Financial constraints and exports: evidence from Portuguese manufacturing firms

Abstract

This paper analyzes the links between financial constraints and firm export behavior, at the firm level, by using data on Portuguese manufacturing enterprises. Previous empirical literature has not yet reached a consensus on these subjects and there is a great heterogeneity in measuring financial constraints and how to assess the causality relationships. Developing a very recent trend, we approximate credit constraints by using a financial score built on eight variables; to assess the effects of exports on the financial status of firms we apply, for the first time to these types of studies, a propensity score matching with difference in differences. This procedure is used to deal with the endogeneity problems, stemming from the fact that new exporters have most likely initial better financial health. We find that firms enjoying better financial health are more likely to become exporters and that new exporters show improvements in their financial situation.

Keywords: Exports; Matching; Financial constraints; Corporate finance

JEL Codes: F10; G32; L25
1. Introduction

Managers of firms, especially, in poor and developing countries often cite financial constraints as the main impediment to their investment, to their internationalization and growth. In line with a recent trend in international finance literature, we argue that the very fact of starting to export could improve firms’ access to external financial funds. However, the first theoretical contributions to this literature, e.g. Chaney (2005), argue in another direction, as if there are fixed costs associated with entry in foreign markets and if firms are constrained in their ability to finance these costs, only firms with enough ex-ante liquidity will be able to export.

In what concerns the direction of causality between exports and financial constraints, the recent empirical literature has invoked four kinds of reasons to support the argument that exports could reduce financial constraints:

(i) some authors (e.g., Campa and Shaver, 2002 or Bridges and Guariglia, 2008) argue that exporting firms should in principle benefit of more stable cash flows, as they are able to enjoy from international diversification of their sales. Thus, by assuming that international business cycles are only imperfectly correlated, exporting reduces vulnerability to demand-side shocks;

(ii) in another perspective, selling in international markets can be considered as a sign of efficiency and competitiveness by domestic investors and creditors; thus, in a context of information asymmetries and of financial markets imperfections, exporting would represent a clear signal sent by the firm to external investors, enabling them to obtain better financing. Some authors (e.g., Ganesh-Kumar et al., 2001) find that this kind of mechanism is mainly relevant in an emerging market characterized by low institutional quality;
(iii) meanwhile, other authors (e.g., Tornell and Westermann, 2003) argue that exporting is likely to open up access to international financial markets as well, at least those pertaining to the destination countries. In fact, foreign exchange revenues represent better collateral to access external funds in foreign financial markets;

iv) finally, exporters also tend to be larger, more efficient, have larger cash flows and therefore could have an easier task in getting access to external finance, or also could get preferential terms on their outside funds (Bernard and Jensen, 1999; Clerides et al. 1998; Delgado et al. 2002). This would justify exporting firms’ investments to be less sensitive to internal funds than their domestic counterparts.

Empirically, there are few studies assessing positively the influence of exports on firms’ financial health. Campa and Shaver (2002) conclude that exporting can help firms to reduce their financial constraints but they do not take into account endogeneity or selection issues. Other recent papers provide further evidence that exporting may exert a positive effect on firm financial health; however, the studies of Greenaway et al. (2007) and of Bridges and Guariglia (2008) have reached such conclusions rather indirectly and are subject to several critics in what respects their methodology. Nevertheless, there are also recent studies reaching the opposite conclusions: Manole and Spatareanu (2010) for Czech firms only found proved the thesis that firms with better financial health self-select into exporting but did not find evidence of the opposite direction.

In what follows we present an evaluation of the ex-ante and ex-post financial effects of exports based on a large panel of Portuguese manufacturing firms. Our contribution is twofold. First, we propose a new way of measuring the degree of financial constraint, in a development on the multivariate index proposed by Musso and Schiavo (2008), which we argue is preferable to the existing methodologies of assessing
financial constraints. Second, in an innovative proposal, and in order to adequately deal with selection and endogeneity issues, recognized in several studies, we propose the use of Propensity Score Matching with Difference in Differences in order to evaluate the financial impacts of new exporting activities.

Our main findings are as follows. First, Portuguese manufacturing firms starting to export present a notorious ex-ante financial *premium* compared to their non exporting counterparts, which is consistent with the idea that restricted access to external financial funds may prevent firms from selling their products abroad. Second, we find significant improvement in the financial health of firms entering into export markets, especially in firms belonging to most technologically advanced sectors and of small dimension.

The rest of the paper is organized as follows. Section 2 is an overview of the literature on financial constraints and their links with firm export behavior. Section 3 presents the data, discusses the shortcomings of usual strategies employed to measure financial constraints, and illustrates the methodology adopted in this study. In Section 4, we present propensity score matching and test the two hypotheses that less constrained firms self-select into exporting, and that selling abroad improves firm financial health. Section 5 concludes and draws some policy implications.

2. Literature revision on Financial Constraints

The literature on firm-level international trade has been so far mostly concentrated on the interactions between international trade and productivity. Credit constraints have not yet been included in most (firm-level) empirical studies of international trade. This paper belongs to a small list of papers that considers the interactions between international trade and financial constraints, at the firm level.
At the theoretical level, there are some models that try to explain the causality nexus between financial constraints and exports, but no model explains the opposite causality direction. Chaney (2005) expands Melitz’ (2003) model in order to account for liquidity constraints; in that model firms are heterogeneous with regard to both their productivity and liquidity. At the extensive margin both factors matter: more liquid (wealthier) and more productive firms are more likely to export than others; however, at intensive margin only productivity (and not liquidity) seems to affect the exported volumes.

