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# THE EFFECTS OF EXPORT AND R&D STRATEGIES ON FIRMS' MARKUPS IN DOWNTURNS: THE SPANISH CASE

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***Abstract***

*The Spanish economy was one of the most hardly hit by the Great Recession in the Euro Area. It suffered a huge decrease in GDP (affecting especially internal demand) and in business and enterprises R&D expenditures, and experienced an important increase in exports as regards the pre-crisis years (the so-called Spanish "miracle"). The incorporation of Spanish SMEs into exports has been spectacular since 2008. Further, this has coincided with a drop in markups (stronger for SMEs). Our main objective is uncovering whether SMEs export and R&D participation strategies have aided to offset their fall in markups. We obtain that exporting helps SMEs to balance the decrease in markups, especially in downturns, and increases the likelihood to continue in operation. Contrarily, financial constraints and recessive demand have a negative impact on SMEs continuing prospects. Finally, we find evidence that SMEs export participation was a response to the fall in domestic demand (the "venting out" hypothesis in Almunia et al., 2018).*

**Keywords:** Export, research and development, markups

## *1. Introduction.*

The Great Recession that began by late 2007 constituted a significant shock for most of the western economies. Among these economies, countries in south Europe, including Spain, were more hit. The financial crisis, the burst of the housing bubble and the risk premium of the public and private debt plunged Spain into a deep recession. In Figure 1 panel (a) we plot the evolution of the GDP in Spain, Germany and the Euro Area along the period 2000-2014, to provide evidence on the severity of the crisis in Spain.[1]

In the boom years, 2000-2008, the Spanish GDP grew substantially faster than that of the Euro Area and Germany (the accumulated growth rates over the period were 24.60%, 14.12% and 10.31%, respectively). The onset of the crisis had a critical impact on the GDP for the three economies considered. In just one year (2008-2009) the German GDP fell by 5.87%, that of the Euro Area by 4.60% and that of Spain by 3.84%. Nevertheless, the recovery path was much faster for the whole Euro Area and Germany than for Spain. Thus, in 2014 the GDP of the whole Euro Area was virtually at the pre-crisis level, and that of Germany was even 5.12% larger than in 2008. However, the Spanish GDP showed an ever-decreasing trend up to 2013, and it only started to show a mild recovery in the period 2013-14. Thus, in 2014 the GDP in Spain was still 7.57% lower than in 2008.

[Insert Figure 1 about here]

This scenario of fast growth during the 2000-2008 boom period and especially harsh downturn in the period 2008-2014 makes Spain a perfect laboratory to explore whether firms adopt different strategies in the boom and slump periods and, further, to analyse whether these strategies allow firms to survive or even gain from scramble times. Firm's strategic decisions is a complex process, that would entail future effects for

[1] We compare Spain with Germany, as it is the largest economy in the European Union and traditionally considered an export champion, and with the Euro Area as this is natural area of reference for Spain. Spain shares with the other countries in the area, among others, a common currency, monetary policy and trade policy. The data on GDP and exports have been extracted from AMECO database, European Commission (https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/macro-economic-database-ameco/ameco-database_en). The data on BERD expenditure correspond to the series of Intramural R&D expenditures of business and enterprises from EUROSTAT (https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=rd_e_gerdtot&lang=en).

performance. During downturns, businesses face a key dilemma (Chastain 1982; Deans *et al.* 2009), as firms might need to cut costs in order to survive at the risk of reducing capacity, and, on the other hand, businesses might also need to maintain bigger capacity, and thereby incur higher costs in the short-run, to preserve the capability to adapt when the upturn comes and gather opportunities for long-term value creation, Kitching *et al.*, 2009. (Kitching, J., Blackburn, R., Smallbone, D., Dixon, S., 2009. Business strategies and performance during difficult economic conditions. URN09/1031.))

There are different approaches to describing how firms adapt under recession conditions. One view argues that incumbent firms suffer from organizational inertia, which prevents them from adapting to new, hostile environmental conditions. Alternatively, others point that in recessions firms are more willing to innovate or engage in foreign trade, as the opportunity costs of not undertaking such actions are lower than during more buoyant times (Geroski and Gregg 1997). In general, firms' strategies might imply retrenchment or increasing investment, or the combination of both.[2]

Among possible firms' strategies, in Figure 1, panels (b) and (c), we show the evolution of exports and business and enterprises R&D expenditures (BERD expenditures, hereafter). This reveals that the analysis of these two strategies in Spain is very interesting as they follow different patterns to other countries in the same economic area. Furthermore, we consider the joint analysis of these two strategies as firms' R&D strategies affect the profitability of exporting and firms' exporting strategies affect the profitability of performing R&D.

During the boom, the average annual growth rate of exports in the Euro Area and Germany was higher (4.52% and 6.29%, respectively) than in Spain (3.58%). However,

[2] It is important noting that many of the studies report the perceptions and actions of surviving firms, and therefore might suffer from a survivor bias, Kitching *et al.*, 2009. This points to the need to consider all results on firms actions conditional on surviving.

after the initial trade collapse (2008-09), and the consequent reduction in exports (exports fell in the Euro Area, Germany and Spain by 15.47%, 18.32% and 12.14%, respectively), Spanish exports exhibited a remarkable strength. They grew at a similar rate than in Germany, considered an export champion, and at a faster pace than in the whole Euro Area (the annual growth rates between 2009-2014 were 5.07%, 6.1% and 6.02% for the Euro Area, Germany and Spain, respectively). Furthermore, it is noteworthy to remark that in Spain the annual growth rate of exports during the slump was more than 1.5 times larger than during the boom.[3]

As it is possible to observe in panel (c) of Figure 1, during the boom period the accumulated growth of BERD expenditures in Spain tripled that of the Euro Area and was almost four times that of Germany (BERD expenditure grew by an accumulated 67.65% in Spain and 22.89% and 17.45% for the Euro Area and Germany, respectively). In contrast, in the slump period, whilst BERD expenditures continued growing in Germany and the whole Euro Area, in Spain they fell by an accumulated rate of 18.07% between 2008 and 2014.

[Insert Figure 2 about here]

Focusing in the case of Spain, in Figure 2 we plot the evolution of the internal demand.[4] As GDP, exports and BERD, internal demand steadily grew during the period 2000-2008. The accumulated growth of internal demand (24.40%) was quite similar to the growth in GDP. However, the Great Recession hit tougher the internal demand than GDP and so it accumulated a 16% loss between 2008-14 (in comparison to the 7.57% reduction in GDP). Meanwhile, the exports of goods displayed a quite striking and different path as it can be seen in Figure 2. After a significant reduction in real exports

[3] This spectacular growth in exports has been coined as the "Spanish miracle" (Eppinger et at., 2017).

[4] As in Almunia *et al.* (2018), internal demand is calculated as final consumption expenditure of households and non-serving institutions serving households plus investment plus acquisition of public administrations minus imports. We extract the data from AMECO database.

during the global trade collapse between 2008-09, Spanish exports of goods grew at an even faster pace in the period 2009-14 than during the pre-recession period. During the five years between 2009-14 the yearly growth of exports (5.74%) was higher than in the eight years between 2000-08 (3.79%). Two possible explanations have been proposed for this phenomenon. On the one hand, supply side factors contributing to increasing competitiveness. On the other hand, the so-called "venting out" hypothesis (see Almunia *et al.*, 2018 and de Lucio *et al.*, 2019), i.e., the huge progress in exports as a reply to the downfall in internal demand.[5]

As for BERD, the start of the Great Recession broke its increasing trend, accumulating an 18% loss between 2008-14. The procyclical behaviour of BERD expenditures in Spain is compatible with the recent contributions by Ouyang (2011), Aghion *et al.* (2012) and Beneito *et al.* (2015), who argue that procyclicality of R&D may be explained by the existence of financial constraints. As Aghion *et al.* (2012) find for a sample of French firms, in the absence of credit constraints R&D investment behaves counter cyclically,[6] but becomes pro-cyclical as firms face sufficient credit constraints. As explained below, the Great Recession brought over an important episode of credit restrictions that contributed to worsen the financial health of Spanish firms, and among them SMEs were more severely affected.[7]

[5] Almunia *et al.* (2018) explore the possible link between domestic slump and export growth, and recognize that it is difficult to accommodate it in the benchmark of the modern trade models "a la Melitz" (Melitz, 2003) in which firms export participation is dependent upon productivity and firms' domestic sales and exports can be analyzed independently. De Lucio *et al.* (2019) argue that the observed evidence in export behavior could also be compatible with the capacity-constrained exporter model. This model predicts that in the event of a fall in demand, the resulting excess of capacity reduces the cost of producing goods for international markets, and consequently more firms find it profitable to export.

[6] According to the opportunity cost theory (Hall, 1991; Aghion and Saint-Paul, 1998) it might be optimal for firms to invest in R&D activities in recessive periods, since their opportunity cost in downturns will be at its lowest.

[7] See Carbó (2009) for an analysis of the Spanish credit crunch.

Firms' responses to the crisis, and among them firms R&D and exporting strategies, are necessarily conditioned by firm dimension. Thus, we observe significant differences between export and R&D strategies of SMEs and large firms in Spanish manufacturing from 2000 to 2014 (see Table 1): while most of large firms exported (93.27%), only 56.29% of SMEs did. In the same line, the proportion of large firms that undertook R&D was more than 50 percentage points higher than that for SMEs (73.35% and 22.50%, respectively). Finally, the percentage of firms that neither exported nor performed R&D was more than 10 times higher for SMEs (40.13%) than for large firms (3.82%).

[Insert Table 1 about here]

[Insert Figures 3 and 4 about here]

Further, in Figures 3 and 4, we plot the evolution of the percentage of SMEs and large firms exporting and undertaking R&D along with the evolution of internal demand during the period 2000-14.[8] In Figure 3 we be observe that during the boom period (2000-08) whereas the percentage of SMEs exporting grew by an accumulated rate of 8.14%, the percentage of large firms exporting fell by an accumulated rate of 3.39%. The start of the crisis reversed the decreasing trend observed for large firms and accelerated the pattern of growth observed for SMEs. Thus, the Great Recession brought a remarkable incorporation of SMEs to foreign markets: during the five years following the onset of the Great Recession, whilst the percentage of exporting SMEs grew by an accumulated rate of 22.63% that of large firms only grew by 4.53%.[9] This behaviour, for large firms and SMEs, but especially for SMEs, is compatible with the "venting out" hypothesis proposed by Almunia *et al.* (2018).

[8] The data on export participation and the percentage of firms undertaking R&D have been obtained from the ESEE. See the data section for a more detailed description of this database.

[9] De Lucio *et al.* (2019), using data on the universe of merchandise exporters, also find an important increase of the number of exporters in Spain during the period 2008-13.

As regards R&D, we observe that its evolution was significantly different from that of exporting (see Figure 4). On the one hand, the percentage of large firms undertaking R&D activities was quite stable regardless of whether the economy was in a boom or in a crisis phase, and its level was quite similar in 2000 and 2014 (from 2000-08 the accumulated growth of the percentage of large firms undertaking R&D fell by an almost negligible -0.06%; the same percentage increased 1.3% from 2008 to 2014). On the other hand, for SMEs, the start of the Great Recession slowed down the irregular trend of incorporation to R&D activities observed during the boom period. Whilst the percentage of SMEs performing R&D grew by an accumulated 11.85% in the boom period, the accumulated growth in the slump period was 7.55%.

