unobservable productivity shocks. Further details on the estimation methods are provided in the appendix.

[6] Pieri and Zaninotto (2013), in a study on the Italian machinery tool industry, find that: "the most efficient builders of MTs choose integrated structures, while less efficient firms choose to outsource part of their production process by buying intermediate inputs from other firms" (p. 413).

Let us explore the effect of belonging to a supply chain on the probability to export, taking into account the features of the firm and disaggregating our sample in order to check whether the relation is consistent to different specifications.

Our baseline specification is a standard Probit model:

$$(1) \qquad Pr(Y_i = 1) = \Phi(\alpha + \beta_1 SC_i + \beta_2 X_i + \gamma_i + \delta_i + \varepsilon_i)$$

where $Y_i=\{0,1\}$ is the export dummy for firm i,[7] $\Phi(\bullet)$ is the c.d.f. of the standard normal distribution, α is the constant term, γ_i and δ_i are regional and sector effects, respectively, and ε_i is the random error term.

Our variable of interest is the dummy variable measuring the participation of the firm in supply chains (SC_i). In line with the literature, we control for size, age, group, and innovation (see for instance Barba Navaretti et al., 2011; Giovannetti et al., 2013; Bartoli et al., 2014). We also explicitly control for firm's network participation at the local, domestic or global level.[8] TABLE 3 reports the descriptive statistics.

TABLE 3 HERE

Results from the regressions, reported in TABLE 4, are consistent across the different samples highlighting an overall stability of the relations observed.[9] In line with the existing evidence, we

[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. This choice is consistent with the consideration that firms along the supply chain, upstream or downstream, have different degrees of proximity to the market.

[8] For consistency, the network variables that we include in the regressions are mutually exclusive. Hence, while some firms are involved in different types of networks simultaneously (e.g. local and domestic, domestic and global or local and global), our definitions are such that each firm is univocally attributed to the wider type of network.

[9] Results are robust to the inclusion of each regressor separately and 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 (without checking for the TFP). Results are available on request.

find that the probability of exporting increases with the age of the firm and with the participation to a group, and that innovation is a key driver of internationalization (Grossman and Helpman, 1991). The introduction of a dummy variable for small and medium sized enterprises (less than 50 employees) confirms that larger companies are more likely to internationalize (Melitz, 2003; Mayer and Ottaviano, 2007).[10]

Firms belonging exclusively to local networks are less likely to export, while networking with foreign firms fosters internationalization, reducing transaction costs of exploring far-away markets. The negative and significant sign of a "local network" seems to suggest that firms able to exploit the positive impact of local networks on their productivity have fewer incentives to internationalize. This is in line with the literature stating that benefits from clustering are very localized (Duranton and Overman, 2008) and that geographical proximity, organizational proximity and social interactions are the channels through which the externalities have an impact on firm's decisions. Last but not least, belonging to a supply chain is positively correlated with the probability of exporting, and this result is robust to the introduction of regional and sector fixed effects (column 2). Hence, exporting can be considered a positive spillover of being part of a supply chain.

TABLE 4 HERE

We introduce the lagged level of TFP and its percentage change over the period 2007-2011 as controls (columns 3 and 4 of TABLE 4).[11] Controlling for changes in productivity allows us to

[10] Replacing the SMEs dummy with the logarithm of the number of employees produces similar results, with the coefficient of the latter regressor being positive. Regressions with the SMEs dummy, however, are more consistent with the following analysis, where we split the sample between SMEs and LEs.

[11] Note that using the initial productivity level and the change in productivity helps also to avoid concerns over a possible simultaneity bias with the dependent variables. Moreover, there is general consensus among trade

analyze the possibly asymmetric effects of the recent crisis on the different types of firms in the sample. This, in turn, allows us to say that the results for the supply chain are not driven by post-crisis specific circumstances. Both the initial levels of productivity and its growth seem to have a positive impact on the probability of exporting. This result meets our expectations and the literature on heterogeneous firms. First, in line with Melitz (2003), firms with higher initial productivity are more likely to be exporters. Second, given the initial level of productivity, firms that experienced a higher increase in the TFP are more likely to be exporters. This seems to suggest that they are likely to be relatively less affected by the crisis. Finally, and more importantly for our purposes, controlling for productivity does not change our findings: being integrated into a supply chain has a positive effect on the probability of exporting. More precisely, considering the marginal effect of our preferred model (column 4 of TABLE 3) we can say that belonging to a supply chain can increase the probability of exporting between 6.2 and 8.1 percentage points on average[12] and correctly predicts 72.5 percent of the observations.[13]

3.1 Supply chain and internationalization of SMEs

To check whether size matters, we estimate the previous model separately for SMEs and LEs. Columns 5 and 6 of TABLE 4 suggest that the aggregation masks important differences. Participation to a group does not affect the probability to export of SMEs. On the other hand, the introduction of new products seems to matter. This is not surprising, especially if seen in relation to the participation in 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

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.