While Chaney focuses on internal finance, Manova (2010) extends Melitz’ (2003) model to account for issues of external finance. Specifically, she argues that the better a country's contracting environment (regarding accessibility to external finance) and the lower the need for external finance of the firm's sector, the more likely is the participation of firms in the export market. She assumes that both extensive and intensive margins of exports are negatively affected by credit constraints.

Muûls (2008), incorporating the possibility of both internal and external financing into Melitz' model, finds that financial constraints provide for an impact on both the extensive margin and the intensive margin of exports, as in Manova (2010). Li and Yu (2009) also extend Melitz' model, they consider affiliates of multinational firms to have access to internal financing from their parent company and thus to be affected by (external) credit constraints in a lesser extent than other “independent” firms. Since exporting means higher fixed costs than serving the domestic market, thus multinational affiliates are more likely to be exporters than other “independent” firms.

At the empirical level, some recent papers (e.g., Greenaway et al., 2007) show that exporters are less liquidity constrained than domestic firms; however such papers are not able to discuss further the causality nexus involved; in fact, such relationship could
be explained by two non-mutually exclusive hypotheses: the first assuming that only unconstrained firms self-select into exporting, the second arguing that starting to export decreases the financial constraints of previously constrained firms.

Nevertheless, several issues are still unsolved. At one hand, the way financial constraints are identified and measured remains largely debated; the first methodology used to assess financial constraints employed the investment cash flow sensitivity but such methods are increasingly challenged and some recent theoretical works cast doubts also on other widespread proxies. At the other hand, the econometric specifications used in the literature to discuss the causality nexus appear to have several drawbacks, being not consistent with the stated goals of testing both the relevance of self-selection into export markets and the existence of beneficial effects of exports on financial health.

In what concerns the measure of financial constraints and according to classic theory (and under perfect capital markets), internal and external sources of financial funds should be perfectly substitutable (Modigliani and Miller, 1958), so the availability of internal funds should not affect investment decisions. In 1988, Fazzari et al. were the first to define firms as financially constrained based on their dividend payout ratio and have shown that likely constrained firms (low dividend payout) display higher investment-cash flow sensitivity. Those authors show that in the presence of informational asymmetries, external funds are more costly and thus investment should respond positively to increases in internal funds´ availability. In this line, several studies begun to use the investment-cash flow sensitivity to proxy for financial constraints. Among others, the findings of Hoshi et al. (1991) and Gilchrist and Himmelberg (1995) provided supportive evidence of the view of Fazzari et al (1988).

In 1997, Kaplan and Zingales argued that investment-cash-flow sensitivities do not provide a useful measure of financial constraints; their main hypothesis is that
industries that are more dependent on external financing will have relatively higher growth rates in countries that have more developed financial markets. After their work the usefulness of investment-cash flow sensitivity, as a measure of financial constraint, has been definitely questioned. Since then, other authors have even reported evidence of a negative relationship between investment-cash flow sensitivity and financial constraints (e.g., Cleary, 2006). In this line, Almeida et al. (2004) found that credit-constrained firms save more cash when compared to unconstrained firms and they do it as an insurance for bad periods (cash flow sensitivity on cash). This introduces a serious problem in testing whether the choice to internationalize is affected by cash flows.

In 2003, Terra stated that more financially dependent firms would tend to invest more when they have more access to credit, in a credit-constrained environment. Her empirical implementation was carried out by estimating the investment accelerator model, including the interaction between external dependence and credit access; firm size was used as a proxy for credit access. In this sequence, other alternatives to firms’ financial constraints begun to be used, classifying firms according to various proxies of informational asymmetries (as these represent the main source of financial markets imperfections). Hence, variables such as size, age, dividend policy, membership in a group or conglomerate, existence of bond rating, and concentration of ownership have begun to be used to capture financial constraints (e.g., Devereux and Schiantarelli, 1990; Hoshi et al., 1991; Bond and Meghir 1994; Gilchrist and Himmelberg, 1995; Cleary, 2006). The major weaknesses of such strategies — as already noted by Hubbard (1998) — is that most of the criteria tend to be time invariant whereas one can imagine that firms switch between being constrained or unconstrained depending on overall credit conditions, investment opportunities and idiosyncratic shocks. Moreover, as a further potential problem, those proxies rely on one-dimensional definition of financial
constraint, i.e. they assume that a single variable can effectively identify the existence of a financial constraint, viewing it as a binary phenomenon, either in place or not. In another perspective, other studies (e.g. Becchetti and Trovato, 2002) use survey data in which firms give a self-assessment of their difficulty to obtain external financial fund.

Recently, some authors (e.g., Musso and Schiavo, 2008) proposed a time-varying and continuous measure of financial constraints which recognizes the multifaceted feature of this phenomenon and allows one to capture their different degrees. Such indices considering several financial factors may be regarded as more balanced and effective mechanisms of financial constraint assessment, nevertheless, the empirical literature using such indicators is still quite rare.

