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Where Export Thresholds and Technology Interact: A New Way of Looking at Exporting Firms

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Abstract

Policies aimed at increasing firm participation in international markets have been playing an increasing role. Using a new approach to estimate export threshold for manufacturing firms, and considering the technology prevailing in each industry, this paper provides a new taxonomy allowing to detect a more efficient selection of targets according to preferred policy goals (i.e. intensive or extensive margins). The export threshold – which is estimated on the basis of the ROC methodology – is the minimum combination of productivity and "economic size" (a broad measure of firm size composed of employment, age, turnover and capital intensity) that firms need to achieve in order to access international markets. In turn, the technology prevailing in each industry is expressed in terms of the relative weights of productivity and size corresponding to a (firm-level) technical efficiency higher than the median level within the industry. The interaction between this "technology line" and the export threshold allows deriving a firm-based and an industry-based taxonomy that can be useful: (1) to define, for each industry, which is the most effective lever to boost the export propensity, taking into account possible mismatch with the preferable level to improve efficiency; (2) to qualify the comparison between exporting and non-exporting firms in the light of their position with respect to the prevailing technology of the given industry.

JEL code: F14, L60, L11

Keywords ROC analysis, export threshold, technical efficiency, extensive margin of exports

1. Introduction

Export activity is important for firm competitiveness and, more in general, for the economic growth of countries. As a consequence, policies aimed at increasing firm participation in international markets, both in terms of intensive and extensive margins, have been playing an increasing role. This in turn highlights the importance of being able to detect the firm-level determinants of export, i.e. the minimum requirements firms have to bear to become an exporter.

In a previous paper, we applied the Receiver Operating Characteristics (ROC) analysis to develop a new methodology for the estimation of the "export threshold", i.e. the combination of productivity and "economic size" (a broad measure of firm size composed of employment, age, turnover and capital intensity) corresponding to the transition from non-exporter to exporter status (Costa *et al.*, 2019). In this paper, we enrich that analysis by explicitly taking into account the industry technology, expressed in terms of a combination of the same two variables. The position of firms with respect to this "technology line" and the export threshold determines a new way of analysing firms export orientation and export potential.

On such bases, the main contribution of this paper is to provide a map of the business system that is useful from a policy-making point of view, as it allows for more targeted policies aimed at boosting firm participation to foreign markets.

This work grounds on the literature related to firm heterogeneity, which points out the role of firms structural characteristics (e.g. size, location, business sector, exporting status), strategies (e.g. different forms of innovation, inter-firms relationships) and performance (e.g. revenues, profitability, productivity, innovation) in determining firms competiveness. In particular, we are interested in the relationship among firm productivity, (economic) size and ability to export.

The existence of some export thresholds characterizes all the theoretical works on firm heterogeneity which originated from the seminal paper of Melitz (2003), where only firms above a minimum productivity level are able to sell abroad (Melitz and Ottaviano, 2008; Chaney, 2008; Bernard *et al*., 2011). However, from the empirical point of view, several works showed that in many countries, firm productivity distributions of exporters and non-exporters may overlap,[1] implying that enterprises might not export even though their productivity levels would enable them to (i.e. are "above the threshold"). Moreover, other works have shown that the mismatch between Melitz's theory and empirical evidence is only apparent, being mainly linked to the definition of productivity: empirical works are forced to use average cost-based productivity measures, while theoretical ones rank firms according to their marginal productivity (Schröder and Sørensen, 2012; Geishecker *et al*., 2017).

Firm size may be relevant to explain the ability to export, as it may loosen the constraint represented by sunk costs. Empirical studies did find a direct relationship between export and size: exporters tend to be larger than non-exporters (Bernard and Jensen, 1995; Wagner, 2007). This raises important questions about the sources of export premia and, more specifically, whether, and to what extent, such sources could be size-related. Internal sources include managerial talent, quality of inputs, information technology, R&D, learning by doing, and innovation (Syverson, 2011): small and large firms could differ in terms of access to these sources (Leung *et al*., 2008). External factors such as regulations and access to financing could also be responsible for heterogeneity between small and large firms (Tybout, 2000).

In the empirical literature, causal relationship among productivity, size and export activity has been largely analyzed (see Wagner, 2012 and ISGEP, 2008 for detailed surveys), especially the "self-selection" versus

[1] See Schröder and Sørensen (2012) for a survey, and Castellani and Zanfei (2007) for the Italian case.

learning-by-exporting hypothesis. In the first one, a firm should reach a minimum level (a threshold) of productivity before starting to export. In the second one, knowledge flowing from international buyers and competitors helps improve the post-entry performance of exporters. However, the learning-by-exporting effect may also be related to the size of firms. Focusing on Spanish manufacturing, Máñez-Castillejo *et al.* (2010) demonstrate the existence of a process of self-selection into exporting among small firms but not among large firms, while the learning-by-exporting effect is significant independently from size.

The rest of the paper is organized as follows. Section 2 presents a description of the dataset and empirical strategy. Section 3 illustrates, for each industry, the main results obtained from the interaction between the export threshold and the technology line, describing the new taxonomy of firms according to their ability to export. Section 4 summarizes and provides conclusions.

2. The data

The main statistical source of this work is the business register "Frame-Sbs" for 2016. Released by ISTAT since 2011, it annually provides administrative-based information on the structure (e.g. number of employees, business sector, location, age, belonging to a group) and the main Profit and Loss Account variables (e.g. value of production, turnover, value added, labour cost) for the whole population of about 4.4 million of Italian firms.

This database is then integrated with other information drawn from Custom Trade Statistics, a census-type dataset reporting, for each Italian firm, the values of imports, exports, and trade balance with both EU (intra-EU trade) and non-EU operators (extra-EU trade).

In order to focus on relevant business units, some restrictions are imposed to the dataset. In particular, in the light of the extremely fragmented structure of the Italian business system – where in 2016 the firm average size was less than 4 persons employed, and the enterprises with just one person employed accounted for over 50% of total firms and 12% of total employment – we exclude units which do not have "economic relevance" for the analysis of export strategies. Consequently, we consider firms that have positive value added, no less than 1 employee, and positive consumption of fixed capital. Moreover, we only retain firms operating in manufacturing (excluding Tobacco, Refined petroleum products, Maintenance and repair, and Other manufacturing), which in 2016 accounted for 83% the total Italian exports. Finally, we rule out irregular and one-off exporting firms, and consider only the "stable exporters", namely those always exporting over the three-year period 2014-2016.[2]

The final dataset includes 208,627 firms, accounting for about 54% of manufacturing firms, 85% of workforce, 93% of value added, 84% of exports. Table 1 reports industry composition and main information about the strata of analysis.

Table 1. The sample: Industry classification and firms' characteristics

[2] There is no universally accepted definition of "stable exporter", except that, for a firm to be defined as such, it has to be exporting on a regular basis over a specified (more than a year) period. We preferred the 2014-2016 time span also because it is more homogeneous from a business cycle point of view, as it fully covers the Italian post-recession period.