[12] Average marginal effect and marginal effect at the mean respectively.

[13] The prediction is considered to be correct if the predicted probability is greater than 50 percent and the firm is indeed exporting or if the predicted probability is below 50 percent and the firm is not exporting (Hosmer and Lemeshow, 2000).

with previous results, domestic and global networks are positively related to the internationalization of SMEs, while firms with traditional local connections are less likely to be exporters. More productive SMEs are more likely to be exporters, in line with our expectations. However, for LEs, the TFP coefficients, though positive, are not significant. This asymmetry is possibly due to non-linearities for larger firms, for which further increasing size and productivity is likely to have a small impact on an already relatively high export probability.

More relevant for our research question, belonging to a supply chain has a clear positive effect on SMEs, and is not significant (but still positive) for LEs. This result comes at no surprise if we go back to the mechanisms linking supply chain participation and internationalization described in the introduction. As noted above, involvement in a supply chain relation may entail lower entry costs, due to well-defined contractual arrangements with other companies along the chain and may facilitate access to cheaper and/or higher quality intermediate inputs. In addition, being part of a supply chain may be the preferred strategy when capital and R&D intensity are relatively low, since such inputs are more likely to be controlled by downstream firms. Larger firms, on the other hand, might be relatively unaffected by supply chain participation, since their structural characteristics are more likely to project them internationally independently on whether they belong or not to the chain. The marginal effects computed by running different regression for small and large firms suggest that belonging to a supply chain can increase the probability of exporting by 6.5 to 7.9 percentage points for SMEs. As robustness check, and to have a more detailed picture of how the size affects these results, we run two separate sets of regressions for different size thresholds. In the first set, we consider smaller 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 employees) and 6 for large firms (from 50 employees) are reported in TABLES A3 and A4 in the appendix.[14] FIGURE 2 depicts the marginal effects of belonging to a supply chain, together with their confidence interval, on the probability of exporting, and confirms that they are higher for smaller firms while for large firms no significant effect emerges.

FIGURE 2 HERE

3.2 Intensive and the extensive margins

In order to check whether the positive relationship between participation to supply chains and export performance is also valid for alternative measures of internationalization, we compute the intensive and extensive margins of trade at the firm's level.[15] The intensive margin is calculated as the share of exports over total turnover, while the extensive margin has been constructed as an index including the number of different geographic destinations served by the firm.[16] On average, firms in our sample export 14.2 percent of their turnover whereas firms in supply chains export 21.7 percent. As to the number of destination markets, the average is 2.07 for all exporting firm (0.83 for all firms), while firms in supply chain reach 2.26 markets.

To measure the impact of supply chain on the intensive margin, we estimate a Tobit model with left censoring at 0. The results, displayed in columns 1-3 of TABLE 5, are in line with the previous ones: the same variables that affect the probability of exporting also contribute to the

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

[15] The two indicators are rough, given data limitations.

[16] The extensive margin index goes from 0 (non-exporters) to 8. The different destinations for which we have data are: EU, EXTRA-EU, North America, China, India, rest of Asia, South America, other.

intensity of exports. Again, a significant difference emerges between firms of different sizes. We find that not only does participation in supply chains foster the internationalization of SMEs, but also that their high levels of specialization and the likely deepening of linkages along the chain make SMEs more dependent on foreign network relationships.

Conversely, we do not find any evidence that being part of supply chains has positive spillovers on geographic diversification. The results reported in columns 4-6 of TABLE 5 and obtained by means of a negative binomial estimator, show that the geographic scope of SMEs does not improve when they are in supply chains. Interestingly, LEs in supply chains seem to take advantage of it, with a significant probability of operating in different markets, independently from their distance. Our findings for the extensive margin of trade suggest that size still needs to be considered a structural barrier to the international expansion of SMEs, and that being part of a supply chain cannot be a substitute for the lack of other structural resources.

The above results could be due to the existence of different entry costs. SMEs may therefore benefit more from supply chain participation through reduced entry costs in foreign markets. Hence, firms in supply chains are more likely to become exporters and to export a larger share of their turnover. However, increasing the number of destination markets and reaching distant markets may involve additional costs, and size starts again to be a stringent requirement.