3. Data and methodology

3.1. Data description

The empirical analysis combines two data sources from the Portuguese National Statistics Institute (INE): balance sheet information (IAE) and external trade information (ECE). Datasets are linked by firms’ non-revealed fiscal number. IAE provides information of firms’ balance sheets from 1996-2003, and uses a survey sample of all manufacturing Portuguese firms with less than 100 workers and all the universe of firms with more than 100 workers. We have used number of employees, turnover, exports, investment, labour costs, stock of capital, assets (and their composition), liabilities (and their composition), amortizations, own funds and earnings. Firms are classified according to their main activity, as identified by INE standard codes (CAE), which are correlated with Eurostat Nace 1.1 taxonomy.

Our database contains information for an average of 4,500 firms per year. Capital is proxied by tangible fixed assets at book value (net of depreciation). In turn, ECE
provides information for each firm, on trade volume (exports and imports) aggregated by year and by country (destination of exports and origin of imports), and it also displays information on the types of products/sectors traded for each transaction. All nominal variables are measured in 1996 Euros and are deflated using 2 digit industry-level price indices provided by INE; for capital stock we use the same deflator for all sectors.

3.2. Measure of Financial Constraints

In this paper, we have experimented different measures of firms’ financial constraints. First, we test the liquidity ratio and the leverage ratio as employed by Greenaway et al. (2007). The Liquidity ratio is defined as firm’s current assets minus its short-term debt over total assets; the leverage ratio as firm’s short-term debt over current assets. However, we argue that there are three main shortcomings in these measures: first, they only capture one dimension of access to financial markets: a firm may be liquid but nonetheless present a bad financial situation; on the other hand, strong fundamentals may compensate for a temporary shortage of liquid assets; third, both ratios may suffer from some endogeneity. In other words, there are no clear-cut theoretical priors on the relation between either liquidity or leverage and financial constraints. While liquidity is generally regarded a sign of financial health, firms may also be forced to withhold cash by the fact that they are unable to access external funds. In this line, Almeida et al. (2004) show that financially constrained firms tend to hoard cash, so that liquidity would be associated with financial constraints, not lack thereof. In a similar vein, a high leverage, while signaling potential dangers, suggests also that the firm has enjoyed, at least in the recent past, wide access to external financial funds. Hence, one could argue that highly leveraged firms are not financially constrained.
To account for these potential problems, we build two other measures of financial health according to the methodology first proposed by Musso and Schiavo (2008) and further developed by Bellone et al. (2010). We use information coming from eight variables: size (total assets), profitability (return on total assets), liquidity (current asset over current liabilities), cash flow generating ability, solvency (own funds over total liabilities), trade credit over total assets, repaying ability (financial debt over cash flow) and Total Factor Productivity (TFP)\(^1\).

For each variable, we scale each firm/year observation for the corresponding two-digit CAE sector average and then assign to it a number corresponding to the quintiles of the distribution in which it falls. The resulting information for each of the eight variables (a number ranging from 1 to 5) is then merged into a single index in two alternative ways: (i) a simple sum of the eight numbers (Score A); (ii) a count of the number of variables for which the firm/year lies in the first two quintiles (Score B). In both cases the index is then rescaled to fit on a common 1–10 range.

In what concerns TFP, since it is probable that profit-maximizing firms instantly adjust their input levels each time they notice productivity shocks, productivity and input choices are likely to be correlated and thus TFP estimation involves problems. In line with several authors (e.g., De Loecker, 2007), TFP is estimated using the semi-parametric method of Levinsohn and Petrin (2003), which controls the simultaneity bias. Thus, we compute TFP as the residual of a Cobb-Douglas production function where the firm value added is the independent variable and capital, labor and unobservable productivity level are the dependent ones. This methodology assumes that intermediate inputs have a monotonic positive relationship with productivity and thus could be used as proxies. Given data availability, we use intermediate inputs as the

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\(^1\) We add TFP to the proposal of Bellone et al. (2010) given that we assume economic efficiency is highly correlated with good financial health of firms.
deflated values of “supplies and external services” at book value. We estimate production function for every 2-digit sector separately.

Thus, after having obtained four measures of financial constraints we study the correlations between the four indicators as presented in Table 1; the Spearman’s correlation coefficients are reported. Leverage and liquidity are strongly negatively correlated: more liquid firms are also less leveraged, meaning that these two measures of financial health “go hand in hand”. We expected that something similar would happen for the two multivariate scores: irrespective of the way information was combined, firms should rank in a very similar order in terms of access to external financial resources; however we found no evidence of such hypothesis. In this line, we choose to work with the pair of indicators: liquidity ratio and Score A given this pair “is well behaved”; we leave out the other two variables given the “wrong properties” on Score B and the “redundancy” of the Leverage ratio.

### Table 1 - Correlations between Financial Constraints indexes

<table>
<thead>
<tr>
<th></th>
<th>Liquidity ratio</th>
<th>Leverage ratio</th>
<th>Score A</th>
<th>Score B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liquidity ratio</td>
<td>-</td>
<td>-0.86</td>
<td>0.53</td>
<td>-0.34</td>
</tr>
<tr>
<td>Leverage ratio</td>
<td></td>
<td>-</td>
<td>-0.54</td>
<td>0.33</td>
</tr>
<tr>
<td>Score A</td>
<td></td>
<td></td>
<td>-</td>
<td>-0.06</td>
</tr>
</tbody>
</table>

Source: Own calculations

4. Exports and finance: self-selection or ex-post benefit?

4.1. Summary statistics

Assuming firms financial constraints are measured by Score A and given that this index varies in our final database between 2 and 9, we adopt the assumption that financially constrained firms are those that present an average\(^2\) Score A between 2 and 6; thus 72% of Portuguese manufacturing firms have significant financial restrictions\(^3\).