[Insert Figures 5 and 6 about here]

The observed differences between the exporting and R&D strategies of Spanish manufacturing firms, particularly for SMEs, after the start of Great Recession, has to be considered in a scenario of increasing financial constraints. As we plot in Figure 5, the Spanish rate of growth of loans to non-financial institutions started decelerating in 2007, becoming negative by the end of 2009. This evidences that Spanish firms endured severe financial constraints since 2009 that become especially harsher from 2010 onwards. Unfortunately, we do not have individual data on credit applications and whether these were granted or denied. However, we may conjecture, following Almunia *et al.* (2018), that firms whose financial costs are higher are also more likely to suffer credit rationing. Following suit, Figure 6 shows the density functions for financial costs corresponding to both SMEs and large firms in manufacturing for the period 2000-14. The density function of large firms is almost entirely to the left of that corresponding to SMEs, suggesting that financial costs were larger for SMEs than for large firms, and so indicating that financial constraints were harder for these firms. These tighter financial constraints could explain the different export and R&D behaviours of SMEs during the crisis period. Facing both the need to adapt to the changing credit conditions and to the fall of internal demand, SMEs chose to spend their shrinking resources in internationalization strategies to compensate the decreased internal demand.

The Great Recession also had a significant impact on firms' markups (a major determinant of firms' profits), and its impact differed between large firms and SMEs. [10] In Figure 7, we plot the evolution of markups throughout the period analysed both for SMEs and large manufacturing firms. The figure suggests the existence of a positive relationship between firm size and markups, as those for large firms were higher than those of SMEs along the period studied. Furthermore, the markups show different patterns for SMEs and large firms over time. Those for SMEs remained almost unchanged during the boom period (between 2000-08 SMEs markups fell 1.22%). However, the Great Recession hit them quite hard, as from 2008-12 SMEs markups fell by an accumulated 18.18%. Finally, in the period 2012-14, we observe a moderated recovery of SMEs markups, growing by an accumulated rate of 3.73%. In contrast, large firms' markups fell both in the boom and in the slump period. The accumulated reduction in large firms' markups during the 2000-08 boom period was 6.14%; and, between 2008-12 it was 8.72%. The recovery in markups between 2012-14 (5.22%) was larger for large firms than for SMEs. The smaller magnitude of the reduction of markups for large firms during the crisis period suggests that large firms were better endowed to endure the negative effects of the crisis on markups.

[Insert Figure 7 about here]

The main aim of this paper is to analyse the role that the firms' strategic decisions of exporting and/or performing R&D have on their ability to affect markups. We explore whether these strategies can contribute to moderate the severe reduction in markups observed since the onset of the Great Recession. Further, as we observe that the impact

[10] We calculate markups using the methodology proposed by De Loecker and Warzynski (2012).

of the crisis was especially severe on SME's markups, we seek to provide evidence on possible differential effects between large firms and SMEs.

The empirical literature analysing the effects of firms' export strategies on their markups is scarce. Probably, the most influential reference is De Loecker and Warzynski (2012) that, after proposing a new method to calculate markups, show, using a sample of Slovenian firms, that exporters enjoy a positive markup premium over non-exporters. However, using the same methodology to calculate markups but with data for Hungary, Hornok and Muraközy (2019) do not find any evidence of higher markups for exporters. However, none of these works explore the mediating role of firm size in the relationship between firms' markups and export strategies, and the role of demand conditions.[11] As for the analysis of the relationship between innovation strategies and firms' markups, Cassiman and Vanormelingen (2013) find a positive association between innovation activities and markups using data for Spain. Nevertheless, to the best of our knowledge, this is the first paper analysing the joint effect of firms' R&D and export strategies on markups and, in addition. Further, we also consider the demand conditions related to the business cycle.

In a second step, and based on the evidence that exporting and R&D strategies contribute positively to firms' markups and may help to maintain markups in slumps, we will also explore the firms' and market characteristics that encourage the adoption of exporting or R&D strategies. With this objective, we estimate a *bivariate probit* model of the joint decisions of exporting and undertaking R&D. In this analysis, we pay special attention to whether firm size mediates the effect of the cycle and financial constraints as key variables determining these strategies. From this evidence, we can provide

[11] For Spain, Moreno and Rodríguez (2004, 2010) using a different methodology and data for the 1990s conclude that exporters enjoy higher markups than non-exporters.

conclusions that might help in the design of economic policies and firm strategies to better cope with adverse economic conditions.

It is important to acknowledge that in the analysis of the effects of firms' export and R&D decisions on markups and in the analysis of the determinants of R&D and export decisions, we only observe markups, and export and R&D decisions for firms continuously in operation (and not for those that bankrupted or shut down in previous periods). We will consider this potential bias by using Heckman's methodology. Furthermore, this analysis provides interesting insights on the role of exporting and R&D strategies as determinants of firm continuing in operation.

To anticipate concisely the main results, we find that for SMEs, exporting pays higher returns than R&D activities in terms of markups, especially during downturns. Further, exporting has also improved SMEs continuing in operation prospects. However, these prospects have been negatively hit by financial constraints and recessive demand conditions. These two factors have also had a negative impact on large and SMEs decisions to undertake R&D. Finally, our results confirm that the remarkable increase in SMEs export participation was a reaction to the fall in domestic demand (the so-called "venting out" hypothesis; Almunia *et al.*, 2018). Contrarily, for large firms, the relevant strategy to improve markups is performing R&D activities. Further, we also get that markups are less sensitive to demand conditions for large firms (as compared to SMEs). Finally, large firms' continuing prospects are also more related to R&D activities, are less sensitive to both financial restrictions and recessive demand conditions, than those for SMEs.

The remainder of the paper is organized as follows. In section 2, we describe the data and perform a brief description of the average estimated markups for different firms' categories depending on their size and export and R&D strategies. In section 3, we present the methodology for estimating the production functions, Total Factor Productivity, and markups. Section 4 reports our results for the markups equation, the decisions to export and carry out R&D activities, and firms' continuing in operation. Finally, section 5 concludes.

## *2. Data.*

In this study, we use a firm-level panel data set drawn from the Spanish Survey on Business Strategies (ESEE) for the period 2000-2014. The selected period allows considering both the boom phase (2000-08), and the slump period that occurred after 2008. The ESEE is a yearly survey, carried out by the SEPI Foundation, which is representative (by industry and size) of the manufacturing sector in Spain.

The sampling design of the ESEE is as follows. No firms with employees below 10 are included in the survey. Firms with 10-200 employees (SMEs) are randomly included, being about 5% of the population of firms within this size range in 1990. All firms bigger than 200 workers (large firms) are invited to contribute in the survey, with a participation of about 70% in 1990. To minimize attrition in the initial sample, important efforts have been conducted. Thus, annually new firms are incorporated with the same criterion of the base year to preserve the sample representativeness across time.[12]

In our work, we drop out all firms that do not provide information on the relevant variables used in the analysis. Therefore, after cleansing those observations, we have a main working sample of 16,852 observations that correspond to 2,442 firms.

To obtain the firm's status for exporting and performing R&D from the survey we use the following two questions. The question to classify a firm as exporter is: 'Indicate if the firm has exported this year (including exports to the European Union), either directly or through other firms in the same group'. Firms are classified as R&D

[12] See https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp for more details.

performers using this question: ‘Indicate if the firm has performed or contracted any R&D activity this year’.

After the thorough description of Spanish firms exporting and R&D strategies in the introduction, we present the markups averages for all firms, by size breakdown, and by firms’ export and R&D strategies. We can observe in Table 2, that the average markups for all firms was 1.03, being the markups 1.02 and 1.20 for SMEs and large firms, respectively. Therefore, we confirm that large firms enjoyed higher markups. As regards to the relationship between exporting and performing R&D strategies and markups, we observe that: i) for both size groups, the lowest markups corresponded to firms not exporting and not carrying out R&D; ii) for both size groups, firms exporting were able to set higher markups as compared to firms not exporting and not undertaking R&D activities; and, iii) the highest markups correspond to firms that performed R&D activities.

[Insert Table 2 about here]

### *3. Methodology: Production function, TFP and markups estimation.*

We assume that firms produce using a *translog* technology:

$$\begin{aligned} y_{it} = {} & \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \\ & \beta_{l2} l_{it}^2 + \beta_{k2} k_{it}^2 + \beta_{m2} m_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + tfp_{it} + \eta_{it} \end{aligned} \tag{1}$$

in this expression, $y_{it}$ is the natural log of production (output in real terms) for firm $i$ in period $t$, $l_{it}$ represents the natural log of labour (measured as the number of total hours worked in the firm, in thousands), $k_{it}$ is the natural log of capital and $m_{it}$ is the natural log of intermediate inputs (materials in real terms).[13] In relation to the unobservable variables,

[13] To measure capital, we use capital stock in real terms constructed using the perpetual inventory method and based on current replacement value net of depreciation and adjusted by capacity utilization. Capacity utilization refers to the percentage of the firm’s capacity utilized.

$tfp_{it}$ represents the log of firm's productivity (TFP; not observable by the econometrician, but firms can observe or predict it) and $\eta_{it}$ is a standard i.i.d. error term (neither observable nor predictable by the firm). A central advantage of our dataset is that it is possible to build firm level price indices for output and materials.[14] These firm level price indexes imply an important advantage over more traditional TFP measures ("revenue" TFP) that deflate nominal variables using industry specific price indexes.

In equation (1), as it is standard in the related literature, we assume that capital is a dynamic input that evolves according to a given law of motion, and that is not correlated with current productivity shocks (for this reason capital is termed a state variable in the literature), while employment and materials are inputs that might be adjusted when the firm perceives a shock in productivity (i.e., these inputs are termed variable inputs).[15]

To obtain consistent estimates of input elasticities and estimates of TFP residuals, we follow Wooldridge (2009), who argues that both the semi-parametric Olley and Pakes (1996) and Levinsohn and Petrin (2003) estimation methodology can be reconsidered as comprising two equations that can be jointly estimated by GMM using the appropriate instruments: the first equation deals with the problem of endogeneity of non-dynamic inputs; and, the second equation tackles the issue of the law of motion of productivity.

[14] Output and materials in real terms are computed using firm-specific price indexes for output and materials, respectively. The price indexes, of the Paasche-type, are constructed starting from the percentage price changes in output and the percentage price changes in materials reported by the firm in the ESEE. Capital in real terms is obtained by deflating capital at current replacement values by a price index of investment.

[15] The law of motion for capital is as follows: $k_{it} = (1-\delta)k_{it-1} + I_{it-1}$. It implies that the capital used by a firm in a specific period $t$ was contracted in year $t$–1 (this means assuming that the firm needs a full production year for capital to be ordered, received and fixed before being in operation). Labour and materials (unlike capital) are decided in year $t$, that is the period in which they are utilised by the firm (hence, they can be a function of $tfp_{it}$). These timing assumptions suggest that both labour and materials are taken as non-dynamic inputs (differently to capital).