Industry	Nace Rev.2 code included	Number of firms	Share of firms	Share of value added	Share of employees	Share of exports
Food and beverage	10, 11	39,356	18.9	12.1	12.9	7.9
Textile	13	8,274	4.0	2.8	3.4	2.6
Wearing apparel	14	11,957	5.7	3.3	4.8	4.1
Leather	15	8,634	4.1	3.3	4.0	5.1
Wood	16	15,410	7.4	1.7	2.8	0.5
Paper and print	17, 18	12,927	6.2	4.4	4.7	2.3
Chemicals and pharmaceutics	20, 21	3,679	1.8	9.6	5.2	13.3
Rubber and plastic	22	7,732	3.7	5.6	5.4	5.0
Non metalic minerals	23	11,766	5.6	4.3	4.6	2.8
Metals	24, 25	46,319	22.2	16.5	18.6	13.6
Electronics	26, 27	9,082	4.4	7.8	7.3	7.8
Machinery	28	18,429	8.8	16.3	14.5	20.4
Automotive	29, 30	3,269	1.6	9.5	8.1	12.0
Furniture	31	11,793	5.7	2.8	3.9	2.5
Total		208,627	100.0	100.0	100.0	100.0

Source: Authors' calculation on ISTAT data.

3. ROC methodology and export threshold

3.1. The basics of the ROC analysis

Following the methodology developed in our previous work (Costa et al., 2019), we estimate the export threshold on the basis of the joint application of the Receiver Operating Characteristics (ROC hereinafter) analysis and Youden's (1950) *J* index. This permits the identification of a cut-off point over an independent variable in a logit model (in our case: a combination of productivity and economic size), so as to efficiently cluster observations with respect to a dependent binomial variable (in our case: the exporter status).

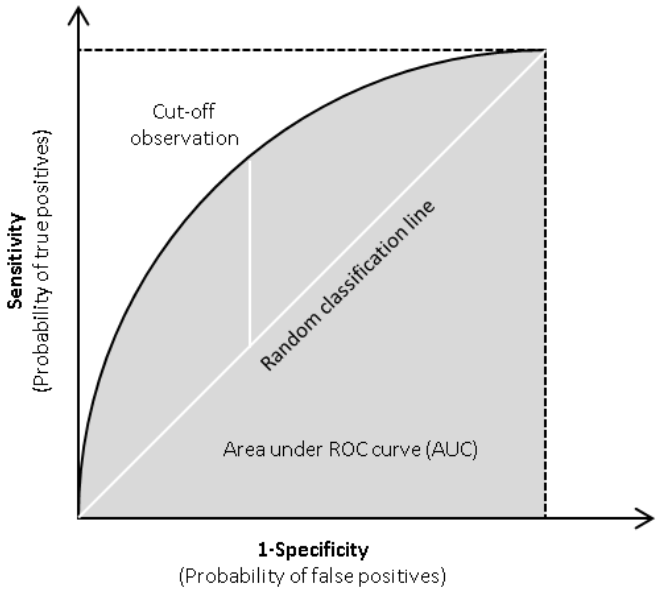
The application of the ROC analysis is quite new in Economics. To the best of our knowledge, so far this methodology has been used to test the accuracy of business cycle classification made by the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER; Berge and Jorda 2011) and in the credit risk literature (Khandani *et al*., 2010). However, it has been widely adopted in medicine (Lusted, 1960), and it is now a common standard of evaluation of medical and psychological tests (Pepe, 2003). Furthermore, ROC methodology is used in machine learning (Majnik and Bosnic, 2013), and natural science (Warnock and Peck, 2010).

According to Fawcett (2005), classification models (or classifiers) can give four possible outcomes: True positive (TP), False positive (FP), True negative (TN), False negative (FN).

The validity of a classifier can be measured based on two main metrics: Sensitivity and Specificity. Sensitivity represents the probability of detecting true positives. Specificity is the probability of detecting true negatives. This latter is usually considered in its reciprocal expression (1–Specificity), which measures the probability of false positives.

Once a classifier is applied, the ROC curve displays the position of each observation in the space of Sensitivity and 1–Specificity (Figure 1), showing the tradeoff between the probability of detecting true positives or false positives across all possible cut-off points (Kumar and Indrayan, 2011).

Figure 1. The ROC curve



The area under the ROC curve (AUC, grey portion in Figure 1) provides a measure of the extent to which the clustering obtained by the given model is more efficient than a pure random classification (the 45° line). In this respect, the AUC criterion is largely used to measure the goodness of fit of logit models, and to define the relative relevance of a set of variables in determining the overall logistic distribution of probability.

In order to single out along the ROC curve the observation that most efficiently discriminates between positives and negatives ($\widehat{\text{Cut}}$), the following equation is to be maximized:

$$\widehat{\text{Cut}} = \text{h} * \text{Sensitivity} - (1 - \text{h}) * (1 - \text{Specificity}) \qquad [1]$$

where h and $(1 - h)$ represent the relative weights to manage the trade-off between true and false positives. By setting up $h = 0.5$, we opt for a "neutral" selection between the two outcomes.[3] In doing so, Equation [1] turns out to be equal to Youden's (1950) J index:

$$(\text{Sensitivity} + \text{Specificity} - 1) \qquad [2]$$

Youden's J – which identifies the observation that maximizes equation [2] and, consequently, the vertical distance between ROC curve and the 45° line (see Figure 1) – is the most commonly used criterion for detecting optimal cut-offs.[4] Moreover, the J index – implying a "neutral" choice between false positives and

[3] Values of $h > 0.5$ (i.e., finding true positives is more relevant than avoiding false positives) would correspond to a "liberal" selection, which assigns positive classification even in the presence of weak evidence. Conversely, setting up $h < 0.5$ (i.e., detecting true positives is less relevant than avoiding false positives) would correspond to a "conservative" selection, which assigns positive classifications only in presence of strong evidence.

[4] Beside the *J* index, two other criteria are used to find optimal threshold point along a ROC curve: *a)* the minimization of the distance from the (0,1) point; *b)* the cost minimization, which considers several types of costs, e.g. for correct and false classification, for further investigation etc., and it is rarely used due to its assessment difficulty.

negatives – is all the more suitable for our purposes because we have no *a-priori* bias in dealing with the trade-off.[5]

3.2. Definition of the "export threshold"

As in our previous work (Costa *et al.*, 2019) in order to apply the ROC analysis to the identification of the export threshold, we firstly estimate the probability to export of the i-th firm in the h-th industry based on the following logit model:

$$\text{Prob (Export} = 1|\text{X})_{\text{h,i}} = \Lambda(\alpha\text{X})_{\text{h,i}} \qquad [3]$$

where Λ is the cumulative distribution of the logistic function, α is the estimated parameter, and X is the covariate.