\(^2\) Computed as all year’s average of Score A

\(^3\) See Appendix A for further details.
These results are in line with previous conclusions (e.g., Silva and Carreira, 2009); moreover, two thirds of the most financially constrained firms are small firms and half of them belong to more traditional manufacturing sectors (food and beverage, textiles, leather and wearing apparel). Using a linear regression, to assess the importance of several factors for financial constraints, similar conclusions arise: the least constrained firms are larger, more efficient, are more likely exporters and belong to more technologically developed sectors.

**Table 2- Score A regressions for two opposite financially constrained groups**

<table>
<thead>
<tr>
<th>Dependent variable: Score A</th>
<th>Employment</th>
<th>Dummy for exporter</th>
<th>TFP</th>
<th>Dummy for developed technological sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Group of the most</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constrained firms</td>
<td>0.001*</td>
<td>0.003*</td>
<td>0.0001*</td>
<td>0.001*</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.03)</td>
</tr>
<tr>
<td><strong>Group of the least</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>constrained firms</td>
<td>0.011</td>
<td>0.021</td>
<td>0.001</td>
<td>1.124</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.000)</td>
<td>(0.41)</td>
</tr>
</tbody>
</table>

Source: Own calculations
Notes: If nothing is mentioned, coefficients are significant at 1%. ** means significant at least at 5%. * means coefficients are significant at least at 10%. + means coefficients are not significant. In parentheses we report robust standard errors.

**4.2. The ex-ante financial advantage of future exporters**

We start by comparing *ex-ante* financial health for new exporters and non exporters. Such comparison tells us whether future exporters were less financially constrained than their non exporting counterparts even before entering foreign markets. The comparison is performed with firms belonging to the same industry and sharing similar characteristics in terms of size and efficiency. The econometric specification is adapted from the literature on export and performance (Bernard and Jensen, 1999), where these kind of empirical exercises are commonly performed. We compare the financial health of non exporting firms and export starters 1, 2, 3, 4, 5 and 6 years before the latter begin to export.
Hence, $t$ is the year firms’ begin exporting (in the case of export starters), while we set it equal to the median year for never exporters (a similar solution is adopted in ISGEP, 2008). Specifically, we estimate:

$$\text{FIN}_{i,t-s} = \alpha + \beta \text{EXP}_{it} + \phi Z_{i,t-s} + \xi_{it}$$  \hspace{1cm} (1)

where $\text{FIN}$ is Score A, $\text{EXP}$ is the dummy for export status, and $Z$ a vector of controls that comprises Size (captured by the log of Employment, measured in terms of total workers employed), Total Factor Productivity ($\text{TFP}$), and a set of industry-year dummies. It must be emphasized that equation (1) does not test for a causal relationship. Rather, it allows us to evaluate the strength of the pre-entry premium — i.e. to see to what extent firms that export in time $t$ were already less financially constrained 1, 2, 3, 4, 5 and 6 years before entering foreign markets— by means of a simple $t$-test on the significance of the $\beta$ coefficient. Results are presented in Table 3.

**Table 3 – Ex-ante financial superiority of future exporters**

<table>
<thead>
<tr>
<th></th>
<th>$t$-6</th>
<th>$t$-5</th>
<th>$t$-4</th>
<th>$t$-3</th>
<th>$t$-2</th>
<th>$t$-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Score A</td>
<td>0.195*</td>
<td>0.215*</td>
<td>0.295</td>
<td>0.331</td>
<td>0.292</td>
<td>0.285</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.12)</td>
<td>(0.050)</td>
<td>(0.067)</td>
<td>(0.058)</td>
<td>(0.050)</td>
</tr>
<tr>
<td>TFP</td>
<td>0.001*</td>
<td>0.001*</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Employment</td>
<td>0.012*</td>
<td>0.017</td>
<td>0.021</td>
<td>0.005</td>
<td>0.003</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.001)</td>
<td>(0.010)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>R squared</td>
<td>0.15</td>
<td>0.23</td>
<td>0.23</td>
<td>0.25</td>
<td>0.35</td>
<td>0.38</td>
</tr>
</tbody>
</table>

Source: Own calculations; see also notes of Table 2.
Note: all regressions include an additional variable (not shown): two digit CAE

By investigating variables in levels (Table 3), we found support for financial *Self Selection* of exporters. In fact, before entry into export markets, the starters are more productive, larger and present better financial health (Score A) than never exporters. The analysis over the six years pre-entry time shows that, beginning in the fifth year before exporting, future exporters have a superior financial score; the ex-ante Score A of
starters is around 30% higher than that observed for never exporters. Future exporters’ TFP and employment is also marginally higher than for never exporters.

Looking for further insights, we also tested if firms modify their behavior in the pre-entry period, according to their future export status. Indeed, it seemed wiser to study the dynamics of future exporters’ financial premium rather than studying only level differences. Table 4 reports the estimates of conditional percentage differential between growth rates of Score A between starters and non-exporters. Future exporters present higher growth rates of Score A, at least three years before exports start; a similar (but weaker) phenomenon is detected for TFP. Thus, starters, even before exporting, have a superior financial health and also a superior financial dynamic.