For the first equation, to solve the problem of endogeneity of labour and materials, we follow Levinsohn and Petrin (2003) and proxy for "unobserved" firm productivity by inverting the materials demand function.[16] Then, productivity can be expressed in terms of observables. For the second equation, to proxy for "unobserved" firm productivity, we assume an endogenous Markov process for the evolution of productivity (De Loecker, 2013):

$$tfp_{it} = f(tfp_{it-1}, E_{it-1}, R\&D_{it-1}) + \xi_{it} \qquad (2)$$

where *f(.)* is an unknown function that relates productivity in *t* with productivity in *t-1* and with past export ($E_{it-1}$) and R&D choices ($R\&D_{it-1}$), and $\xi_{it}$ is an innovation term uncorrelated with capital ($k_{it}$).[17] Further details on the estimation method of the production function in (1) can be found in the Appendix I.

In this paper, the production function is estimated individually for each of the twenty manufacturing sectors (*s*) in the ESEE.[18] This delivers the estimates of the production function parameters in (1), and the firm-specific productivity estimates ($tfp_{it}$) as a residual. The mean estimated sector specific input elasticities derived from (1) are presented in Table 3.[19]

[Insert Table 3 about here]

The estimation of firms' markups follows the procedure proposed by De Loecker and Warzynski (2012). This method estimates markups using a "production

[16] To invert the materials demand function, we assume that this function is strictly monotonic in unobserved productivity.

[17] The non-parametric components, as the function *f(.)*, involved in the implementation of Wooldridge (2009) method are specified by third degree polynomials.

[18] In the ESEE there are 20 manufacturing sectors according to the NACE classification.

[19] Considering all sectors in Table 3, the average elasticity for materials ($e^{m}_{its}$) is 0.639, for labour ($e^{l}_{its}$) 0.235 and for capital ($e^{k}_{its}$) 0.050.

function approach", as it does not require making any assumption on firms' demand systems or about how firms compete. This methodology assumes that: i) there exists at least one variable input in the production function; and, ii) firms behave as cost minimizers.

In this approach, markups are defined as the ratio of the firm's output price ($P_{it}$) over its marginal cost ($MgC_{it}$). De Loecker and Warzynski (2012) show that markups can be calculated as the ratio of the output elasticity of a variable input to the revenue share of the cost of that input. This formula is derived from the first order condition of the firm's cost minimization with respect to this variable input. We calculate markups using the elasticity of materials, as labour (which has also been considered a variable input) may be subject to more frictions. Hence, our markups measure is the following:

$$\mu_{it} = e_{its}^{m} \big/ sh_{it}^{m} \qquad (3)$$

where $e_{its}^{m}$ is the output elasticity of materials and $sh_{it}^{m}$ is the revenue share that the cost of materials represents over firms' total output. Notice that the output elasticity of materials derived from (1) varies across firms and sectors ($s$) and it is given by the following derivative from the production function in (1):

$$e_{its}^{m} = \delta y_{it} / \delta m_{it} = \beta_{ms} + 2\beta_{m2,s} m_{it} + \beta_{lm,s} l_{it} + \beta_{km,s} k_{it} \qquad (4)$$

It is relevant noticing that with *translog* production functions, variation in markups depends not only on revenue shares but also on firms' specific elasticities.[20]

Under perfect competition, prices are equal to marginal costs and, hence, markups originally defined as prices over marginal costs, are equal to one. Differently, under imperfect competition, markups are above one since firms have market power to set prices above marginal costs. However, in empirical applications of this methodology for

[20] In a more standard Cobb-Douglas specification of the production function, within industry markups variation only depends on revenue shares.

obtaining markups estimates, we are typically more interested in the between and within variation of markups among firms undertaking different strategies than in the level of markups *per se* (De Loecker and Warzynski, 2012).

## *4. Empirical approach and estimation results.*

### *4.1. The effects of firms' export and R&D strategies on markups.*

To analyze how firms' export and R&D strategies affect firms' markups, and whether these effects are mediated by firms' demand conditions, we estimate the following dynamic reduced-form equation:

$$\ln \mu_{it} = \beta_0 + \beta_1 \ln \mu_{it-1} + \beta_2 X_{it-1} + \beta_3 R\,\&\,D_{it-1} + \beta_4 \text{Recess\_Demand}_{it-1} + \gamma Z_{it-1} + s_j + \delta_t + u_{it} \tag{5}$$

where $\ln\mu_{it}$ is the log of the markup for firm $i$ in period $t$. Our dynamic specification includes $\ln\mu_{it-1}$ to capture persistence in firms' markups. $X_{it-1}$ and $R\&D_{it-1}$ are dummy variables capturing whether the firm exported and/or performed R&D in period $t$-1. Thus, $\beta_2$ and $\beta_3$ measure, respectively, the percentage markup premium associated to exporting and undertaking R&D, respectively. *Recess Demand* is a dummy variable that proxies for the of firms' demand. We build this dummy variable from an index of market dynamism. In the ESEE, firms are requested to evaluate the situation (recession, stability or expansion) in their five more relevant markets. Using this information, the ESEE calculates an index of market dynamism, as a weighted average of the answers to this question. This index ranges from 0-100 (where values from 0 to 35 correspond to recessive demand; values from 36 to 65 to stable demand; and, values from 66 to 100 to expansive demand). Since we are interested in whether firms' R&D and exporting strategies help to moderate the effects of possible adverse effects of the crisis on markups, from this index we build the *Recess_Demand* variable, that takes value 1 for values of the index between 0 and 35.[21] The main advantage of this variable with respect to macroeconomic variables for the cycle is that it provides information at the firm level about the evolution of their main markets. Therefore, it is a closer proxy for the specific market conditions faced by firms. $Z_{it-1}$ is a vector of firm level control variables including: a dummy variable for foreign capital participation, a dummy variable for size class (the reference category is SMEs -firms up to 200 workers) and the log of age. We also include year and industry dummies, $\delta_t$ and $s_j$ respectively. Finally, $u_{it}=\alpha_i+e_{it}$ is a compound error term, where $\alpha_i$ represents individual unobserved heterogeneity and $e_{it}$ is an idiosyncratic error term.

In the estimation of equation (5) we tackle two econometric issues. The first is related to the treatment of firm unobserved heterogeneity. Unobserved individual effects ($\alpha_i$) are correlated with regressors as by construction they are correlated with lagged markup (included as explanatory variable to capture markup persistence). We control for firms' unobserved heterogeneity using the correlated random effects methodology developed by Blundell *et al.* (1999, 2002). Therefore, we will assume that $\alpha_i$ can be modelled as:[22]

$$\alpha_i = \alpha_0 + \alpha_1 \ln \mu_{i,Mean,0} + \pi_i \qquad (6)$$

[21] This variable can be considered as a firm specific demand shifter. Doraszelski and Jaumandreu (2013) also use this information to proxy for the business cycle in Spain. They show that in the 1990s, this variable mirrored the macroeconomic cycle, i.e., in periods where the economy was growing firms tended to report that their markets were in expansion. We confirm this for the period 2000-08, as the percentage of firms declaring a recessive demand is 17.88%, while in the period 2008-14 the percentage grows to 46.84%. We use the dichotomous indicator of recessive demand instead of the continuous recessive index (from 0 to 100) to ease the interpretation of the cross-product variables of the dummy recessive demand and the firms' business strategies of exporting and/or performing R&D (that are also dichotomous variables). Further, replacing the recessive demand indicator by the continuous recessive index does not qualitatively change our results.

[22] Blundell *et al.* (1999) suggest that permanent individual effects might be captured by the entry pre-sample mean of the dependent variable, which acts as a sufficient statistic for unobserved firm heterogeneity.

where $\ln \mu_{i,Mean,0}$ is the pre-sample mean of the dependent variable; and $\pi_i | \left(\ln \mu_{i,Mean,0}\right) \sim Normal\left(0, \sigma_\pi^2\right)$. Since our sample starts in 2000 and most of our regressors are lagged one period, to avoid potential simultaneity bias, we consider as pre-sample years 1997 and 1998.[23]

The second econometric issue is related to the potential existence of selection bias in the estimation produced by non-random attrition of firms. As we observe markups conditional on firm remaining in operation up to period *t*, estimates in the markups equation (5) may suffer from selection bias, if firms continuing in operation are simultaneously more likely to export and perform R&D and have higher markups. If this were the case, we would be facing an endogenous firms' exit process. We tackle this problem using a two-stage sample selection correction procedure. The first stage consists in estimating a probit model for the probability of firms' in operation up to period *t*, conditional on being active up to period *t*-1. From the estimation of this equation, we calculate the Heckman's lambda of continuing in operation.[24] In the second stage, we include this term as an additional regressor in the estimation of equation (5). Since the estimation of the probit model of firms continuing in operation provides interesting insights for the exploration of the effects of firms' R&D and exporting strategies in a period of crisis, we devote section 4.2 to the analysis of the results of this equation.

In Table 4 we display the results from the estimation of equation (5). A common result in the estimation of all the specifications of equation (5) is that the pre-sample mean of log markups, $\ln \mu_{i,Mean,0}$, is positive and significant (both for SMEs and large firms)

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[23] We have also experimented by considering as pre-sample years 1997, 1998 and 1999, or 1996, 1997 and 1998. However, as results were similar, we opted for a more parsimonious approach.

[24] This term is generically calculated as the ratio of the density over the distribution function of a normal distribution ($\phi(Z\theta)/\Phi(Z\theta)$), in which the argument ($Z\theta$) is the index function from a *Probit* model with a vector of regressors *Z*.

suggesting that persistent firms' effects are relevant to explain firms' markups. A possible interpretation of this positive sign is higher quality or managerial ability. Furthermore, the estimate corresponding to the Heckman's lambda term is positive and significant in all the specifications reported. One can infer two implications from this result: on the one hand, the fact that the Heckman's lambda is significant suggests the need of including it in the markups equation to avoid a sample selection bias; and, on the other hand, the positive sign suggests that unobservables improving firms' continuing prospects are positively correlated with their markups.

[Insert Table 4 about here]

Column (1) of Table 4 provides the estimates of the baseline specification of equation (5). The positive and significant estimates for lagged markups, $\ln\mu_{it-1}$, both for SMEs and large firms, suggests that there exists a high degree of persistence (state-dependence) in the evolution of markups for both groups of firms.

Our estimates in column (1) reveal that the rewards to export and R&D strategies differ between large firms and SMEs. Whilst for SMEs both exporting and performing R&D entail higher margins (markups rewards associated to exporting and performing R&D are 2.5% and 0.9%, respectively); for large firms, only performing R&D has a reward in terms of higher margins (2.5% higher margins). These effects, although smaller in size, are consistent with previous empirical evidence reported in De Loecker and Warzynski (2012) for Slovenian exporters, and Cassiman and Vanormelingen (2013) for Spanish innovators.[25] Finally, results in our baseline specification in column (1) indicate that facing a recessive demand has a negative impact on SMEs markups but not on those of large firms.

[25] Moreno and Rodríguez (2004, 2010) using data from the ESEE for the period 1990-00, and a different methodology to calculate markups, also find that exporters enjoy higher markups.