Once estimates have been obtained, we use Youden's J to identify the cut-off observation in the h-th industry, thus also determining the value of the covariate representing the threshold:

$$\text{X}_h^e = \text{X}_{\text{h,c}} \qquad [4]$$

where c is the cut-off firm.

Using this threshold, each firm can be classified as exporter or non-exporter according to its laying above or under this threshold.

In particular, we use a composite model (Z-model, where $\text{X}_h^e = \text{Z}_h^e$), in which the export threshold is defined over a combination (Z_h^e) of productivity and economic size (which in turn synthesises four size-related variables).[6]

The composite indicator Z is derived from a three-step procedure. In the first step, for each industry, the "economic size" indicator is defined, using factor analysis over a set of four variables: number of workers; turnover; consumption of fixed capital; age (in terms of number of months from the date of inclusion in the Italian Business Register). For each firm in a given industry, economic size is thus obtained from the linear combination of the four variables as resulting from the first (rotated) autovector.

In the second step, the following logit model is estimated for the h-th industry:

$$\text{Prob (Exporter}_i = 1|\text{S}_i, \pi_i, \text{G}_i, \text{I}_i) = \Lambda(\ \alpha_1\text{S}_i + \ \alpha_2\pi_i + \alpha_3\text{G}_i + \alpha_4\text{I}_i\ ) \qquad [5]$$

[5] Actually, the best cut-off depends on whether one needs to maximize sensitivity at the expense of 1-specificity or vice versa. This often happens in medicine. The first case leads to a test that is maximal sensitive (i.e. correctly identifying diseased people at the expense of a high number of false positives). The second case generates a test that is better at ruling out the disease. The Youden's *J* maximizes both.

[6] In Costa et al. (2019), we tested two alternative models: a pure sales model (S-model, where $\text{X} = \text{Sales}$), in which the export threshold is defined over the value of firms' turnover, and a pure productivity model (π-model, where $\text{X} = \text{Productivity}$), in which the export threshold is defined over the value of labour productivity (value added-per-worker). Both S-model and π-model have been proved to be consistent with Melitz's theory (Geishecker *et al.*, 2017). Fitting tests showed that the Z-model outperforms the other two.

where Λ is the cumulative distribution of the logistic function, α_j are estimated parameters, S is the "economic size" of firms, π is their productivity (in terms of value added-per-worker), G is a set of dummy variables indicating the location of firms,[7] and I is a set of dummy variables related to NACE 2-digit levels of economic activity.

In the third step, the estimated coefficients of productivity and economic size from equation [5] are used to obtain, for each industry, the composite indicator $Z^e_{h,i}$ for i-th firm. In particular, the estimated parameters are used as weights, while variables are taken at individual level:

$$Z^e_{h,i} = \hat{\alpha}_{1,\mathrm{h}} S_{h,i} + \hat{\alpha}_{2,\mathrm{h}} \pi_{h,i} \qquad [6]$$

where $Z^e_{h,i}$ is the covariate to be used in equation [3].

Following the ROC methodology, the optimal cut-off observation c (the "export threshold firm") is identified. Finally, substituting the productivity and economic size of c in Equation [6], we obtain the export threshold as:

$$Z^e_{h,c} = \hat{\alpha}_{1,\mathrm{h}} S_{h,c} + \hat{\alpha}_{2,\mathrm{h}} \pi_{h,c} \qquad [7]$$

In the rest of the paper we refer to $Z^e_{h,c}$ as Z^e.

3.3. Fitting tests of ROC estimates

Three types of test are carried out. First, we apply the usual Area Under Curve (AUC) test to compare the model based on the composite indicator Z with an alternative, strictly "Melitz-compliant" pure productivity model (π-model), in which the export threshold is defined over the labour productivity, measured in terms of value added per worker ($X = \pi$ in Equation [3]).

Table 2. Area under ROC curve (AUC): comparison between π-model and Z-model

[7] We refer to five geographical areas: North-West, North-East, Centre, South, Islands.

Industry	AUCs		π -model - Z-model				
	Z-model	π-model	Difference estimate	Standard error	Lower bound	Upper bound	P-value
Food and beverage	0.865	0.849	-0.017	0.002	-0.020	-0.014	0.000
Textile	0.824	0.767	-0.058	0.004	-0.065	-0.050	0.000
Wearing apparel	0.777	0.730	-0.047	0.005	-0.056	-0.037	0.000
Leather	0.756	0.698	-0.058	0.005	-0.067	-0.048	0.000
Wood	0.831	0.753	-0.078	0.005	-0.087	-0.069	0.000
Paper and print	0.843	0.785	-0.058	0.003	-0.064	-0.051	0.000
Chemicals and pharmaceutics	0.787	0.741	-0.046	0.008	-0.063	-0.030	0.000
Rubber and plastic	0.818	0.742	-0.076	0.005	-0.085	-0.066	0.000
Non metalic minerals	0.769	0.732	-0.037	0.004	-0.044	-0.030	0.000
Metals	0.850	0.772	-0.079	0.002	-0.083	-0.074	0.000
Electronics	0.786	0.718	-0.068	0.005	-0.079	-0.058	0.000
Machinery	0.778	0.700	-0.078	0.004	-0.085	-0.070	0.000
Automotive	0.790	0.724	-0.066	0.008	-0.083	-0.050	0.000
Furniture	0.833	0.734	-0.099	0.004	-0.108	-0.091	0.000

Source: Authors' calculation on ISTAT data.

Results are reported in Table 2: both π- and Z-model show a high goodness of fit (never below 70% for the π-model, always over 75% for the Z-model). However, the Z-model significantly outperforms the pure productivity one for all strata.

Second, we consider the capability of the cut-off identified by the J index in classifying firms as exporters and non-exporters in terms of Precision and Accuracy. In particular, Precision measures the share of true positives over the total number of observations the model classifies as positives (i.e. the percentage of firms correctly classified as exporters):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad [8]$$

In turn, Accuracy measures the share of true positive and negative outcomes of the model (i.e. the proportion of firms correctly classified as exporters and non-exporters) over the total number of observations:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{Total observations}} \qquad [9]$$

On such bases, we assess the capability of our model in detecting the bulk of Italian exporters by calculating the weight of true positive observations in terms of total exports.