<table>
<thead>
<tr>
<th>Table 4 – <em>Ex-ante</em> dynamic of future exporters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Annual Growth of Score A</td>
</tr>
<tr>
<td>Annual growth of TFP</td>
</tr>
<tr>
<td>Annual growth of Employment</td>
</tr>
</tbody>
</table>

Source: Own calculations
Note: all regressions include an additional variable (not shown): two digit CAE

Overall, both Tables 3 and 4 suggest that firms deciding to start exporting enjoy better financial health *ex-ante*. This conclusion is in line with a similar methodology adopted by Bellone et al. (2010); however, we must recognize that other studies, using different methodologies reached opposite conclusions.

**4.3. Detecting *ex-post* financial effects**

**4.3.1. Propensity score matching**

Previous results suggest that less financially constrained firms tend to become exporters. However, this does not rule out the possibility that beginning to export
further boosts firms’ financial health. Thus, in this section we study such causality nexus.

Methodologically, we use Propensity Score Matching (PSM) with Difference in Differences to obtain tests of the effects of exporting in firms’ financial health. Given that Portuguese firms with best efficiency and financial health are clearly more likely to be exporters, the use of other methodologies could be risky given the endogeneity associated with decision to become exporter. Ideally, the effects (on financial or economic levels) of becoming an exporter should be measured by comparing a firm’s performance, some years after starting to export to what their hypothetical performance would have been at the same time if they had never exported. Under the impossibility of such a measure, matching methods aim to evaluate the Average Treatment effect on the Treated (ATT), which means in practice, to evaluate the better as possible the effects of a treatment model, where treatment is the export entry. Thus, conceptually, we aim to measure the ATT, the average effects of a “treatment”, as the decision to start exporting on starters’ performances, by computing:

\[
ATT = E[Y_{i,t}(1) - Y_{i,t}(0)| D_t = 1] = E[Y_{i,t}(1)| D_t = 1] - E[Y_{i,t}(0)| D_t = 1]
\] (2)

where \(Y_{i,t}(1)\) is the outcome (financial or other) of a starter firm i at t given it began exporting at a certain time; \(Y_{i,t}(0)\) is the outcome of i at t given it did not begin exporting at the stated time; D is the decision made by i if it was starting to export (1) or not (0). In practice, we can only compute \(E[Y_{i,t}(0)| D_t = 0]\) thus, the solution is to replace the unobservable \(E[Y_{i,t}(0)| D_t = 0]\) with the observable \(E[Y_{i,t}(0)| D_t = 0]\); i.e., we use as measure of the effect \(E[Y_{i,t}(0)| D_t = 1] - E[Y_{i,t}(0)| D_t = 0]\) which originates selection bias in ATT computation.
Matching techniques pair each new exporting firm, in each year – on the basis of some observable variables, named as covariates – with a larger control group of most similar firms that stay non-exporters until that year. Given the variety of observable variables (covariates) that can be used to pair starters with non-starters (e.g., productivity, size, ownership, capital, sector, liquidity, general financial health), a problem of dimension of treatable variables arises. In line with Rosenbaum and Rubin (1983), this problem is solved by computing an average index: the “propensity score”. Using this index from a large group of untreated firms, we can find those that are the most similar to starters in the pre-treatment period.

In the first phase and in the purpose of estimating the propensity score, we chose as covariates to identify the probability of a firm beginning to export: TFP, size measured by logarithm of total assets, a dummy controlling for small firms (with fewer than 50 employees), capital stock, investment, dummies indicating whether the firm has R&D workers, if the firm has a foreign share of capital, if the firm imports, liquidity ratio, leverage ratio, financial health (Score A), loans and also sectoral dummies. We assume each one year lagged variables to affect export entry decision and the outcomes of starters and controls. In order to compute the propensity scoring the choice of the functional form seems to be robust since the binary treatment with logit or probit regressions yields similar results. In a second phase, we must match starters (treated firms) with controls (non-treated firms) by using the estimated propensity scores. To achieve it, there are several algorithms, which differ due to the different weighting regimes used to assess the importance of each control for each treated firm. We tested two of these weighting schemes: kernel matching and nearest neighbour matching. Given that the different methods reach different points on the frontier of the trade-off

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4 To free up the functional form of the propensity score, we also included higher order polynomials and some interaction terms.
between quality and quantity of the matches, and, in line with Caliendo and Kopeinig (2008), as neither of them is a priori superior, we use both\(^5\); in fact, their joint consideration offers a way to assess the robustness of the estimates. Given the narrowness of our database, we perform the referred matching by pooling all cohorts of starters, after we have ensured it does not affect the matching quality. Complementarily, in order to assess matching quality, we compare the average level of the covariates before and after matching and look for differences between treated and control units; if there are differences for the matched sample, the matching was not fully successful. Furthermore, to assess the quality of our matching we implemented a balancing test proposed by Becker and Ichino (2002) and a standard T-test for equality of means; they both ensure the quality of the matching performed.