TABLE 5 HERE

3.3 The role of firms within the supply chain

We showed that SMEs, less likely to internationalize, may partly overcome their intrinsic weaknesses through an active involvement in a supply chain. However, SMEs are themselves heterogeneous and different firms involved in the production of the same final good may have different roles, degrees of monopoly power and proximity to the final market. More precisely, the position along the chain is likely to determine the benefits that can be obtained and often the activities offering greater revenues are intangible. Ignoring these differences may affect the results, even when firms are of a similar size and share other dimensions. In a pioneer model, Antràs and Chor (2012) consider a setup in which the existence of a number of many (sequential) suppliers gives raise to differential incentives to integrate along the supply chain. The position, i.e. being upstream or downstream, determines whether a given task or a given input is better produced by an independent supplier or by an integrated firm.

In Italy, firms tend to outsource part of their production, either domestically or internationally, more than in other countries while being less prone to international integration (Federico, 2012). This could be linked to the diffuse presence of industrial districts, characterized by tight division of labor and a large diffusion of subcontracting practices among firms (Accetturo et al., 2011). These stylized facts are in line with theoretical models showing that smaller, less productive, firms are more likely to outsource and hence to be part of production networks (Antràs and Helpman, 2004). However, while this could explain, together with other factors, why Italian SMEs may find convenient to be involved in supply chains to outsource, little has been said on their role as subcontractors. The (scant) existing evidence highlights a consistent *subcontracting discount*, reporting a marginal role of subcontractors in terms of performance, when compared to final producers (Razzoloni and Vannoni, 2011). Moreover, Accetturo et al. (2011) and Agostino et al. (2011) find a large degree of heterogeneity even within the group of subcontractors.

In order to take into account such a heterogeneity, we re-estimate our baseline model by introducing a new set of variables. From our database, we know for each respondent the share of total sales by type of product (final vs. intermediate) and to which extent each firm produces for other firms or on their own. We therefore distinguish three different types of firms: 1) a *final-good producer*, a firm whose sales are entirely constituted by final consumption and final industrial goods; 2) a *subcontractor*, a firm which works only on a contractual basis for other firms; and 3) a "*own-branded" firm*, a firms that 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).[17]

TABLE 6 HERE

We account for these considerations by introducing other controls into our baseline model (TABLE 6). Once again, the regressions are robust to the inclusion of the new variables: all coefficients have the same sign and their numerical value is similar to previous results. While belonging to the supply chain keeps its explanatory power, final-good producers strongly emerge as those with the highest probability of exporting; furthermore, in line with the above mentioned existing empirical evidence, we find confirmation of a subcontracting discount.

In columns 2-4 we restrict the sample to subcontractors, own-branded firms and final-good producers respectively. We find that belonging to a supply chain strongly increases the probability of exporting of final-good producers as well as of own-branded firms. The supply chain coefficient is positive also for the group of subcontractors, but is not statistically significant.

Our results suggest that participation in supply chains is particularly beneficial to downstream producers, such as final firms, possibly due to a more effective organization of the upstream

[17] 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.

production process. Moreover, the supply chain participation is likely to enhance the specialization of firms with own-designed proprietary products, increasing their probability of exporting. All in all, these findings seem to suggest that downstream firms, which have some decisional power and are able to benefit more from the division of labor, are the most likely to increase their probability of exporting due to their supply chain participation. This hypothesis is consistent with the results reported in column 5, where we restrict the analysis to the subgroup of own-branded and final firms. While all other coefficients confirm previous estimates, the numerical value of the supply chain coefficient increases, thus corroborating our hypothesis. In columns 6 and 7, we confine out attention to SMEs only, which represent the vast majority of the own-branded/final group (69 percent) and confirm that the results hold even when we exclude LEs.

3.4 Robustness checks

The econometric analysis performed in the previous section suggests that belonging to a supply chain is positively correlated with the probability of exporting. We performed different robustness checks. First, as already mentioned, the results are confirmed when the regressions are run on the whole survey sample.[18] Second, results are robust to the exclusion of services. In this section we report, as an additional robustness check, the results obtained with a different, non-parametric, methodology, i.e. the Propensity Score Matching (PSM), which can, to a certain extent, help us addressing the issue of causality. 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. This has to do with the issue of 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

[18] To run regressions on the whole sample, however, we cannot control for TFP.

correlation might overestimate the causal effect of the supply chain. Such a problem is difficult to overcome, without panel data and/or valid instruments. However, matching procedures may be employed. Despite being subject to a number of criticisms, mainly linked to the difficulty of selecting the control group, PSM has two main advantages: first, matching, under the common support condition, focuses on comparable subjects only; second, it is a non-parametric technique, and this avoids potential misspecification of the conditional mean.