Table 3. Fitting tests of the ROC estimates

Industry	Precision	Accuracy (correct clustering)	Share of false positives	Share of false negatives	Share of export for true positives
Food and beverage	50.4	81.6	15.0	3.4	99.6
Textile	63.7	75.8	16.7	7.5	98.6
Wearing apparel	60.5	72.1	18.4	9.6	97.3
Leather	66.8	72.1	16.0	11.9	98.2
Wood	38.4	79.3	17.5	3.2	97.3
Paper and print	55.3	77.9	16.7	5.4	99.4
Chemicals and pharmaceutics	84.3	70.9	11.1	17.9	99.3
Rubber and plastic	81.3	74.0	11.1	14.8	98.3
Non metalic minerals	55.6	74.4	17.5	8.0	98.3
Metals	59.2	79.9	14.2	5.9	98.7
Electronics	83.9	72.4	8.7	18.9	97.3
Machinery	81.6	69.9	12.0	18.1	97.5
Automotive	74.0	71.3	15.2	13.5	99.3
Furniture	66.0	79.2	13.0	7.8	97.7

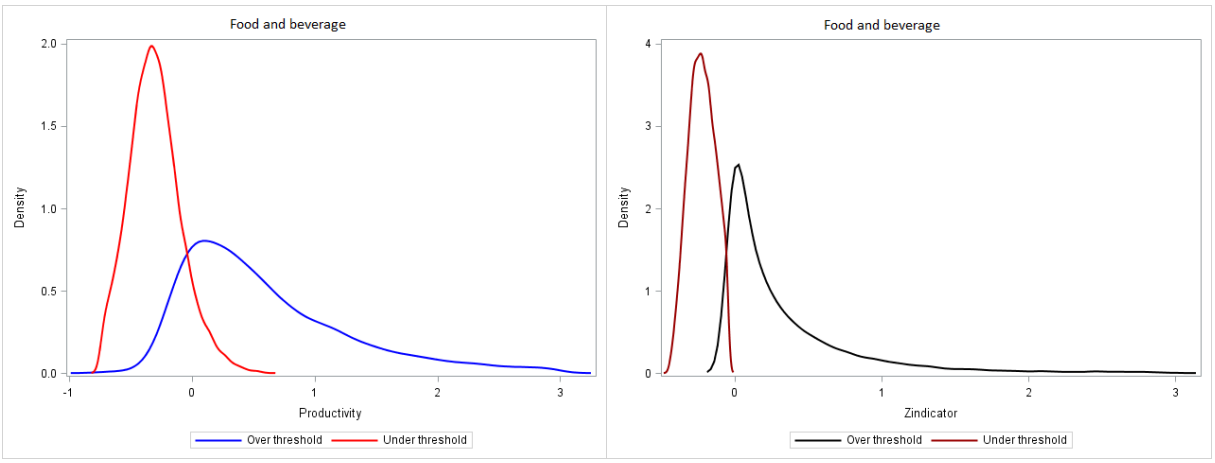
Source: Authors' calculation on Istat data

The results of these latter tests are reported in Table 3. Our model shows a high capability of correctly clustering exporters: in 9 out of 14 industries, the Precision (column 2) is over 60% (over 80% in four industries). With regard to correct and wrong classifications (columns 3 to 5), the model shows a good performance in detecting true positives (i.e. in correctly classifying exporters), so discharging clustering errors on false negatives (i.e. firms that the model classifies as non-exporters despite they actually sell abroad some of their products). The last column confirms that our clustering method grasps an extremely large share of total exports (over 97% in all industries), suggesting that false negatives (which largely bear the bias of the model) are negligible exporters.

Third, another way of looking at how the Z-model outperforms the pure productivity model concerns the distribution of exporting and non-exporting firms according to their values of productivity and Z. As Figure 2 clearly shows, once we take into account the Z indicator – i.e., once we move from considering just productivity as in Melitz (2003) to considering a combination of productivity and economic size – in all industries the distributions overlap substantially shrinks to a very limited area.

Figure 2. Labour productivity and Z indicator for firms over and under the export threshold[8]

[8] We included in the text only Food and beverage. Figures for all industries in Appendix A.



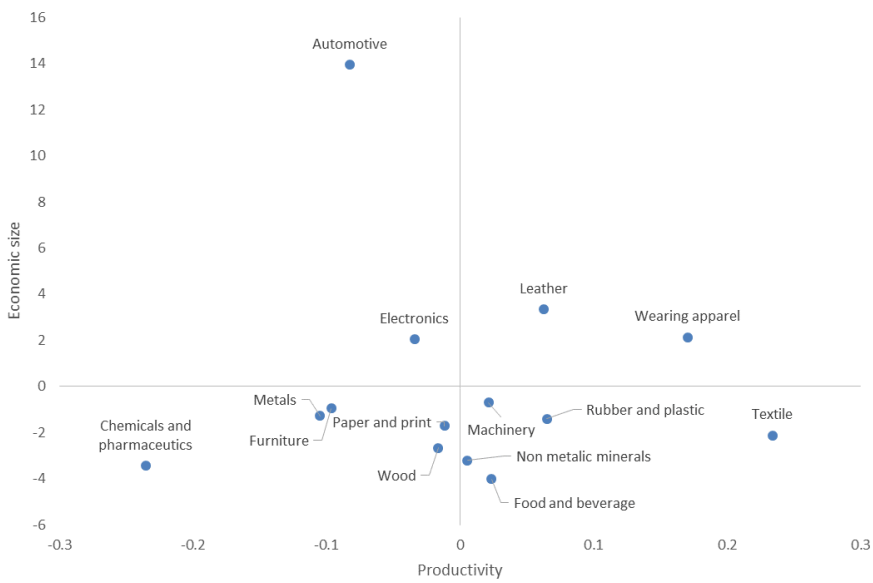
Source: Authors' calculations on Istat data

3.4. Across the export threshold

Z-model implies that in manufacturing sectors a given degree of complementarity between productivity and economic size emerges, in order to cope with sunk costs related to enter international markets.

For each industry, Figure 3 shows a relevant degree of sectoral heterogeneity according to the relative role of productivity and economic size in determining the export threshold

Figure 3. Relative importance of productivity and economic size in determining the export thresholds, by industry (*Effect of productivity – economic size – for i-th industry minus effect of productivity – economic size – for whole manufacturing*)



Source: Authors' calculations on Istat data

The capability to export for firms in industries laying in the first quadrant (i.e. leather and wearing apparel) depends on higher-than-average levels of both productivity and economic size. This implies that the conditions for these firms to export appear structurally more favourable with respect to the ones prevailing in the other industries. On the opposite, lower-than average conditions characterise industries laying in the third quadrant (e.g. metals, chemical and pharmaceutics). In the second and the fourth quadrants, instead, the export threshold results more sensitive with respect to one or the other of the two variables. In particular, internationalisation appears to be productivity-driven for industries laying in the fourth quadrant (e.g. Machinery, Textile). In other terms, given the technology prevailing in the Italian manufacturing system, for firms operating in these industries an increase in productivity would result more effective than one in economic size to reach the export threshold. A symmetric case characterizes industries laying in the second quadrant (i.e. Electronics and especially Automotive), where a growth in size-related variables (workforce, turnover, capital intensity) may be more effective in reaching the threshold than an increase in labour productivity.

To sum up, the export threshold points out the minimum combination of productivity and economic size that manufacturing firms needs to acquire in order to become exporters. These two factors are combined based on their relative weights, which can also be thought of as a compensation measure between the two variables in order to be an exporter.