Nevertheless, in spite of all precautions when performing PSM, the self-selection bias may still exist, due to the bias coming from unobservables. In fact, if there are unobservable variables affecting both “assignment” into exporting and the outcome variable simultaneously, a hidden-bias may arise. A method for dealing with time-invariant unobservable bias is to add a differences-in-differences (DID) estimator to PSM. According to Blundell and Costa Dias (2000), this approach can improve the quality of non-experimental evaluation. Using DID, we compare differences in outcomes before and after the treatment (i.e., export entry) for the treated group – starters – to the same differences computed for the untreated group – controls. Naturally, without the treatment, the differences across both groups should not exist. To evaluate the impact of exporting on new exporters’ performances (ATT), we performed the PSM-DID estimator applying it every year after entry into the export markets with respect to the year prior to entry (\(t-1\)); such implemented estimator could be written as

\(^5\) Nevertheless, we only report kernel algorithm results.
\[ M_{PSM-DID} = \frac{1}{n_i} \sum_{i,j,n} \left( Y_{i,Post} - Y_{i,pre} \right) - \sum_{j=0}^{\infty} w_{i,j} \left( Y_{j,Post} - Y_{j,pre} \right) \]  

(3)

In (3), Y is the required outcome (in logarithms, \( \ln \), instead of absolute values to obtain differences in growth rates between starters and non-starters); Post and pre denote that the variable is in the post-entry and pre-entry period; \( D_i = 1 \) (\( D_j = 0 \)) denotes the group of starters (non-starters) in the region of common support; \( n_i \) is the number of treated units on the common support; \( w_{i,j} \) is the weight of the \( j^{th} \) observation of controls in constructing the counterfactual to the \( i^{th} \) treated firm. When using the nearest neighbour algorithm each treated firms is matched with a single control, but using Kernel means that all controls, in the common support region, are weighted for matching each treated firm. We have calculated ATT effects from \( t \) to \( t+6 \).

4.3.2. Results

As mentioned, by using \( \ln \), values in Table 5 are percentage point differences in growth rates between starters and controls for each variable, observed cumulatively from \( t-1 \) to the that year. Propensity score matching was performed either by the program \textit{psmatch2} (developed by Leuven and Sianesi, 2003) and by the programs\(^6\) \textit{pscore} and \textit{attnd(w)/attk} (developed by Becker and Ichino, 2002). For both programs we used either nearest neighbour matching and kernel matching. When using kernel matching, standard errors are obtained by bootstrapping the entire estimation framework, including the propensity-score computation stage.

---

\(^6\) We only report results from \textit{psmatch2}; other results are available upon request.
Table 5 – General PSM-DID estimations

<table>
<thead>
<tr>
<th></th>
<th>( t / -1 )</th>
<th>( t+1 / -1 )</th>
<th>( t+2 / -1 )</th>
<th>( t+3 / -1 )</th>
<th>( t+4 / -1 )</th>
<th>( t+5 / -1 )</th>
<th>( t+6 / -1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP</td>
<td>0.008(\star)</td>
<td>0.026(\star)</td>
<td>0.045(\star)</td>
<td>0.039(\star)</td>
<td>0.059(\star)</td>
<td>-0.002(\star)</td>
<td>-0.071(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.013)</td>
<td>(0.025)</td>
<td>(0.027)</td>
<td>(0.027)</td>
<td>(0.044)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Score A</td>
<td>0.014(\star)</td>
<td>0.017(\star)</td>
<td>0.019(\star)</td>
<td>0.033*</td>
<td>0.039*</td>
<td>-0.008*</td>
<td>0.041*</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.012)</td>
<td>(0.018)</td>
<td>(0.024)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Solvency</td>
<td>0.088(\star)</td>
<td>0.003(\star)</td>
<td>0.081(\star)</td>
<td>0.118(\star)</td>
<td>0.154(\star)</td>
<td>-0.124(\star)</td>
<td>0.144(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.007)</td>
<td>(0.061)</td>
<td>(0.062)</td>
<td>(0.102)</td>
<td>(0.132)</td>
<td>(0.172)</td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.015(\star)</td>
<td>0.022(\star)</td>
<td>0.012(\star)</td>
<td>-0.043(\star)</td>
<td>-0.028(\star)</td>
<td>0.012(\star)</td>
<td>0.131(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.032)</td>
<td>(0.040)</td>
<td>(0.051)</td>
<td>(0.068)</td>
<td>(0.061)</td>
<td>(0.141)</td>
</tr>
<tr>
<td>ROA</td>
<td>-0.088(\star)</td>
<td>-0.093(\star)</td>
<td>-0.088(\star)</td>
<td>-0.107(\star)</td>
<td>-0.098(\star)</td>
<td>-0.192(\star)</td>
<td>-0.265(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.064)</td>
<td>(0.066)</td>
<td>(0.098)</td>
<td>(0.094)</td>
<td>(0.132)</td>
<td>(0.185)</td>
</tr>
<tr>
<td>Financial Debt share</td>
<td>0.019(\star)</td>
<td>0.131(\star)</td>
<td>0.211(\star)</td>
<td>0.293(\star)</td>
<td>0.063(\star)</td>
<td>0.021(\star)</td>
<td>0.017(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.210)</td>
<td>(0.102)</td>
<td>(0.182)</td>
<td>(0.213)</td>
<td>(0.023)</td>
<td>(0.042)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Bond share</td>
<td>0.017(\star)</td>
<td>0.127(\star)</td>
<td>0.201(\star)</td>
<td>0.263(\star)</td>
<td>0.061(\star)</td>
<td>0.025(\star)</td>
<td>0.017(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.200)</td>
<td>(0.100)</td>
<td>(0.172)</td>
<td>(0.243)</td>
<td>(0.025)</td>
<td>(0.044)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Trade credit</td>
<td>0.142(\star)</td>
<td>0.247(\star)</td>
<td>-0.347(\star)</td>
<td>-0.817(\star)</td>
<td>-0.188(\star)</td>
<td>-0.217(\star)</td>
<td>-0.277(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.540)</td>
<td>(0.650)</td>
<td>(0.990)</td>
<td>(0.890)</td>
<td>(0.145)</td>
<td>(0.310)</td>
</tr>
<tr>
<td>Cash Flow</td>
<td>-0.057(\star)</td>
<td>-0.061(\star)</td>
<td>-0.062(\star)</td>
<td>0.115(\star)</td>
<td>0.171(\star)</td>
<td>0.147(\star)</td>
<td>0.026(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.040)</td>
<td>(0.073)</td>
<td>(0.071)</td>
<td>(0.058)</td>
<td>(0.137)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.001(\star)</td>
<td>0.004(\star)</td>
<td>0.016(\star)</td>
<td>0.003(\star)</td>
<td>-0.019(\star)</td>
<td>0.021(\star)</td>
<td>0.039(\star)</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.011)</td>
<td>(0.021)</td>
<td>(0.015)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Number of Treated</td>
<td>732</td>
<td>723</td>
<td>489</td>
<td>381</td>
<td>281</td>
<td>181</td>
<td>111</td>
</tr>
<tr>
<td>Number of Controls</td>
<td>2,782</td>
<td>2,747</td>
<td>1,822</td>
<td>1,298</td>
<td>869</td>
<td>509</td>
<td>233</td>
</tr>
</tbody>
</table>