In column (2) of Table 5, we expand our baseline specification adding as additional regressor the log change of productivity. The aim is to explore whether the effects of export and R&D strategies on firms' markups operate through the price channel (i.e., the ability to charge higher prices -market power) or through the cost channel (i.e., gains in efficiency that reduce marginal costs allow firms increasing their markups if there is not a full transmission to prices). Since markups are defined as the ratio of prices ($P_{it}$) to marginal costs ($MgC_{it}$), taking logs we get $\ln\mu_{it}=\ln P_{it}-\ln MgC_{it}$. Therefore, as suggested by De Loecker and Warzynski (2012), we may use $TFP_{it}$ as a proxy for the inverse of $MgC_{it}$. Thus, including the log change of productivity as an additional regressor in our dynamic equation (5), the estimated coefficients in column (2) will capture the effects of firms' exporting and R&D strategies on firms' prices. Furthermore, the comparison of the estimated coefficients in columns (1) and (2) would allow to disentangle whether the effect of firms' export and R&D strategies on markups are driven either through higher productivity (cost channel) and/or the ability so set higher prices (price channel). Three cases are of interest in this comparison: i) similar positive estimated coefficients in columns (1) and (2) would suggest that the effects of firms' exporting and R&D strategies operate through the price channel; ii) higher positive estimated coefficients in column (1) than in column (2) would indicate that these firms' strategies operate both through the costs and price channels; and, iii) positive and significant estimates in column (1) and non-significant estimates in column (2) would imply that the considered firms' strategies act through the cost channel.

For SMEs, the estimated coefficient for exporting in column (2), 1.4%, is substantially lower than that in column (1), 2.5%. However, the estimated coefficient for R&D, while positive and significant in column (1), it is non-significant in column (2). These results suggest interesting differences in the channels through which exporting and R&D strategies operate on margins: on the one hand, higher margins for exporters are explained both through lower marginal costs and higher prices; on the other hand, higher markups for R&D performers seem to be only explained by increased efficiency (i.e. cost reductions).[26] For large firms, the similar size of the coefficients associated to R&D in columns (1) and (2) points to the price channel: R&D activities enhance large firms ability to set prices above marginal cots with the result of higher margins.[27] Finally, the similar size of the negative estimate for the *Recess_Demand* dummy for SMEs, in columns (1) and (2), indicates that the negative effect of demand slumps on markups operate through the price channel. In recessive periods, SMEs ability to set prices above marginal costs shrinks.

In column (3) of Table 4, we widen the baseline specification in column (1) including as additional variables the interactions between firms' strategies and the recessive demand dummy. The aim of including these interactions is to allow the impact of firms' exporting and R&D strategies to differ between expansive/stable and recessive demand periods. The estimates in column (3) confirm that whilst for SMEs both exporting and R&D pay higher markups, for large firms the only strategy that pays higher markups is performing R&D. The only significant difference that our estimation results suggest in column (3), as compared to the baseline, is that for SMEs rewards (in terms of higher markups) to exporting are larger in slump periods than in periods where firms perceive an expansive/stable demand (4.9% and 1.5%, respectively). Hence, exporting in recessive periods helps SMEs to mitigate the negative effects that downturns have on SMEs markups. For large firms, we do not find any evidence of different returns to export and R&D strategies between expansive/stable and recessive demand periods.

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[26] The higher prices set by exporting firms may arise from: quality differences in the products they export and/or a different elasticity of demand in foreign markets. Hallak and Sivadasan (2009) and Kugler and Verhoogen (2012) report evidence in favour of the higher quality of products sold by exporting firms.

[27] For instance, product innovation R&D may result in product quality upgrading or product differentiation. Factors that contribute to reduce the price elasticity of demand.

Finally, specification in column (4) is analogous to specification in column (2), but as in column (3) we allow the impact of exporting and R&D strategies to differ between expansive/stable and recessive demand periods. Recall that when including the log of TFP change (from *t*-1 to *t*), the estimated coefficients for the R&D and the exporting dummies capture the effects of these strategies on firms' prices. Further, comparison of the coefficients in column (4) with those in column (3) allows to explore whether the effects of R&D and exporting on markups accrue through the price and/or the cost channels.

From the comparison of results in columns (4) and (3) we observe that for SMEs, export activities have a positive on markups both in good times and bad times, as according to column (3), these markup rewards are higher in recessions, 4.9%, than in good times, 1.5%. Looking at column (4), we may conclude that while in good times higher markups for SMEs exporting are explained through enhanced productivity, in recession periods, both gains in efficiency and a higher ability to set prices above marginal costs contribute to explain higher markups (the increase in markups due to market power is 2.9%, and the remaining 2% can be attributed to enhanced efficiency). Further, and also for SMEs, performing R&D pays rewards in terms of higher margins regardless of the cycle. These rewards (about 0.09%), that are lower than those associated to exporting, accrue exclusively through increased productivity. As regards to large firms, performing R&D allows them to enjoy higher markups (about 2% larger) regardless of the cycle. These higher markups seem to have its origin exclusively in an increased ability of large firms to set prices above marginal costs (what might be related to the higher quality products obtained by innovations). Finally, neither in expansive/stable nor in recessive demand periods we get evidence of a positive effect of exporting on the markups of large firms.

As regards the control variables, we get that foreign participation only affects positively markups when firms' variation in TFP is not included, what might indicate that the effect of foreign participation acts through increasing firm's productivity (i.e. decreasing marginal costs) but not through increasing the firm's capacity to set prices above marginal costs. The effect of firm age is non-significant and the effect of the size dummy variable is either non-significant, or negative and significant in the two specifications that include variation in TFP.

***4.2. Specification and results of the continuing in operation equation.***

The continuing in operation equation, that we have used to correct for selection bias in the estimation of equation (4), has been specified as a probit model in which the dependent variable takes value 1 if the firm continues in operation in period $t$ and 0 otherwise. In order to analyze whether firms' exporting and performing R&D activities influence the decision of continuing in operation, we include as explanatory variables both past firms' export and R&D dummies. We also control for demand conditions by means of the firm's market recession index (that varies from 0 to 100, where 100 represents the most severe demand situation). Further, we include a variable measuring the degree of financial constraints faced by the firms. Since the financial crisis has gone hand in hand with an increase in the difficulty to access to credit (see Figure 5), our first best would have been proxying for financial constraints using a variable built on firms' credit applications and whether these credits were granted or denied. Unfortunately, this information is not available. Given this restriction, we assume, as in Almunia *et al.* (2018), that firms facing higher loan costs are also those suffering most from credit restrictions. Hence, we proxy for financial constraints using the firms' financial cost of loans with financial institutions. This cost is measured in deviations with respect to the average cost paid by other firms in the same year (see Beneito *et al.*, 2015; Mañez *et al.,* 2014).[28] Finally, we include a set of firm variables likely to affect firms continuing in operation prospects (see Esteve and Mañez, 2008; Esteve *et al*, 2004), such as TFP (in logs), firm size (proxied by a dummy variable) and firm age (in logs).

[Insert Table 5 about here]

The estimates of the probit model of firms' continuing in operation are reported in Table 5. Our estimates suggest that whereas exporting increases the SMEs likelihood of, for large firms better continuing prospects are associated to undertaking R&D. Both for SMEs and large firms, those with higher productivity are better endowed to continue active. Harsher financial restrictions or facing a recessive demand have a negative impact in SMEs continuing prospects but not in those of large firms. Further, our estimates suggest that foreign participation *per se* does not guarantee continuing in operation. Finally, we find evidence of positive duration dependence since the older the firm the better is its probability of continuing in operation.[29]

### *4.3. The determinants of firms' export and R&D strategies.*

In section 4.1, we found evidence suggesting that, both in boom and slumps, exporting and performing allow SMEs to enjoy higher margins. However, for large firms higher markups seem to be exclusively associated to performing R&D. Further, we found that for SMEs markups rewards from exporting are higher in the slumps than in the boom periods. Therefore, it seems convenient to explore which are the characteristics that make firms more prone to follow these strategies. The aim is providing policy makers with

[28] We have also tried with the alternative measure of calculating the cost of loans deviation with respect to the average of the sector in which the firm operates. In spite of results being qualitatively similar, we believe that our choice is more reliable since there may be sectors particularly affected by adverse borrowing conditions and this would not be reflected in a measure that uses sector averages for comparison.

[29] We find that foreign capital participation has a negative effect on firms' continuing in operation. This result has been found in previous studies with the ESEE data (see, for instance, Beneito *et al.*, 2015).

some recommendations to design policies that may encourage firms to pursue these strategies.

With this objective, we estimate by pseudo-simulated maximum likelihood (following Roodman, 2011) the *Heckman-bivariate probit* model described in equation (7):[30]

$$X_{it} = \begin{cases} 1 & if \quad \theta_0^X X_{it-1} + \theta_1^X R\&D_{it-1} + \theta_2^X \log(TFP_{it-1}) + \theta_3^X Financial\_Restrictions_{it-1} + \\ & \qquad \theta_4^X Growth\_Domestic\_Sales_{it-1,t} + \gamma^X Z_{it-1} + s_j^X + \delta_t^X + \varepsilon_{it}^X \geq 0 \\ 0 & otherwise \end{cases}$$

$$R\&D_{it} = \begin{cases} 1 & if \quad \theta_0^{RD} R\&D_{it-1} + \theta_1^{RD} X_{it-1} + \theta_2^{RD} \log(TFP_{it-1}) + \theta_3^{RD} Financial\_Restrictions_{it-1} + \\ & \qquad \theta_4^{RD} Recessive\_Index_{it-1} + \gamma^{RD} Z_{it-1} + s_j^{RD} + \delta_t^{RD} + \varepsilon_{it}^{RD} \geq 0 \\ 0 & otherwise \end{cases} \tag{7}$$

where $\theta_0$ controls for persistence in each strategy related to sunk costs; $\theta_1$ accounts for the fact the firms' R&D activities might enhance exporting and *vice versa* (Aw *et al.,* 2011); $\theta_2$ captures the potential existence of a self-selection mechanism (i.e., the most productive firms would start/continue exporting and performing R&D activities); $\theta_3$ captures the impact of firms' financial constraints on the likelihood of exporting or performing R&D; $\theta_4$ accounts for the effect of demand conditions; and, $Z_{it-1}$ is a vector of firm level control variables (a foreign capital participation dummy, log of age and the size dummy). We also include industry ($s_j$) and year ($\delta_t$) dummies. Finally, $\varepsilon_{it}$ is a composite error term that includes permanent individual unobserved heterogeneity and an idiosyncratic error term.

At this point, it is important to note that we use different variables to capture firms' demand conditions in the export and R&D equations. In particular, we conjecture that firm's R&D decision is related to the evolution of the overall demand of the firm,

[30] We name this estimation method as *Heckman-bivariate probit*, since the two strategies are estimated jointly and we correct for non-random selection into exports and performing R&D. We correct for sample selection as we only observe firms' choices for those continuing in operation.

including both domestic and export markets. Hence, in the R&D equation we proxy for firm's demand conditions using the *Recessive_index* variable, calculated as a weighted average of the firm's demand conditions in the five main market it serves (both domestic and/or foreign markets).