We match firms with the same observable characteristics but their participation to supply chains by performing a PSM estimator. 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.

Formally, our parameter of interest is the “average treatment effect on the treated” (ATT), which represents an estimate of the difference in the average probability of exporting for firms belonging to a supply chain, had they not been part of the supply chain (the counterfactual). The ATT is defined as:

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

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 be written as:

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

where P(X) is the propensity score, that is the probability of receiving the treatment.[19]

Heckman-Ichimura-Todd (1998) show that in observational studies it is desirable (i) that the same questionnaire is 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 these 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 exogenous or independent from the potential outcomes (Imbens-Wooldridge, 2009; Becker-Caliendo, 2007). 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, the choice of participating 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 to access the foreign market, then the unconfoundedness assumption may not be violated (Imbens-Wooldrige, 2009; Becker-Caliendo, 2007).

Confining attention to SMEs, we report estimates of the average treatment effects for different propensity score matching specifications. We start from a basic specification including sectoral and regional dummies only and then turn to more complete specifications including different sets of covariates. We estimate five different models. For all, the matching procedure uses the common support condition and the balancing property of the propensity scores is satisfied both

[19] We refer to the literature for a more detailed discussion of the methodology (Caliendo-Kopeinig, 2008; Becker-Ichino, 2002; Dehejia-Wahba, 1999; Heckman-Ichimura-Todd, 1998; Rosenbaum-Rubin, 1983).

according to the stratification t-test procedure and to the standardized percentage bias.[20] The ATT are estimated with the nearest neighbor matching both according to the Becker-Ichino (2002) and the Leuven-Sianesi (2003) algorithms, with indistinguishable results.[21] The estimated ATT indicate that SMEs belonging to a supply chain are at least 7.7 percentage points more likely to export on average (TABLE 7). These numbers are largely consistent with the marginal effects from the previous regression analysis (where the range was between 6.5 to 7.9 percentage points, model 5 in TABLE 4). Thus, the propensity score matching analysis seems to reinforce our results.

TABLE 7 HERE

4 CONCLUSION

The recent literature on supply chains has emphasized the importance of international fragmentation of production and specialization in functions better fitting the specific capacities of firms, focusing on firms already operating at a global level (Grossman and Rossi-Hansberg, 2008; Humphrey and Schimtz, 2002; Gereffi, 1999). The existing literature on heterogeneous firms has highlighted different self-selection mechanisms (Melitz, 2003; Bernard et al., 2007; Melitz and Redding, 2013). Larger and more productive firms are more likely to access the foreign market. Smaller and less productive firms are more likely to choose disintegrated production structures either domestically or globally.[22] In this paper we build on existing results

[20] Aggregate tests are reported in the appendix.
[21] 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.
[22] See Antràs and Helpman (2004) for a theoretical framework where only the most efficient firms are expected to be vertically integrated; Antràs and Yeaple (2013) for an empirical application to Spain; Pieri and Zaninotto (2013) for an empirical study of Italian machine tool industry.

and study the impact of the participation of firms to supply chains on internationalization, with a specific focus on Italian SMEs. The main findings can be summarized as follows: (i) in line with the existing literature on heterogeneous firms, SMEs are less likely to export than LEs; (ii) however, SMEs belonging to a supply chain are more likely to be exporters; (iii) SMEs participating to a supply chain tend to export a higher share of their turnover, but there is no evidence that they also reach a higher number of markets; (iv) the position of the firm along the supply chain matters, and so does the scope for specialization within the supply chain; in particular downstream firms, such as final-good producers, and firms with own-designed proprietary products are likely to gain more from participating to the supply chain compared to upstream firms or subcontractors.

Our results are robust to different specifications and estimation methods, including non parametric techniques. Estimates of the effect of the supply chain on the probability of being an exporter obtained through the regression analysis and through the Propensity Score Matching are consistent and suggest that firms in supply chains are on average more likely to export, *ceteris paribus* (with a range that varies between 6.5 to 7.9 percentage points). While the size and productivity of a firm are the key determinants of its internationalization, supply chain participation may help smaller and less productive firms to internationalize. This paper contributes to a better understanding of the mechanisms through which small and less productive firms may benefit from supply chains, at the same time justifying the coexistence of firms internationalized or domestic and/or with different productivity levels and organizational forms in the Italian economy.