4. The "Technology line"

In this section, we further use productivity and economic size to estimate firms' positioning within the industry in terms of technical efficiency. In fact, the "degree of substitution" between the two variables which is necessary to become an exporter might not be consistent with an efficient use of productive factors.[9] Therefore a mismatch between the conditions required to export and those necessary to successfully operate in the sector may emerge, implying that some exporters (non-exporters) may turn out to be less (more) efficient than some non-exporters (exporters).

In order to shed lights on such mismatch, we set up a two-step procedure. First, we estimate the relative weights of economic size and productivity corresponding to an efficient use of productive factors, here defined as a level of technical efficiency at least median within the industry. Second, to compare the efficiency of exporters and non-exporters with respect to the export threshold, we apply these relative weights to the values of productivity and economic size of the "export threshold firm". This defines the "technology line", i.e. all the combinations of economic size and productivity which guarantee the same probability of lying above the median efficiency of the export threshold firm. In doing so, we are able to position each firm in the space characterised by the crossing of export threshold and technology line (where the export threshold firms is the intersection point).

More in details, in the first step, following a well-established approach (Aigner et al., 1977; Meeusen and Van den Broeck, 1977), firm efficiency is measured by using a model of stochastic production frontier that estimates the level of value added a firm is able to generate given its factors endowment. A logarithmic transformation of the Cobb-Douglas production function is estimated, having the added value as dependent variable and the input of labour and the value of depreciation (as a proxy of the input of capital)

[9] The literature has showed that firm internationalization requires high productivity levels, which in turn requires an increase in technical efficiency (Mayer and Ottaviano, 2007).

as explanatory variables. Error decomposition has been estimated following the model by Battese *et al*. (1998).[10]

Successively, for each industry, a logit model of the probability for a firm to have an efficiency level higher than the median value of the sector is estimated, using the same covariates and controls as in Equation [5]:

$$\text{Prob (Tech. Efficiency}_i > \text{Median} \mid \mathrm{S}_i, \pi_i, \mathrm{G}_i, \mathrm{I}_i) = \Lambda(\alpha_1 \mathrm{S}_i + \alpha_2 \pi_i + \alpha_3 \mathrm{G}_i + \alpha_4 \mathrm{I}_i) \qquad [10]$$

The coefficients of covariates give the relative weights of economic size (S) and productivity (π) assuring a level of efficiency at least median within the industry. This corresponds to obtain, for each firm in the h-th industry, the following composite indicator:

$$Z_{h,i}^{t} = \widehat{\alpha}_{1,\mathrm{h}} S_{h,i} + \widehat{\alpha}_{2,\mathrm{h}} \pi_{h,i} \qquad [11]$$

In the second step, we identify the "technology line" among the bundle of parallel lines represented by Equation [11] as the line passing through the values of economic size and productivity of the export threshold firm c ($S_{h,c}$ and $\pi_{h,c}$, respectively):

$$Z_{h,c}^{t} = \widehat{\alpha}_{1,\mathrm{h}} S_{h,c} + \widehat{\alpha}_{2,\mathrm{h}} \pi_{h,c} \qquad [12]$$

where $Z_{h,c}^{t}$ (hereinafter: Z^t) is the minimum combination of productivity and economic size which corresponds to a level of technical efficiency equal to the export threshold firms' (hereinafter: the "benchmark").

From the interaction of export threshold and technology line, it is possible to derive two taxonomies. The first classifies industries with respect to relative efficiency of productivity and economic size in improving the positioning of firms in terms of Z^{e} and Z^{t}. The second classifies firms according to their positioning with respect to Z^{e} and Z^{t}. These taxonomies allows: (1) to define, for each industry, which is the most effective lever to boost the export propensity, taking into account possible mismatch with the preferable level to improve efficiency; (2) to qualify the comparison between exporting and non-exporting firms in the light of their position with respect to the prevailing technology of the given industry. The next two paragraphs present the two taxonomies.

5. Mapping the business system: a new taxonomy of industries

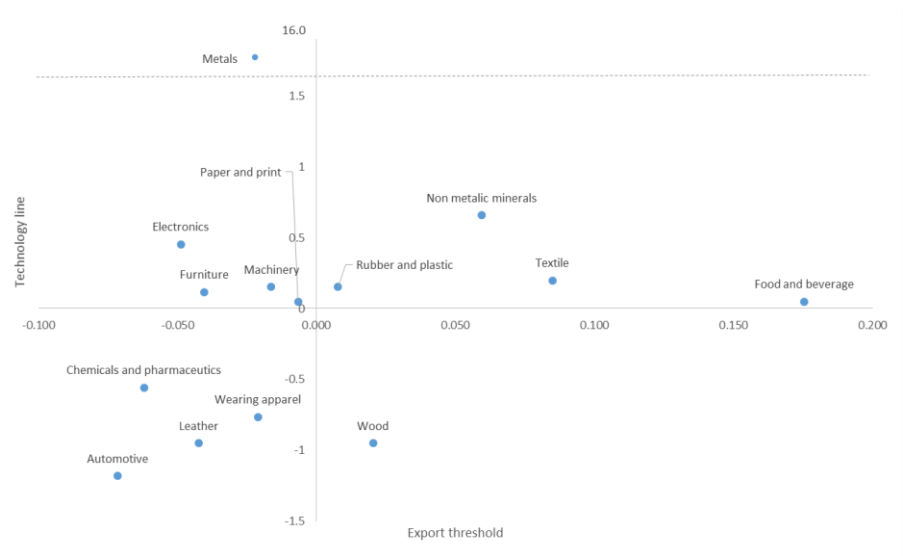
As pointed out in the previous paragraphs, both export threshold and technology line are determined by a combination of productivity and economic size. For each industry it is now possible to look at the relative

[10] See also Kumbhakar and Lovell (2000).

importance of productivity and economic size in determining Z^e taking into account the combination of the same variables needed to reach a minimum level of Z^t.

By jointly considering Z^e and Z^t, we can analyse how the use of a given lever (productivity or economic size) to improve export propensity of firms in a given sector affects their positioning in terms of efficiency. Figure 4 is indeed obtained by taking into account, for each industry, the relative relevance of productivity and economic size (as difference with respect to the total average) in the definition of the export threshold (horizontal axis) and technology line (vertical axis).

Figure 4. Relative importance of productivity and economic size in determining the export thresholds and the technology line, by industry (*relative weight of productivity and economic size for export threshold – technology line – for i-th industry minus relative weight of productivity and economic size for export threshold – economic size – for whole manufacturing*)



This way, quadrants implicitly define a taxonomy of industries based on the identification of the preferable lever in order to boost export capabilities of firms taking into account also the effect of the same instrument on the positioning of firms with respect to the technology line.