Nevertheless, in line Almunia *et al.* (2018), who find evidence of a negative relationship between changes in domestic sales and exports, we conjecture that firms' exports decisions might be particularly sensitive to the evolution of the domestic demand. To verify this hypothesis, in the export equation we include the variable *Growh_domestic_sales* (from period *t-1* to *t*).[31] Notwithstanding, this variable may suffer from a reverse causality problem in the export equation (see Almunia *et al.*, 2018): given the firms' production capacity, those increasing their exports would be reducing domestic sales. Therefore, there might be a negative spurious correlation between the variable *Growh_domestic_sales* and the firms' export decisions. To tackle this potential endogeneity problem, we implement a control function approach (Rivers and Vuong, 1988; Wooldridge, 2010) to instrument and test for this endogeneity bias. In the control function approach, the first step consists of regressing the variable *Growth_domestic_sales* on the instruments and the rest of exogenous regressors in the export equation. In this regression, the instruments must be significant to be valid. Next, in a second step, we include the residual from this regression as an additional regressor in the export equation. The statistical significance of this residual allows checking for the existence of an endogeneity problem for the variable *Growth_domestic_sales* (Rivers-Vuong endogeneity test). If this is the case, the inclusion of the residual would correct for the bias.

[31] As in Almunia *et al.* (2018), we also control for supply side factors, such as firms' TFP and financial restrictions.

In our case, we use two instruments for the variable *Growth_domestic_sales*: the average capacity utilization (in percentage) of non-exporting firms in the same sector and year than firm *i* (excluding the value for firm *i*), $\left(\textit{Mean Capacity Utilization}\right)_{it-1}^{-i}$; and, the average growth rate of domestic sales (in logs) of non-exporting firms in the same sector and year than firm *i* (excluding the value for firm *i*), $\left(\textit{Mean Growth Domestic Sales}\right)_{it-1,t}^{-i}$ . These instruments are exogenous to the firm's export decision. For the first one, we expect that a low usage of the production capacity of non-exporting firms in a sector would be indicative of a domestic slump. Therefore, we expect a positive correlation between the average capacity utilization in a sector and the real growth rate of domestic sales for a firm in that sector. For the second instrument, we anticipate a negative correlation between the average growth rate of domestic sales of non-exporters in a sector and the growth rate of domestic sales for a firm in that sector, as more competition for sales in the domestic market may decrease the sales growth rate for a particular firm in that market. We formally test for the validity of our instruments (see Table A.1 in the Appendix II). According to these results, both instruments are significant (taken individually and jointly) and show the expected signs. Thus, we will intrument the variable *Growth_domestic_sales* using the procedure explained.

Further, in the system of equations (7) we will deal with two additional econometric issues: individual unobserved heterogeneity and sample selection. To account for (correlated) individual unobserved heterogeneity we follow Blundell *et al.* (1999, 2002) methodology and include in the regressors set the pre-sample means of the corresponding dependent variable in each decision equation (i.e., the pre-sample means $\bar{X}_{i0}$ and $\overline{R\&D}_{i0}$).[32] To control for sample selection we include in the export and R&D

[32] As we start estimation in 2000 and our regressors are lagged one period, we use as pre-sample years 1997 and 1998.

equations the Heckman's lambda sample selection bias correction term (calculated in previous section).

[Insert Table 6 about here]

In Table 6 we present the coefficient estimates from the *Heckman-bivariate probit* model for the decisions of exporting and performing R&D. In the results reported we do not instrument the *Growth_domestic_sales* variable as we reject the null of endogeneity of this variable based on the Rivers-Vuong test.[33] After ruling out possible reverse causality problems between export decisions and firms' growth in domestic sales we proceed to discuss the results.

First, the positive and significant correlation coefficient ($\rho_{Export\text{-}R\&D}$) confirms the appropriateness of estimating jointly the export and R&D decisions. As regards estimates for the selection correction terms (Lambda cont. operation), they are statistically significant only for SMEs. The positive sign of the selection correction term for SMEs in the R&D equation indicates that unobservable factors that make SMEs' continuing in operation more likely also affect positively their propensity to perform R&D. The negative sign of this term in the export equation suggests that unobservables that improve SMEs' continuing prospects decrease their likelihood of exporting. The fact that the selection mechanism is in operation only for SMEs is evidence suggesting that exporting is a strategy that SMEs may consider as a safeguard when facing risk of failure. Consequently, when failure is less of a problem, SMEs may have less incentives to enter foreign markets.

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[33] At the bottom of Table 6 we report the results for the Rivers-Vuong endogeneity test. As the retrieved residual from the first step instrumentation procedure is non-significant in the export equation, we may conclude that the variable *Growth_domestic_sales* does not suffer from endogeneity. We reinforce this conclusion by testing the second condition for their validity. We re-estimate our specification augmenting the export equation with the residual and the *l*-1 instruments (in our case, *l*-1 is 1, as the number of instruments is 2). We provide an F-test for the exclusion of the IVs in the export equation, and report this result at the bottom of Table 6. As before, we cannot reject the null of excluding them in the export equation.

The positive and significant signs of lagged exports and R&D in the exports and R&D equations, respectively, should be interpreted as an evidence of persistence (state dependence) on exports and R&D. This persistence could arise from the sunk costs associated to both firms' strategies. It is worth to note, that persistence is stronger in exports than in R&D (both for large firms and SMEs), and more intense for large firms than for SMEs. Further, the positive and significant estimates for the pre-sample means for export and R&D participation in their corresponding equations, suggest the existence of unobserved fixed effects that affect the probability of exporting and performing R&D. These unobserved permanent fixed effects are more important for SMEs than for large firms both in the exports and the R&D equations.

Furthermore, since lagged firm's export (R&D) status has a positive and significant coefficient in the R&D (export) equation, our estimates also reveal that exporting affects positively the decision to perform R&D activities and *vice versa*. Besides, both for large firms and SMEs, the estimates for lagged exporting in the R&D equation (0.394 and 0.499 for SMEs and large firms, respectively) are larger than that for lagged R&D in the exports equation (0.302 and 0.195 for SMEs and large firms, respectively). This indicates that past export participation is a more relevant factor on firms' R&D decisions than past R&D participation on firms' exports decision. Moreover, whereas the influence of past exporting on the R&D decision is bigger for large firms than form SMEs, the opposite is true when analysing the influence of lagged R&D participation on the exports decision. Our estimates also suggest for both size groups that the (previously) more productive firms self-select into exports and R&D activities.

As regards the variables that capture financial constraints, we get that financial restrictions are only binding for R&D investments (both for SMEs and for large firms). In relation to demand conditions, our results uncover that a slump in domestic sales boosts SMEs' export decisions (the coefficient on the variable *Growth_domestic_sales* is negative and significant in the export decision for SMEs, but not for large firms). This confirms the "venting out" hypothesis examined in Almunia *et al.* (2018) and de Lucio *et al.* (2019), but only for SMEs. Further, for both groups of firms, facing a recessive cycle discourages firms R&D activities (i.e. firms' R&D decisions behave procyclical).

Finally, among the results for other firm-level control variables only the variables foreign capital participation in the export equation and age in the R&D equation render statistical significance. The positive sign for foreign capital participation indicates that being participated by foreign investors may facilitate access to foreign markets and, hence, facilitate exports. As regards age, the positive and significant coefficient for age indicates that more experienced firms are more likely to perform R&D.

## *5. Concluding remarks.*

This paper investigates the role of exporting and carrying out R&D activities on firms' markups. We calculate markups using De Loecker and Warzynski (2012) methodology. Although, we provide results for large firms and SMEs, our main interest is this last group of firms. Thus, we will discuss the relevant results for SMEs and their policy implications. The dataset we use is drawn from the ESEE for the period 2000-2014. This survey is a panel dataset on firms' business strategies that is representative of Sapnish manufacturing firms.

As stated above, our central objective is studying how firms' markups are affected by export and R&D strategies. In relation to this, we uncover whether the adverse evolution of firms' markups since the start of the Great Recession, especially for SMEs, was offset through exporting and/or performing R&D activities. A second goal in our research is analysing the determinants of these strategies. Furthermore, a supplementary objective in the paper, introduced to tackle an econometric problem, consists in examining whether exporting and undertaking R&D activities had an effect on firms' continuing in operation.

From the markups equation, we get that persistence related either to unobserved individual heterogeneity or to state dependence plays an important role in the evolution of markups. In addition, SMEs attain rewards in markups associated to exporting and performing R&D activities (being the effect of exports about three times larger). However, whereas the R&D effect operates through increasing efficiency (i.e. the cost channel), that of exports operates both through increasing efficiency and increasing the ability of SMEs to set prices above marginal costs (i.e. the price channel). As regards the cycle, our results uncover that for SMEs facing favourable demand conditions the effect of exports operates only through increasing efficiency, while under adverse demand conditions this effect is more intense as the efficiency channel gets reinforced by the price channel. We found no difference across the cycle for the SMEs R&D effect.

For large firms, only the R&D strategy attains rewards in terms of markups, being the effect about three times larger than that of SMEs). In addition, this effect operates by increasing the capacity to set prices above marginal costs (i.e., the price channel), and is not sensitive to the cycle.

Next, as regards the results from the firms' continuing in operation equation, we get that previous TFP enhances firms' continuing prospects for both size groups. Further, while for SMEs we obtain that the exporting strategy contributes to their continuation in operation, for large firms it is the R&D strategy. Finally, our results also indicate that recessive demand conditions and financial constraints have a negative on SMEs continuing prospects.

Finally, we turn to the results on the decision to export and perform R&D. As before, we find that (unobserved individual heterogeneity or state dependence) persistence is relevant for both firms' export and R&D decisions. Further, we find evidence of cross-effects between the two activities, although the effect of exporting on the decision to undertake R&D is larger. Foreign ownership has a positive impact on SMEs likelihood to export. From our results, we confirm the self-selection hypothesis of the most productive firms into the performance of both activities. As regards financial constraints, one of the most relevant variables in our analysis, we obtain that they have a negative impact on the decision to invest in R&D, that points to the procyclicality of R&D.

It is important noting that a decline in domestic demand is resolved by SMEs increasing export participation, thus we verify the "venting out" hypothesis for SMEs. This result might be combined with the effect of the sample selection correction term in both equations. The positive effect of the selection term for SMEs on the decision to perform R&D indicates that unobservable factors that increase firms' continuing in operation also have a positive effect on the propensity to perform R&D. The negative sign of this term in the export equation suggests that unobservables that improve SMEs' continuing prospects decrease their likelihood of exporting. The fact that the selection mechanism is in operation only for SMEs indicates that exporting might be considered as a protection when facing risk of failure. Consequently, SMEs may have less incentives to export if failure is not a problem. For large firms, selection is not an issue.

From our results we can extract several relevant policy recommendations, especially for SMEs. Public policy should facilitate SMEs exporting activity, both through direct and indirect means, as exporting in recessive periods aids SMEs to offset the negative effects of downturns on markups and it is also the best strategy for keeping SMEs in operation. The direct channel is related to enhancing SMEs managerial ability, facilitating their access to foreign markets and promoting productivity enhancing policies. The indirect channels are as follows. First, policies encouraging R&D performance would enhance firms exports as R&D affects positively to the payoffs of exporting. Second, policies easing access to credit can also enable exports as financial restrictions reduce firms R&D activities, further if exports counterbalance a slowdown in domestic demand and R&D is procyclical, alleviating financial restrictions may also create a virtuous circle. Finally, the virtuous circle for SMEs exporters, may be superior as both the relief in financial constraints and the better demand prospects support SMEs continuing in operation.