Source: Own calculations.
Notes: By using a Kernel algorithm and program psmatch2, we report bootstrapped standard errors (250 replications), the number of treated on the common support and the number of matched controls. See also notes of Table 2. Bold numbers refer to statistically significant coefficients.

Table 5 shows that the effect of exports on financial health (Score A) is positive and statistically significant from one year after export entry up to four years later; in fact, the growth of Score A, is higher for starters relative to control firms, for each year and always compared with pre-entry period. That growth advantage of starters, in financial health, is on average of 3 to 4 percentage points, compared with non-starters and reaches a maximum in the fourth year after exports begin.
These positive effects of new exporting activity seem to spread to efficiency (TFP growth of starters is also higher in the same four years period) and to other individual financial variables such as solvency (for two years), cash flow, financial debt share on total liabilities and bond share in total liabilities. In fact, there is some evidence that starters are more able to reach higher growth in cash flow and are also more able to obtain higher increase in the importance of financial debt and of bond debt, suggesting that exports improve firms’ ability to obtain financial credit. In addition, in the first two years after entry we notice starters to have a disadvantage in what concerns the growth of the return on assets (ROA); a similar fact is observed in cash flow growth for the same period. Such results could suggest that new exporters take some time to recover from sunk entry costs; moreover, the cash flow generating ability of starters begins to growth in a superior path only four years after export entry, thus “rewarding” new exporters for their “investment” in foreign markets. The fact that ROA never shows exporters’ superiority may be due to the fact that the increase in returns is inferior to the increase in investing in assets associated with foreign competition.

At another level, other sign of increased financial health of starters is presented by the decreasing share of “trade credit” relative to domestic firms; in fact, some years after entry the new exporters clearly decrease their trade credit share, relative to domestic firms; thus, suggesting new exporters get higher abilities to finance themselves from banks or directly from the markets (bonds) and thus reducing their dependence from suppliers. In line with the arguments of Ganesh-Kumar et al. (2001), Campa and Shaver (2002), Greenaway et al. (2007) or Bellone et al. (2010) we also argue that exports may exert a positive effect on firm financial health, namely by a revenue diversification effect (by reducing exposure to demand-side shocks) and by a signaling effect to financial markets (reducing informational asymmetries). The very
fact of exporting could be a signal of efficiency given to creditors as only the best achieve to export. Nevertheless, one could always argue that the mere fact of exporting part of the production is not sufficient to trigger those beneficial effects, unless the export intensity reaches certain threshold; in order to discuss those arguments we present, in the next sub-section a more detailed analysis.

4.3.3. Heterogeneity in financial “learning” of new exporters

In order to take account of sectoral heterogeneity in the manufacturing industry we aggregated the initial 23 two-digit sectoral codes and 201 five-digit sectoral codes (the original INE desegregation) into five groups in a sectoral classification based on technological sophistication (in line with Pavitt, 1984 - adapted): Group 1 (Gr1) with the lowest technical sophistication (food, beverages and tobacco); Group 2 (Gr2) - (textiles, wearing apparel and leather); Group 3 (Gr3) - (wood, pulp, paper, printing and furniture); Group 4 (Gr4) - (chemicals, rubber, plastic, non-metallic goods, basic-metallic goods, fabricated-metallic goods and recycling sectors); Group 5 (Gr5) with the highest technical sophistication -(machinery, office machines, computers, electrical machinery, medical instruments, motor vehicles and other transport equipment).