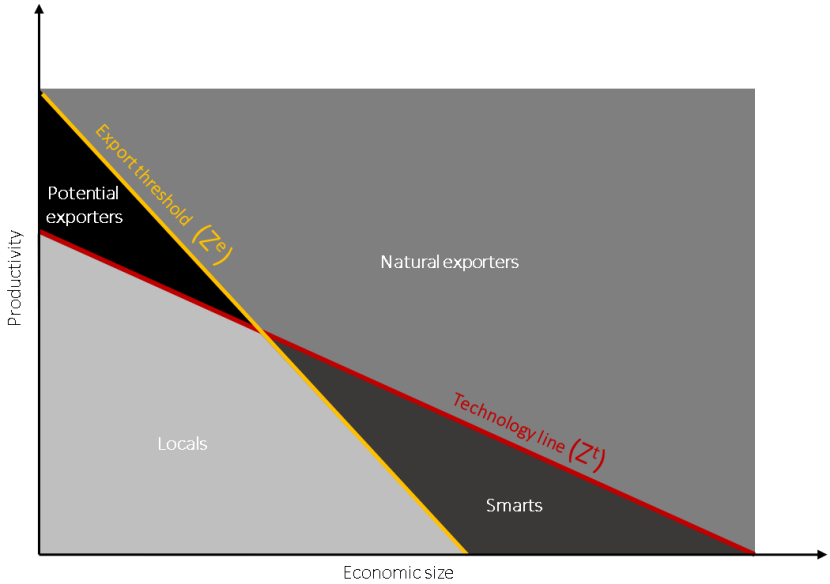
The first and third quadrant identify industries in which the preferable lever to improve the positioning of firms with respect Z^e is also the most effective to improve the positioning with respect to Z^t. In particular, industries laying in the first quadrant are productivity-driven, while industries laying in the third quadrant are size-driven.

Instead, the second and fourth quadrant identify industries in which the preferable lever to improve the positioning of firms with respect Z^e is not the most effective to improve the positioning with respect to Z^t. Industries laying in the fourth quadrant are productivity-driven, while industries laying in the second quadrant are size-driven.

6. Mapping the business system: a new taxonomy of firms

The space defined by the interaction of Z^e and Z^t ideally defines four areas as depicted in Figure 5.

Figure 5. The taxonomy of firms export orientation



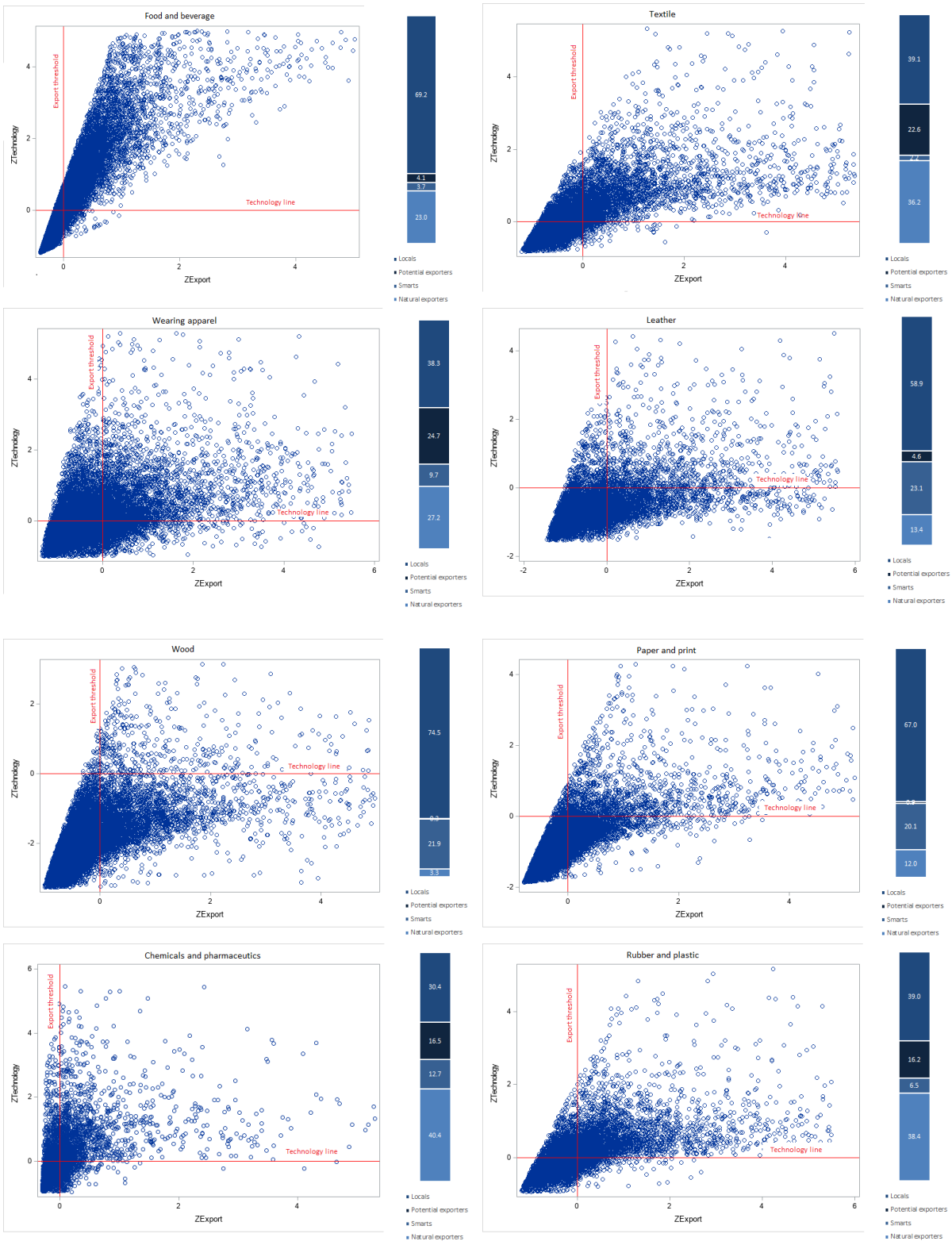
Depending on how the firms distribute across these areas, it is possible to derive the following four-class taxonomy of firms export orientation:

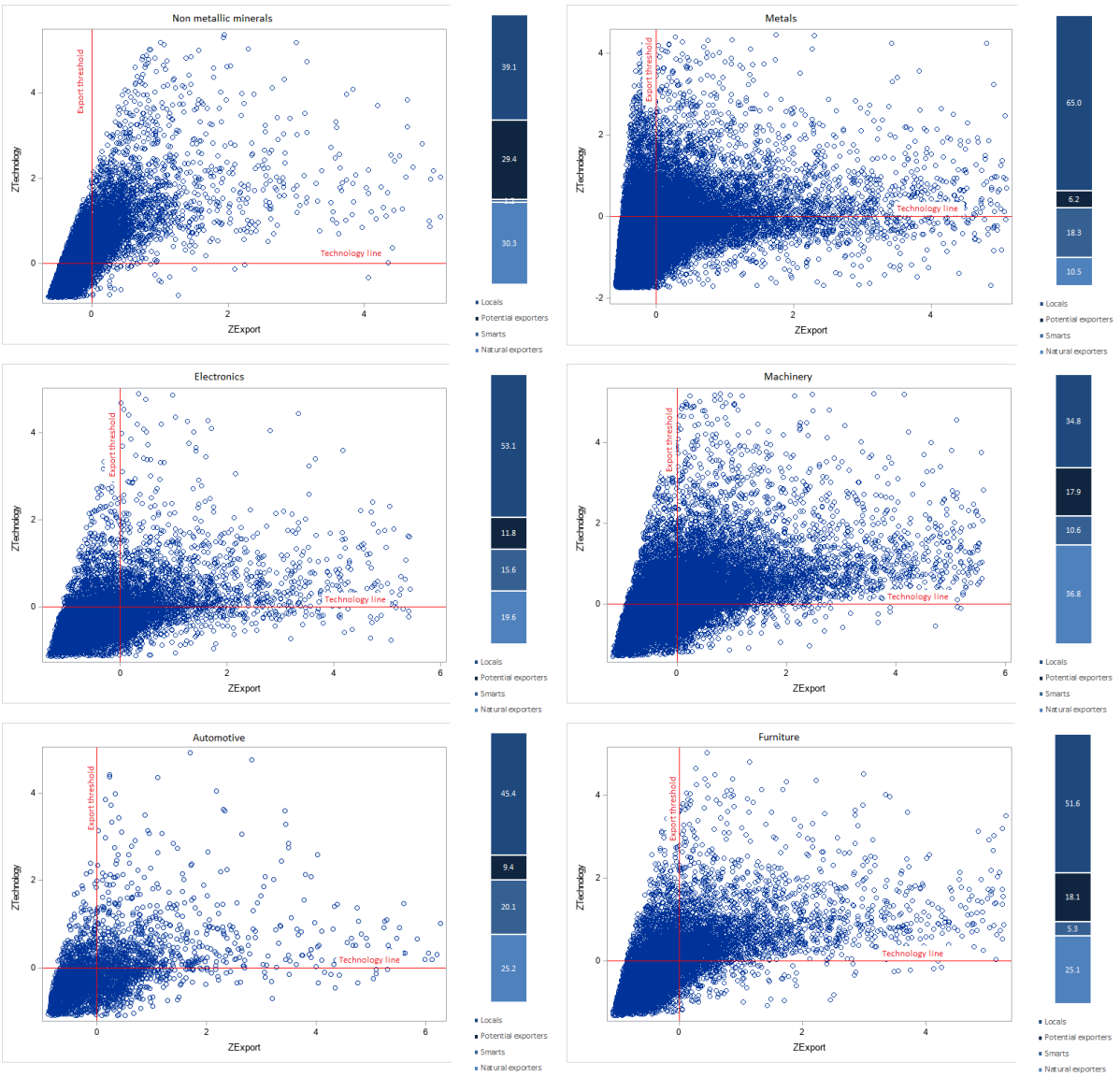
- "Natural exporters": firms with $Z_i^e > Z^e$ and $Z_i^t > Z^t$, i.e. with a combination of productivity and economic size higher both than the export threshold and the technology line. These units are productive and/or "large" enough to produce efficiently and export.
- "Smarts": firms with $Z_i^e > Z^e$ and $Z_i^t < Z^t$. These units are thus classified as exporters notwithstanding their combination of productivity and size corresponds to an efficiency lower than the benchmark.
- "Potential exporters": firms with $Z_i^e < Z^e$ and $Z_i^t > Z^t$. These units have levels of productivity and size consistent with an over-the-benchmark efficiency, but insufficient to export.
- "Locals": firms with $Z_i^e < Z^e$ and $Z_i^t < Z^t$. These units do not reach the minimum combinations of productivity and economic size required to be relatively efficient or to export.

Smarts and Potential exporters are the two classes where a mismatch between economic size and productivity need to satisfy the minimum combination of Z^e and Z^t emerges.

The distribution of firms in the four classes are plotted in Figure 6 according to their respective values of the Zs referring to export and technology. The noticeable heterogeneity among the exporters (Smarts and Naturals) and the non-exporters (Locals and Potentials) clearly emerges. Moreover, in all industries, the class of Locals tends to outnumber the others with the exceptions of Machinery and Chemical and pharmaceutics, i.e. the industries with the highest percentages of exporting firms and especially of "Natural exporters" (but these latter are numerous also in Textile and Rubber and plastic).

Figure 6. Mapping business system with respect to the interaction between export threshold and technology line





Source: Authors' calculation on Istat data.

Moving from this taxonomy, Table 4 reports some descriptive evidence about the different classes by industry. Italian manufacturing comes out as a polarized system: in almost every industry, Locals account for the majority of firms, while Natural exporters largely dominate in terms of share of value added and turnover.

From analytical and policy-making points of view, however, the most interesting groups are Smarts and Potential exporters.The formers, which lay above the export threshold despite a size-productivity combination under the technology line, are numerous especially in Leather, Wood, Automotive, Paper and print and Metals, i.e. industries of the Italian specialization models. This peculiarity might be related to factors such as the participation in GVC (e.g. through subcontracting) and intra-group trade. In this respect, the last column of Table 4 reports, for each class, the share of firms belonging to a multinational group. However, the incidence among Smarts is generally low, ranging from 1.3% within Non metallic minerals and 25.1% in Automotive. This implies that the class of the taxonomy is marginally affected by this aspect, and among Smarts some "bright stars" of the Italian internationalized firms could be detected.

Also Potential exporters, which show combinations of productivity and economic size corresponding to a relatively high technical efficiency but do not export, are linked to the typical activities of Italian manufacturing, as they are relatively numerous (with shares ranging from 18 to over 29%) in Furniture, Textile, Wearing apparel, Machinery and Non metallic minerals. This class represents the target that measures aiming at increasing the number of exporting firms (i.e. to stimulate domestic units to cross the export threshold) should actually focus on.