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**Declaration of interest statement**

No potential conflict of interest was reported by the authors.

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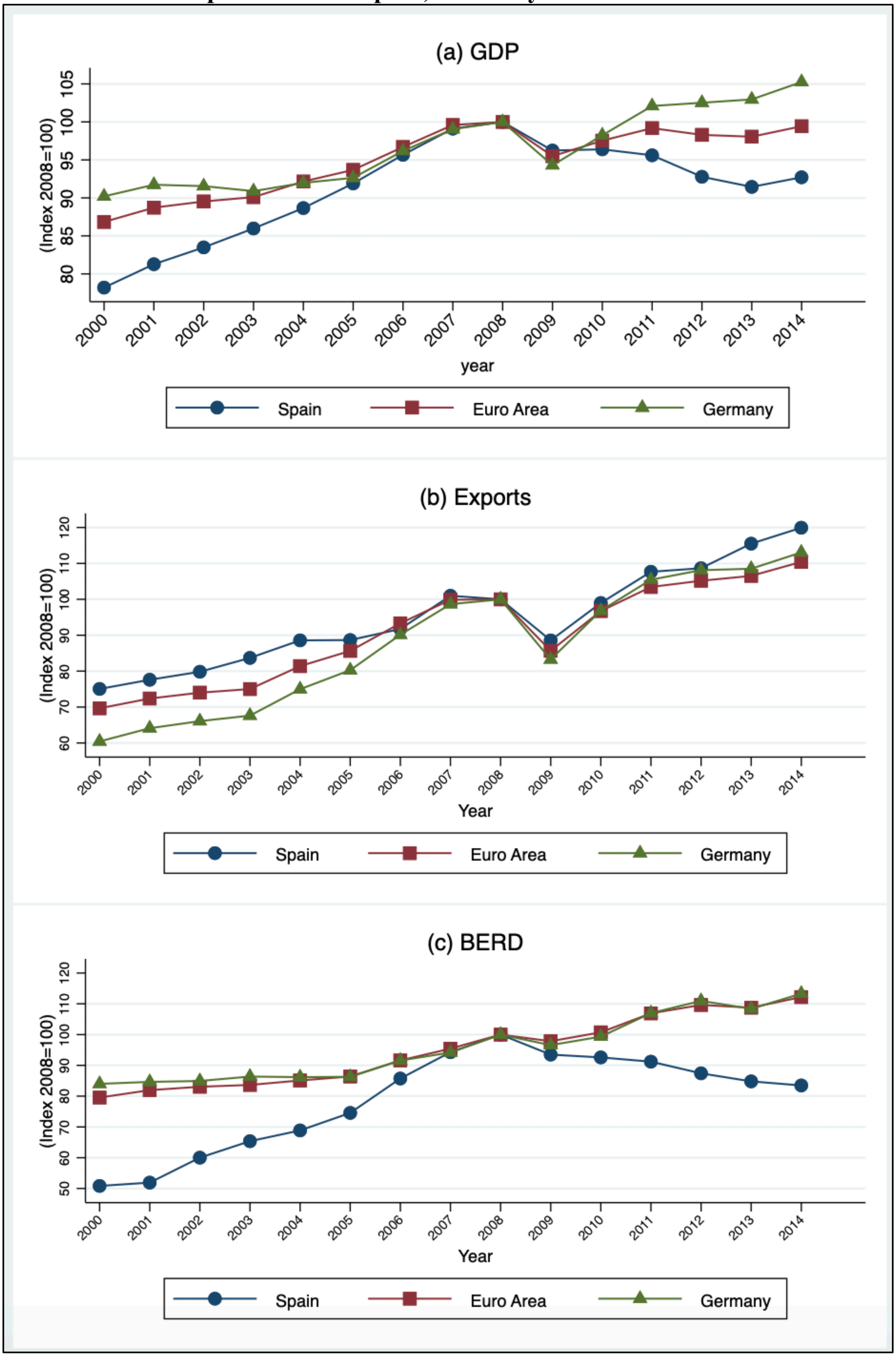
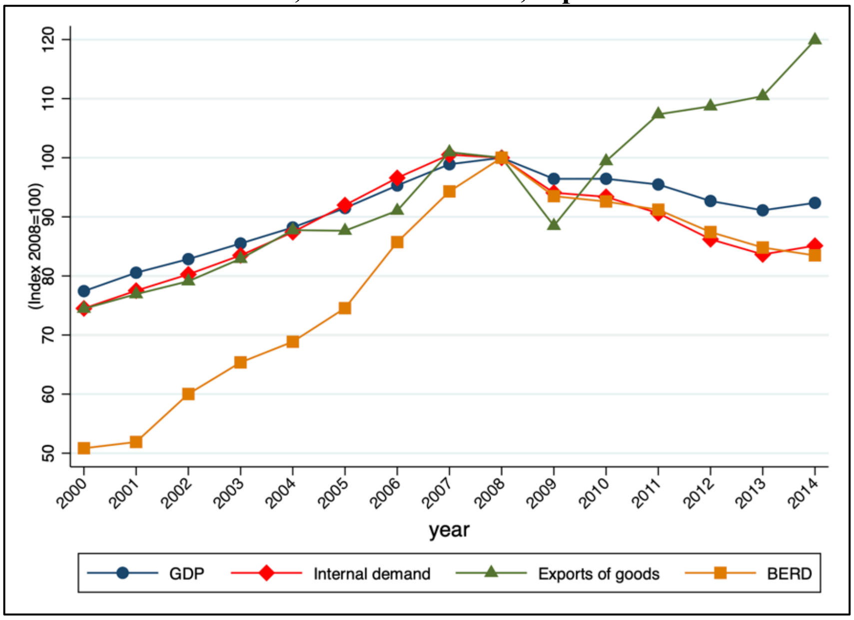
**Figure 1: Evolution of GDP, exports, and business and enterprises R&D (BERD) expenditures in Spain, Germany and Euro Area**



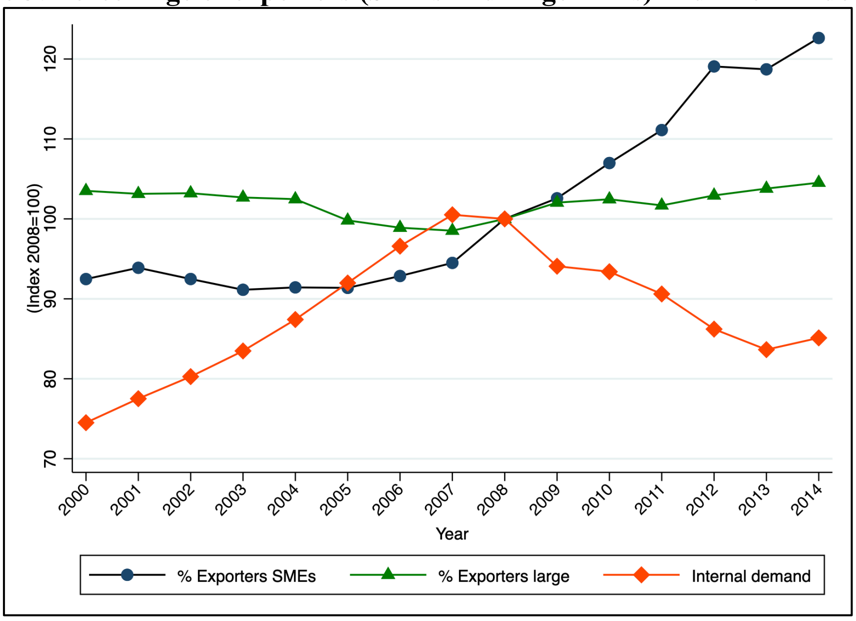

Source: Data from AMECO-EU for GDP and exports and data from EUROSTAT for BERD expenditure.

**Figure 2: Evolution of GDP, Internal demand, exports and BERD. All firms.**



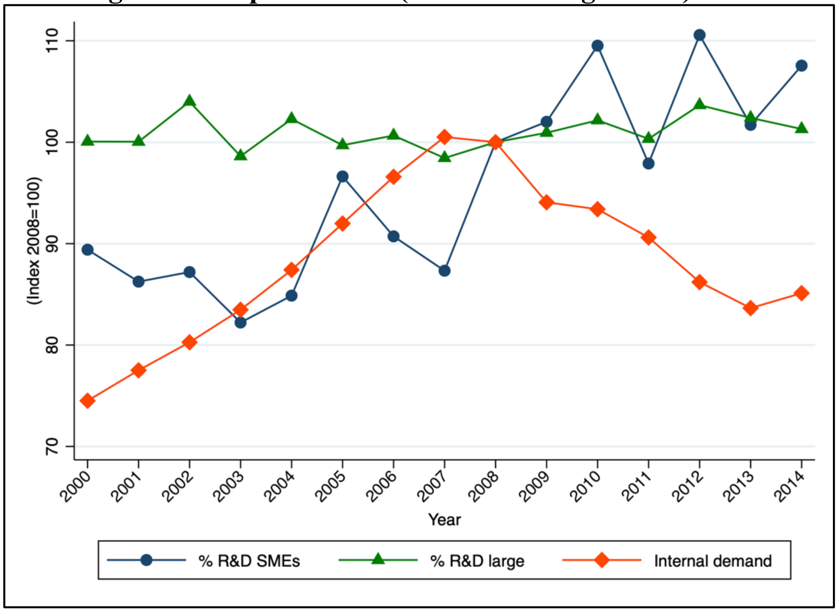

Source: Source: Data from AMECO-EU for GDP, internal demand and exports. Data from EUROSTAT for BERD expenditure.

**Figure 3: Percentage of exporters (SMEs and large firms) and internal demand**




Source: Data from AMECO-EU for Internal demand, and data from the Encuesta sobre Estrategias Empresariales for the exporters percentages.

**Figure 4: Percentage of R&D performers (SMEs and large firms) and internal demand**

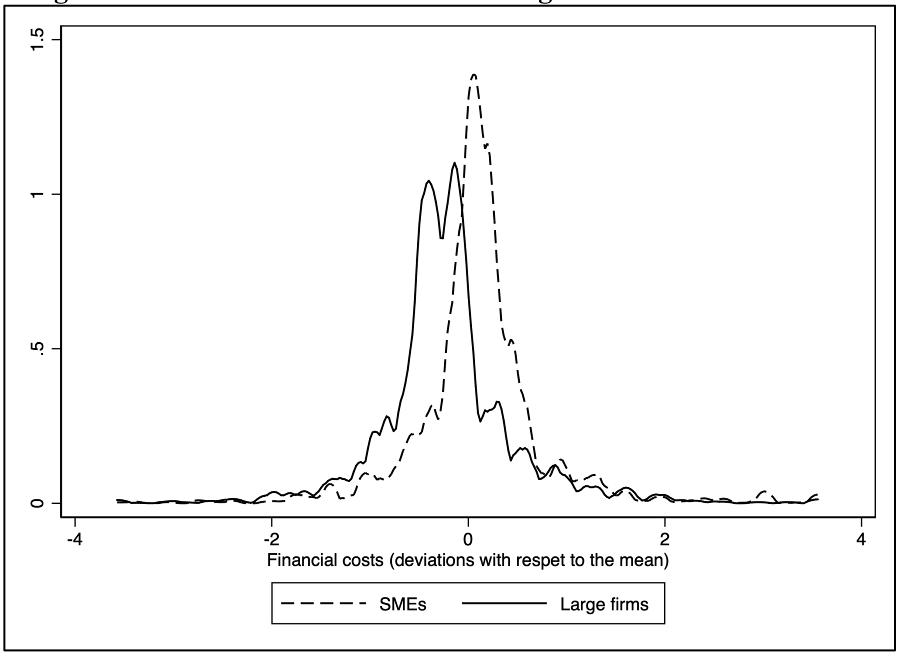



Source: Data from AMECO-EU for Internal demand, and data from the Encuesta sobre Estrategias Empresariales for the R&D percentages.