Using these five groups we repeated the PSM-DID (only for the general financial health variable – Score A) for each of the sub-groups and we present the results in Table 6. The firms belonging to industries of highest technological-level (Groups 4 and 5) are the only ones that show positive effects of exports on financial health; moreover such benefits are higher for the most technologically developed group of firms (Group 5). Given the fact that exporters of these kind of products sell mainly to developed markets, we argue these firms are more able to take advantage of the contact with financially more developed markets (than their own) and with clients less financially constrained.
At another level, we also divided firms according to their size ("small" firms with less than 20 employees and “other” firms with more than 20 employees) and performed for each group the correspondent PSM-DID. Results of Table 7 show clearly that only starters of small size benefit (financially) from beginning to export; this could mean that the “other” starters, given their superior dimension, have (even prior to exporting) a healthier financial situation, which is not improved by sales abroad.

Finally, in order to answer to the question of the last sub-section, we perform a last robustness check by splitting starters in accordance with their export intensity level in the first two years⁷; results of Table 8 show that to trigger the beneficial effects of

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⁷ We divide starters in two groups: one obtaining export intensity higher than 15% in the two first years of exporting; the other with export intensity lower than 15%.
exports there is no threshold of export intensity needed. These results have important policy implications given that they suggest that the simple fact of beginning to export is sufficient to improve rapidly the financial health of starters.

Table 8 - PSM-DID for different export intensity groups and for Score A

<table>
<thead>
<tr>
<th></th>
<th>(t / t-1)</th>
<th>(t+1 / t-1)</th>
<th>(t+2 / t-1)</th>
<th>(t+3 / t-1)</th>
<th>(t+4 / t-1)</th>
<th>(t+5 / t-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High intensity starters</td>
<td>-0.01(^*) (0.011)</td>
<td>0.012(^*) (0.013)</td>
<td>0.010(^*) (0.014)</td>
<td>0.026(^*) (0.019)</td>
<td>\textbf{0.032}(^**) (0.021)</td>
<td>-0.020(^*) (0.030)</td>
</tr>
<tr>
<td>Low intensity starters</td>
<td>0.015(^*) (0.014)</td>
<td>\textbf{0.011}(^**) (0.08)</td>
<td>\textbf{0.016}(^*) (0.012)</td>
<td>\textbf{0.026}(^*) (0.015)</td>
<td>0.029(^*) (0.028)</td>
<td>0.005(^*) (0.024)</td>
</tr>
</tbody>
</table>

Source: Own calculations
Notes: See Table 2

5. Conclusions

This paper belongs to the recent stream of the literature that studies the links between exports and financial constraints. Given that the measure of financial constraints is still far from consensus, we propose a new way to assess the degree of financial constraint, in a development of the multivariate index proposed by Musso and Schiavo (2008). Our main goal is twofold, at one hand we investigate whether limited access to external financial resources may prevent firms from exporting, and at another hand, whether internationalization has any positive effect on financial health. Methodologically, we present, for the first time, a propensity score matching with difference in differences in order to evaluate the effects of new exports on the financial health of firms, overcoming the main handicaps of previous studies on these subjects.

We find consistent evidence that the least credit-constrained firms are more able to begin exporting. In fact, export starters display better financial health both statically and dynamically than their non exporting competitors, even before they start to export. Complementarily, we also found that internationalization leads to faster improvements in the financial health of starters. Such positive effects are especially important for small
firms belonging to the most developed technologically sectors and do not seem to require a significant threshold of export intensity.

In terms of policy evaluation these findings seem to justify the public support to new exporters given the positive properties that exports generate on financial variables. Nevertheless, several issues need further discussion; here we highlight two: at one hand, the assessment on the quantitative influence of financial constraints on firm-level exports both at intensive and extensive margins, at the other hand, the qualitative study of the specific channels through which firms improve their financial situation.
Appendix A

<table>
<thead>
<tr>
<th>Score A</th>
<th>Share of firms for each Score level</th>
<th>Index of technological sophistication (1 is maximum)</th>
<th>Liquidity Index (1 is maximum)</th>
<th>Solvency Ratio</th>
<th>ROA</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.1%</td>
<td>50%</td>
<td>24%</td>
<td>8%</td>
<td>4%</td>
</tr>
<tr>
<td>3</td>
<td>1.5%</td>
<td>49%</td>
<td>84%</td>
<td>2%</td>
<td>8%</td>
</tr>
<tr>
<td>4</td>
<td>11.6%</td>
<td>54%</td>
<td>86%</td>
<td>13%</td>
<td>6%</td>
</tr>
<tr>
<td>5</td>
<td>27.4%</td>
<td>55%</td>
<td>82%</td>
<td>22%</td>
<td>6%</td>
</tr>
<tr>
<td>6</td>
<td>31.8%</td>
<td>59%</td>
<td>100%</td>
<td>30%</td>
<td>8%</td>
</tr>
<tr>
<td>7</td>
<td>20.5%</td>
<td>60%</td>
<td>78%</td>
<td>28%</td>
<td>10%</td>
</tr>
<tr>
<td>8</td>
<td>6.4%</td>
<td>66%</td>
<td>96%</td>
<td>27%</td>
<td>12%</td>
</tr>
<tr>
<td>9</td>
<td>0.7%</td>
<td>68%</td>
<td>90%</td>
<td>24%</td>
<td>13%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>58%</td>
<td>85%</td>
<td>22%</td>
<td>8%</td>
</tr>
</tbody>
</table>

Source: Own calculations

References