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TABLES AND FIGURES

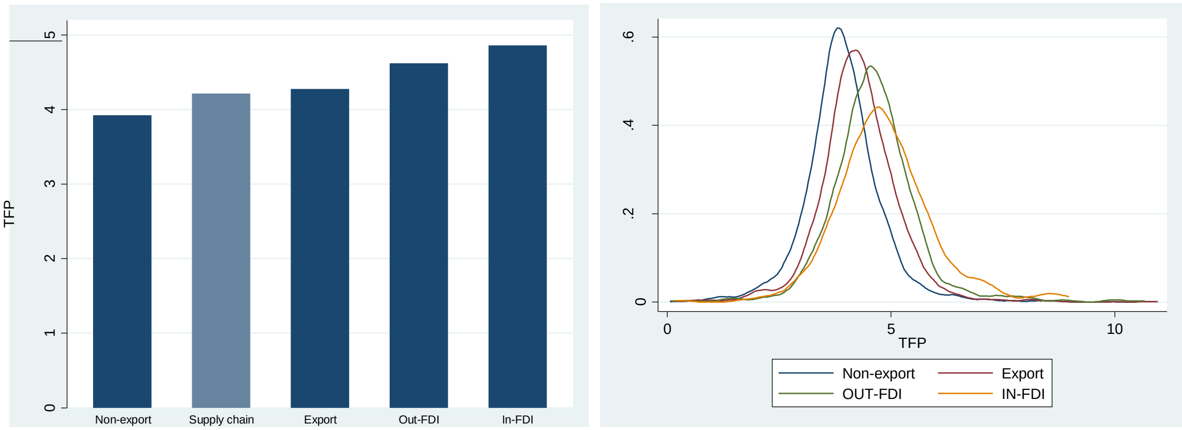
TABLE 1
Probability of exporting by class of employment.

	Share of exporters		
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

TABLE 2
Share of firms by type of activity within networks.

	Local network		Domestic network		Foreign network	
Type of relationship	total	supply chain	total	supply chain	total	supply chain
Buy	51,2	57,9	54,1	59,0	51,4	58,4
Sell	60,3	62,4	64,9	69,4	67,4	68,8
Design	12,6	12,6	14,1	11,9	12,2	9,6
Services	15,3	11,8	12,2	8,3	6,9	6,4
Marketing	13,7	18,7	12,8	17,3	15,1	14,4
Activities abroad	1,6	2,4	3,0	3,2	15,4	16,0
R&D	2,7	5,0	3,7	4,7	3,2	3,2
Other	4,9	2,9	4,0	2,9	2,8	2,4
Any kind	100	100	100	100	100	100
N	1835	380	1124	278	436	125

FIGURE 1
Total factor productivity by mode of internationalization.



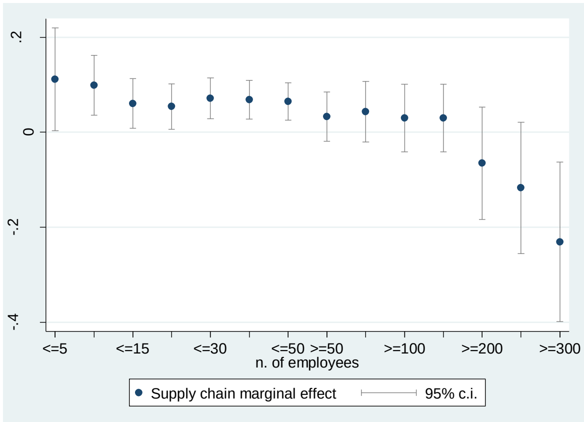
(a) Average TFP by mode of internationalization.

(b) TFP distribution by mode of internationalization.

TABLE 3
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 2
Supply chain coefficients for different firm's sizes.



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

TABLE 4

Probability of exporting.

	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 5
Intensive and extensive margins.

	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
Note: Estimates for the intensive margin regressions are done by means of a Tobit model censored at zero. Estimates for the extensive margin are done by a Negative binomial regression.

TABLE 6
Firms' role within the supply chain.

					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 7

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.

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. This sample of firms has been built using a stratification procedure by size, sector and region of the firms, to ensure representativeness at a national level. Firms in the dataset belong to different sectors of manufacturing and services and are located in all Italian regions. The information contained in the survey is mostly qualitative and ranges from employment to investments, innovation and internationalization. To also have quantitative information (particularly for the TFP estimation), we match and merge the MET survey and the balance sheet information from AIDA (Bureau Van Dijk) and the ICE Reprint data (confining to the foreign direct investments information). 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. Further controls, and the necessity to estimate the TFP reduce the sample size to 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 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 A2). 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) $y_{it} = \beta_l l_{it} + \varphi(k_{it}, m_{it}) + u_{it}$

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.