**Figure 5: Yearly growth of loans to non-financial institutions, 2000-2014**

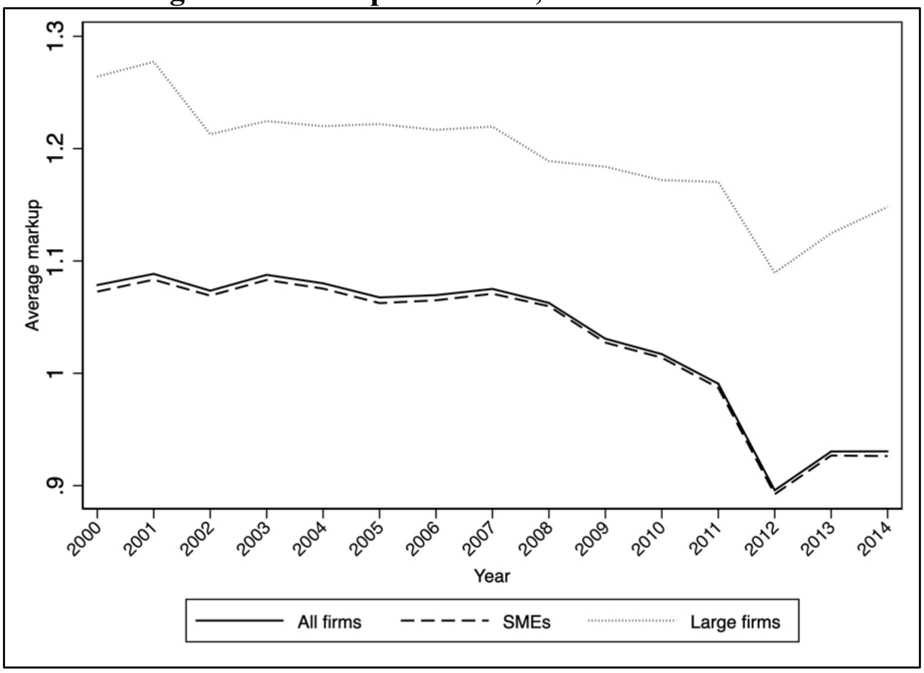

Source: Data from the Bank of Spain.

**Figure 6: Financial costs densities for large firms and SMEs**




Source: Data from Encuesta sobre Estrategias Empresariales.

**Figure 7: Markups evolution, 2000-2014**




Source: Data from Encuesta sobre Estrategias Empresariales.

**Table 1: Exports and R&D.**

| | All firms | SMEs | Large |
|---|---|---|---|
| **Not export/Not R&D** | 39.23 | 40.13 | 3.82 |
| **Export** | 57.21 | 56.29 | 93.27 |
| **R&D** | 23.77 | 22.50 | 73.35 |

**Table 2. Average markups.**

| | All firms | SMEs | Large |
|---|---|---|---|
| **Not export/Not R&D** | 1.01 | 1.01 | 1.04 |
| **Export** | 1.03 | 1.03 | 1.21 |
| **R&D** | 1.08 | 1.06 | 1.25 |
| *Total* | 1.03 | 1.02 | 1.20 |

**Table 3. Estimated sector specific input elasticities from *Translog* production functions.**

| **Industry** | Labor ($e^{l}_{its}$) | Materials ($e^{m}_{its}$) | Capital ($e^{k}_{its}$) |
|---|---|---|---|
| 1. Meat | 0.233 | 0.808 | 0.010 |
| 2. Food and tobacco | 0.198 | 0.622 | 0.055 |
| 3. Beverages | 0.322 | 0.516 | 0.041 |
| 4. Textiles and clothing | 0.316 | 0.546 | 0.049 |
| 5. Leather and shoes | 0.209 | 0.565 | 0.047 |
| 6. Timber | 0.257 | 0.576 | 0.121 |
| 7. Paper | 0.405 | 0.524 | 0.122 |
| 8. Printing products | 0.268 | 0.590 | 0.070 |
| 9. Chemical and pharmaceutical products | 0.201 | 0.549 | 0.043 |
| 10. Plastic and rubber | 0.167 | 0.724 | 0.033 |
| 11. Non-metallic minerals | 0.261 | 0.573 | 0.100 |
| 12. Ferrous and non-ferrous metals | 0.081 | 0.752 | 0.083 |
| 13. Metallic products | 0.265 | 0.633 | 0.023 |
| 14. Industrial and agricultural machinery | 0.203 | 0.590 | 0.097 |
| 15. Electronics and data processing | 0.293 | 0.487 | 0.151 |
| 16. Electrical materials and accessories | 0.251 | 0.744 | 0.035 |
| 17. Motors and vehicles | 0.148 | 0.796 | 0.013 |
| 18. Other transport equipment | 0.224 | 0.721 | 0.069 |
| 19. Furniture | 0.320 | 0.538 | 0.036 |
| 20. Other manufacturing industries | 0.328 | 0.596 | 0.072 |
| Total | 0.235 | 0.639 | 0.050 |

**Table 4. The relationship between firms' Markups and the export and R&D decisions.**

| Variables | | (1) | (2) | (3) | (4) |
|---|---|---|---|---|---|
| **Log(Markup$_{t-1}$)** | SME | 0.743*** | 0.755*** | 0.742*** | 0.758*** |
| | | (0.024) | (0.022) | (0.024) | (0.022) |
| | Large | 0.696*** | 0.722*** | 0.694*** | 0.726*** |
| | | (0.074) | (0.082) | (0.077) | (0.085) |
| **Export$_{t-1}$** | SME | 0.025*** | 0.014*** | 0.015*** | 0.006 |
| | | (0.005) | (0.005) | (0.006) | (0.005) |
| | Large | 0.007 | 0.010 | 0.025 | 0.027 |
| | | (0.020) | (0.024) | (0.018) | (0.021) |
| **R&D$_{t-1}$** | SME | 0.009* | 0.004 | 0.009* | 0.005 |
| | | (0.005) | (0.004) | (0.005) | (0.005) |
| | Large | 0.025* | 0.026* | 0.020* | 0.019* |
| | | (0.014) | (0.015) | (0.011) | (0.011) |
| **Export$_{t-1}$ * Recessive demand$_{t-1}$** | SME | | | 0.034*** | 0.029*** |
| | | | | (0.010) | (0.009) |
| | Large | | | -0.100 | -0.096 |
| | | | | (0.116) | (0.126) |
| **R&D$_{t-1}$ * Recessive demand$_{t-1}$** | SME | | | -0.001 | -0.002 |
| | | | | (0.009) | (0.008) |
| | Large | | | 0.026 | 0.036 |
| | | | | (0.024) | (0.025) |
| **Recessive demand$_{t-1}$** | SME | -0.033*** | -0.031*** | -0.053*** | -0.048*** |
| | | (0.006) | (0.005) | (0.010) | (0.009) |
| | Large | -0.004 | -0.002 | 0.070 | 0.062 |
| | | (0.007) | (0.007) | (0.103) | (0.112) |
| **Foreign participation$_{t-1}$** | | 0.013** | 0.003 | 0.012** | 0.002 |
| | | (0.006) | (0.007) | (0.006) | (0.007) |
| **Size$_{t-1}$** | | -0.014 | -0.063** | -0.032 | -0.078** |
| | | (0.017) | (0.024) | (0.023) | (0.035) |
| **Log(Age$_{t-1}$)** | | -0.001 | 0.002 | -0.000 | 0.003 |
| | | (0.003) | (0.003) | (0.003) | (0.003) |
| **ΔLog(TFP$_t$)** | SME | | 0.473*** | | 0.472*** |
| | | | (0.030) | | (0.030) |
| | Large | | 0.404*** | | 0.402*** |
| | | | (0.024) | | (0.024) |
| **Log(Markups) Pre-sample Mean** | SME | 0.201*** | 0.167*** | 0.203*** | 0.165*** |
| | | (0.024) | (0.022) | (0.024) | (0.022) |
| | Large | 0.250*** | 0.270*** | 0.253*** | 0.269*** |
| | | (0.045) | (0.041) | (0.048) | (0.045) |
| **Lambda cont. operation** | SME | 0.159** | 0.309*** | 0.174** | 0.327*** |
| | | (0.068) | (0.060) | (0.068) | (0.060) |
| | Large | 0.291*** | 0.469*** | 0.301*** | 0.487*** |
| | | (0.080) | (0.075) | (0.077) | (0.072) |
| **Constant** | | 0.007 | -1.023*** | 0.011 | -1.022*** |
| | | (0.014) | (0.066) | (0.014) | (0.066) |
| N. observations | | 16,852 | 16,852 | 16,852 | 16,852 |
| N. firms | | 2,442 | 2,442 | 2,442 | 2,442 |

Notes:

1. All estimations include industry and time dummies.
2. Robust *standard errors* are in parentheses.
3. ***, ** and * mean significant at the 1%, 5% and 10% level, respectively.

**Table 5. *Probit* estimates for firms' continuation in operation.**

| Variables | | Continuation in operation$_t$ |
|---|---|---|
| **Export$_{t\text{-}1}$** | SME | 0.104** |
| | | (0.043) |
| | Large | 0.143 |
| | | (0.120) |
| **R&D$_{t\text{-}1}$** | SME | 0.047 |
| | | (0.052) |
| | Large | 0.173** |
| | | (0.074) |
| **TFP$_{t\text{-}1}$** | SME | 0.420*** |
| | | (0.058) |
| | Large | 0.396*** |
| | | (0.058) |
| **Financial restrictions$_{t\text{-}1}$** | SME | -0.054*** |
| | | (0.020) |
| | Large | 0.027 |
| | | (0.038) |
| **Recessive index$_{t\text{-}1}$** | SME | -0.004*** |
| | | (0.001) |
| | Large | -0.000 |
| | | (0.001) |
| **Foreign participation$_{t\text{-}1}$** | | -0.204*** |
| | | (0.053) |
| **Size$_{t\text{-}1}$** | | -0.159 |
| | | (0.181) |
| **Age$_{t\text{-}1}$** | | 0.107*** |
| | | (0.025) |
| **Constant** | | -1.162*** |
| | | (0.445) |
| Log pseudo-likelihood | | -4861.0302 |
| N. observations | | 19,824 |
| N. firms | | 2,827 |

Notes:

1. All estimations include sector and time dummies.
2. Robust *standard errors* are in parentheses.
3. ***, ** and * mean significant at the 1%, 5% and 10% level, respectively.

**Table 6. *Heckman-bivariate probit* estimates for Export and R&D strategies.**

| Variables | | $\text{Export}_t$ | $\text{R\&D}_t$ |
|---|---|---|---|
| **$\text{Export}_{t\text{-}1}$** | SME | 2.463*** | 0.394*** |
| | | (0.050) | (0.044) |
| | Large | 3.179*** | 0.499*** |
| | | (0.151) | (0.106) |
| **$\text{R\&D}_{t\text{-}1}$** | SME | 0.302*** | 2.076*** |
| | | (0.055) | (0.044) |
| | Large | 0.195* | 2.363*** |
| | | (0.112) | (0.071) |
| **$\text{TFP}_{t\text{-}1}$** | SME | 0.219*** | 0.431*** |
| | | (0.082) | (0.071) |
| | Large | 0.218*** | 0.431*** |
| | | (0.083) | (0.070) |
| **Financial $\text{restrictions}_{t\text{-}1}$** | SME | 0.004 | -0.045** |
| | | (0.029) | (0.021) |
| | Large | -0.057 | -0.059* |
| | | (0.068) | (0.035) |
| **Growth domestic $\text{sales}_{t\text{-}1,t}$** | SME | -0.086* | |
| | | (0.052) | |
| | Large | 0.101 | |
| | | (0.103) | |
| **Recessive $\text{index}_{t\text{-}1}$** | SME | | -0.002*** |
| | | | (0.001) |
| | Large | | -0.002** |
| | | | (0.001) |
| **Foreign $\text{participation}_{t\text{-}1}$** | | 0.216*** | -0.073 |
| | | (0.068) | (0.050) |
| **$\text{Size}_{t\text{-}1}$** | | 0.116 | 0.219 |
| | | (0.224) | (0.170) |
| **$\text{Age}_{t\text{-}1}$** | | 0.007 | 0.079*** |
| | | (0.029) | (0.028) |
| **Export Pre-sample Mean** | SME | 1.039*** | |
| | | (0.051) | |
| | Large | 0.528*** | |
| | | (0.164) | |
| **R&D Pre-sample Mean** | SME | | 0.778*** |
| | | | (0.047) |
| | Large | | 0.583*** |
| | | | (0.072) |
| **Lambda cont. operation** | SME | -1.244** | 0.973* |
| | | (0.523) | (0.585) |
| | Large | -0.732 | 0.854 |
| | | (0.777) | (0.698) |
| **Constant** | | -3.190*** | -5.460*** |
| | | (0.650) | (0.573) |
| RV endog. test (1st step residual from regressing Growth_domestic_sales on IVs) | | 0.049 (0.220) | |
| F-test of exclusion of IVs | | 1.073 | |
| p-value | | 0.214 | |
| $\rho_{Export\text{-}R\&D}$ | | 0.063 (*p*-val.= 0.099) | |
| Log pseudo-likelihood | | -6657.6225 | |
| N. observations | | 18,064 | |
| N. firms | | 2,603 | |

Notes:

1. All estimations include sector and time dummies.
2. Robust *standard errors* are in parentheses.
3. ***, ** and * mean significant at the 1%, 5% and 10% level, respectively.

## Appendix I: Details on the estimation of the *translog* production function and the TFP residual.

Olley and Pakes (1996, henceforth OP), assuming that capital is a state variable and labour and materials are adjustable inputs when a firm faces a productivity shock, demonstrate how to get consistent estimates of the production function parameters in (1) through a semi-parametric approach (see also Levinsohn and Petrin, 2003, hereafter LP, for a similar related estimation strategy).

In our methodology we use Wooldridge (2009) approach, who shows that OP and LP estimation methodologies can be reassessed as comprising two equations that might be jointly estimated by GMM: the initial equation accounts for the endogeneity of the non-dynamic inputs (the variable inputs); and, the second equation accounts for the law of motion of productivity. In what follows, we explain in detail both equations.

The first problem we consider is the endogeneity of the non-dynamic inputs. The fact that labour and materials might be correlated with firms' productivity makes the estimation of equation (1) complicate, as OLS is biased and either the instrumental variables or the fixed-effects methodologies are usually not consistent (see Ackerberg *et al.*, 2015). OP and LP propose a control function approach to solve this problem. OP use the investment in capital demand function and LP the materials demand function, respectively, to proxy for 'unobserved' productivity.

In particular, the methodology proposed by OP assumes that the firm's investment in capital demand function, $i_{it} = i\left(k_{it}, tfp_{it}\right)$, depends on capital and productivity (Total Factor Productivity). However, to avoid the problem of zeros in the investment in capital for some firms, LP methodology uses instead the materials demand function, $m_{it} = m\left(k_{it}, tfp_{it}\right)$. In our work, we follow for the same reason the LP approach, so we will focus on the firms' materials demand function.

Strictly following the standard OP and LP approaches to estimate productivity, researchers assume an identical materials demand function for different types of firms (as in our case they would be firms with different export and R&D statuses). However, we consider that heterogeneity in firms' export and R&D strategies might have an impact on the demand for materials. Accordingly, we allow for the demand function of materials to vary depending on firms' export and R&D statuses. Our demand function for materials is as follows:

$$m_{it} = m_J\left(k_{it}, tfp_{it}\right) \tag{a.1}$$

where the subscript $J$ indicates that the demand of materials is not only firm specific but also specific to the different exporting and R&D strategies ($J$) taken by the firm. Under the assumption of a monotonic in productivity demand function for materials, (a.1) is invertible in productivity:

$$tfp_{it} = h_J\left(k_{it}, m_{it}\right) \tag{a.2}$$

where $h_J$ is an unknown function that depends on the observables $k_{it}$ and $m_{it}$ and on firms' export and R&D strategies ($J$). Substituting (a.2) in the production function in (1), we obtain the first equation for the estimation of the production function:

$$\begin{aligned} y_{it} = {} & \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \\ & \beta_{l2} l_{it}^2 + \beta_{k2} k_{it}^2 + \beta_{m2} m_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + h_J\left(k_{it}, m_{it}\right) + \eta_{it} \end{aligned} \tag{a.3}$$

In (a.3), the unknown function $h_J$ will be proxy by a third degree polynomial in $k_{it}$ and $m_{it}$ and allowed to differ depending on the $J$ combination of export and R&D firm's strategies.

In (a.3) there are some identification problems since the non-parametric approximation of the unknown function $h_J$ generates some multicolinearity problems with the included elements in the *Translog* production function that involve $k_{it}$ and $m_{it}$. Therefore, we require the inclusion of a second equation in estimation. This second equation incorporates the law of motion of productivity.

In the OP/LP methods, it is assumed that productivity evolves following an exogenous Markov process:

$$tfp_{it} = E\left[tfp_{it} \middle| tfp_{it-1}\right] + \xi_{it} = f\left(tfp_{it-1}\right) + \xi_{it} \tag{a.4}$$

where $f$ is an unknown function that links productivity in period $t$ with productivity in period $t$-$1$ and $\xi_{it}$ is an innovation term that by definition is uncorrelated with $k_{it}$. Differently in our approach, we allow for an endogenous Markov process where previous firm's exporting and R&D experience can influence the dynamic process of productivity:

$$tfp_{it} = E\left[tfp_{it} \mid tfp_{it-1}, E_{it-1}, R\&D_{it-1}\right] + \xi_{it} = f\left(tfp_{it-1}, E_{it-1}, R\&D_{it-1}\right) + \xi_{it} \tag{a.5}$$

Furthermore, as by (a.2) $tfp_{it} = h_J\left(k_{it}, m_{it}\right)$, we can rewrite (a.5) as:

$$tfp_{it} = f\left(tfp_{it-1}, E_{it-1}, R\&D_{it-1}\right) + \xi_{it} = f\left[h_J\left(k_{it-1}, m_{it-1}\right), E_{it-1}, R\&D_{it-1}\right] + \xi_{it} = F_J\left(k_{it-1}, m_{it-1}\right) + \xi_{it}$$

(a.6)

where the unknown function $F_J$ will be proxy by a third degree polynomial in $k_{it-1}$ and $m_{it-1}$. As for $h_J$ in (a.3), the polynomial coefficients are allowed to vary depending on export and R&D firms' strategies.

Finally, substituting (a.6) in the production function in (1), we obtain the second equation for the estimation of the production function:

$$\begin{aligned} y_{it} = {} & \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \\ & \beta_{l2} l_{it}^2 + \beta_{k2} k_{it}^2 + \beta_{m2} m_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + F_J\left(k_{it-1}, m_{it-1}\right) + u_{it} \end{aligned}$$

(a.7)

where the error term $u_{it} = \xi_{it} + \eta_{it}$.

Wooldridge (2009) suggests estimating the system of equations (a.3) and (a.7) by GMM, utilising the suitable instruments and moment conditions in each equation. Wooldridge (2009) claimed that both OP and LP methodologies could be understood as containing two equations that can be jointly estimated by GMM in a one-step estimation procedure. This joint estimation has some benefits: i) increases efficiency as compared to two-step procedures; ii) there is no bootstrapping required for standard errors calculation; and, iii) it resolves the identification problem raised above.

We use Wooldridge (2009) method to get sector specific coefficient estimates for the production function in (1) and obtain the output elasticity of materials that is used to calculate markups (as explained in section 3 of the main text). We also obtain estimates of firms' TFP as the residuals from the *translog* production function:

$$\hat{tfp}_{it}^{s} = y_{it}^{s} - \hat{\beta}_{l}^{s} l_{it} - \hat{\beta}_{k}^{s} k_{it} - \hat{\beta}_{m}^{s} m_{it} - \hat{\beta}_{l2}^{s} l_{it}^{2} - \hat{\beta}_{k2}^{s} k_{it}^{2} - \hat{\beta}_{m2}^{s} m_{it}^{2} - \hat{\beta}_{lk}^{s} l_{it} k_{it} - \hat{\beta}_{lm}^{s} l_{it} m_{it} - \hat{\beta}_{km}^{s} k_{it} m_{it} \quad \text{(a.8)}$$

where $\hat{tfp}_{it}^{s}$ is the estimated log TFP for firm *i* operating in sector *s* in period *t*.

## Appendix II: First step instrumental variables procedure.

**Table A.1. Instrumental variables (1st step).**

| Instrumental variables | *Growth Domestic Sales*$_{it-1,t}$ |
|---|---|
| *Mean Capacity Utilization*$_{it-1}^{-i}$ | 0.004*** |
| | (0.001) |
| *Mean Growth Domestic Sales*$_{it-1,t}^{-i}$ | -1.043*** |
| | (0.092) |
| *Constant* | 0.822*** |
| | (0.124) |
| F-test joint significance of IVs (null: non-significance) | 63.63 |
| p-value | 0.000 |
| Observations | 18,064 |
| $R$-squared | 0.124 |
| Number of firms | 2,603 |

Notes:

1. Estimation includes also the set of regressors (different to the variable being instrumented) in the second-step export equation.
2. Robust *standard errors* are in parentheses.
3. *** means significant at the 1% level.