Table 4. Characteristics of firms by typology and industry

Industry	Taxonomy	Firms (shares of total industry)	Value added (Shares of total industry)	Turnover (Shares of total industry)	Employment (Mean, Workers)	Labor productivity (Mean, thousand euro)	Export/turnover ratio (%)	Shares of firms belonging to Multinational groups
Food and beverage	Local	69.2	8.1	4.7	4.1	18.4	-	1.1
	Potential Exporter	4.1	1.0	0.6	4.1	37.2	-	0.3
	Smart	3.7	1.6	1.2	12.3	22.2	1.2	1.9
	Natural exporter	23.0	89.3	93.5	29.4	84.6	8.1	13.3
Textile	Local	39.1	3.7	3.1	3.9	16.8	-	0.8
	Potential Exporter	22.6	5.2	4.0	4.5	35.4	-	1.9
	Smart	2.2	0.9	0.9	15.7	18.7	6.0	1.4
	Natural exporter	36.2	90.2	92.1	27.4	63.7	16.4	19.4
Wearing apparel	Local	38.3	4.7	3.7	4.8	14.7	-	0.1
	Potential Exporter	24.7	6.4	5.5	4.5	33.2	-	1.0
	Smart	9.7	11.4	10.6	23.4	29.1	7.7	5.1
	Natural exporter	27.2	77.5	80.1	26.4	62.7	18.3	16.7
Leather	Local	58.9	9.0	6.1	5.3	23.1	-	0.7
	Potential Exporter	4.6	1.2	1.0	3.5	60.2	-	0.6
	Smart	23.1	23.9	21.9	25.0	33.2	16.0	15.5
	Natural exporter	13.4	65.9	71.0	40.2	98.1	26.7	12.1
Wood	Local	74.5	18.2	14.8	2.5	22.5	-	1.6
	Potential Exporter	0.3	0.1	0.1	1.3	73.7	-	0.1
	Smart	21.9	58.4	59.5	14.7	41.4	5.3	11.9
	Natural exporter	3.3	23.4	25.5	15.4	105.2	6.1	1.7
Paper and print	Local	67.0	8.6	7.0	3.4	26.4	-	1.6
	Potential Exporter	0.9	0.2	0.2	2.0	70.5	-	0.1
	Smart	20.1	17.0	14.9	14.4	41.5	3.6	9.9
	Natural exporter	12.0	74.2	78.0	50.8	85.6	9.7	9.6
Chemicals and pharmaceutics	Local	30.4	1.0	1.0	5.3	32.6	-	1.7
	Potential Exporter	16.5	1.9	1.9	7.6	80.9	-	15.8
	Smart	12.7	5.7	8.4	36.4	67.0	12.8	14.4
	Natural exporter	40.4	91.5	88.8	90.7	136.0	24.0	61.8
Rubber and plastic	Local	39.0	4.3	3.7	5.6	29.3	-	1.9
	Potential Exporter	16.2	3.8	3.4	6.4	55.0	-	4.1
	Smart	6.5	2.6	2.5	18.9	32.4	9.4	3.5
	Natural exporter	38.4	89.3	90.4	45.2	77.8	19.6	32.1
Non metalic minerals	Local	39.1	2.4	2.3	3.1	15.2	-	1.1
	Potential Exporter	29.4	6.0	5.4	4.6	34.0	-	3.7
	Smart	1.2	0.4	0.9	15.9	15.3	7.1	1.3
	Natural exporter	30.3	91.1	91.3	30.8	74.8	11.8	17.5
Metals	Local	65.0	12.6	8.9	4.4	32.8	-	1.5
	Potential Exporter	6.2	2.8	1.8	4.3	77.9	-	1.3
	Smart	18.3	28.0	26.3	26.2	43.3	9.1	16.2
	Natural exporter	10.5	56.7	63.1	43.9	91.6	17.0	8.7
Electronics	Local	53.1	6.4	5.2	6.3	34.1	-	2.5
	Potential Exporter	11.8	2.9	2.4	6.1	73.2	-	9.1
	Smart	15.6	10.4	10.8	30.2	39.2	18.0	21.5
	Natural exporter	19.6	80.3	81.6	83.5	87.6	28.4	29.9
Machinery	Local	34.8	3.8	3.4	5.9	34.4	-	1.5
	Potential Exporter	17.9	4.3	3.7	6.9	64.8	-	6.8
	Smart	10.6	3.3	3.3	16.6	35.4	17.3	7.6
	Natural exporter	36.8	88.6	89.6	52.9	84.2	30.7	38.4
Automotive	Local	45.4	2.0	1.1	8.2	31.8	-	1.5
	Potential Exporter	9.4	0.9	0.6	9.1	66.1	-	5.7
	Smart	20.1	13.2	30.5	99.6	40.1	13.6	25.1
	Natural exporter	25.2	83.9	67.7	208.8	96.8	29.4	41.4
Furniture	Local	51.6	7.0	5.6	3.4	20.2	-	1.4
	Potential Exporter	18.1	5.7	4.3	3.9	40.7	-	2.7
	Smart	5.3	3.3	3.2	13.8	22.5	10.9	3.1
	Natural exporter	25.1	84.0	86.9	28.5	58.9	17.0	11.4

Source: Authors' calculation on Istat data.

Even more interestingly, Potential exporters and Smarts appear symmetric in terms of employment and productivity: in virtually each industry the former are substantially smaller and more productive than the latter. On the one hand, this suggests that on average, in order to have the Potential exporters cross the export threshold, a recovery in size in more necessary than an increase in productivity. On the other hand,

in order for Smarts to become Natural exporters, an increase in productivity appear to be more necessary than a recovery in size.

7. Conclusions

In this paper, we use a ROC-based approach to measure the role of firms' productivity and economic size in determining their ability to access international markets. More in detail, we provide a methodology that allows to cluster business units according to their export orientation and capability, so that it becomes possible to distinguish what firms are able to export despite their relatively (within the sector) low efficiency, and, even more importantly, what domestic firms have more potential to enter international markets.

To do so, we firstly estimate, for every industry, the "export threshold", defined as the firm-level minimum combination of (levels of) productivity and economic size (the latter defined on the basis of a firm's turnover, workers, capital, and age) corresponding to the transition from the non-exporter to exporter status. Successively, we introduce the "technology line", that is the estimated combination of productivity and economic size which corresponds to a level of technical efficiency higher than the median of the industry.

The interaction between the export threshold and the technology line permits to derive two taxonomies for industries and firms. The first classifies industries according to the coherence between the factor that is more effective (productivity or economic size) to boost firms export propensity and the one that more effectively improves firms efficiency. The second classifies firms in terms of their competitive positioning with respect to the minimum conditions needed to export and to operate with a relatively high degree of technical efficiency.

These classifications are mostly important from a policy-making point of view. In particular, they are especially useful with reference to two aspects: *a)* they provide an instrument to select more precisely targets (firm- and/or industry-level) for policies aimed at fostering firms internationalization (e.g. intensive or extensive margins); *b)* they help detect which lever – productivity or economic size – is better to stimulate in order to maximize the effectiveness of those policies.

In particular, the presence of a compensation between productivity and economic size in exporting generates the possibility of a mismatch between the conditions required to export and those necessary to efficiently operate in the industry. This mismatch, which emerges at individual and sectoral level, implies that policies have to consider the most effective lever for the specific class of firms (e.g. productivity for Smarts and economic size for Potential exporters), but also the relative role of productivity and economic size in determining the export threshold and the technology line in the given industry. For example, an increase in economic size may help Potential exporters become Natural exporters, especially in industries where economic size is relatively more relevant for both exporting and efficiently operating. Symmetrically, an increase in productivity may help Smarts become Natural exporters, especially in industries where a recovery in productivity appears more needed for both exporting and efficiently operating.

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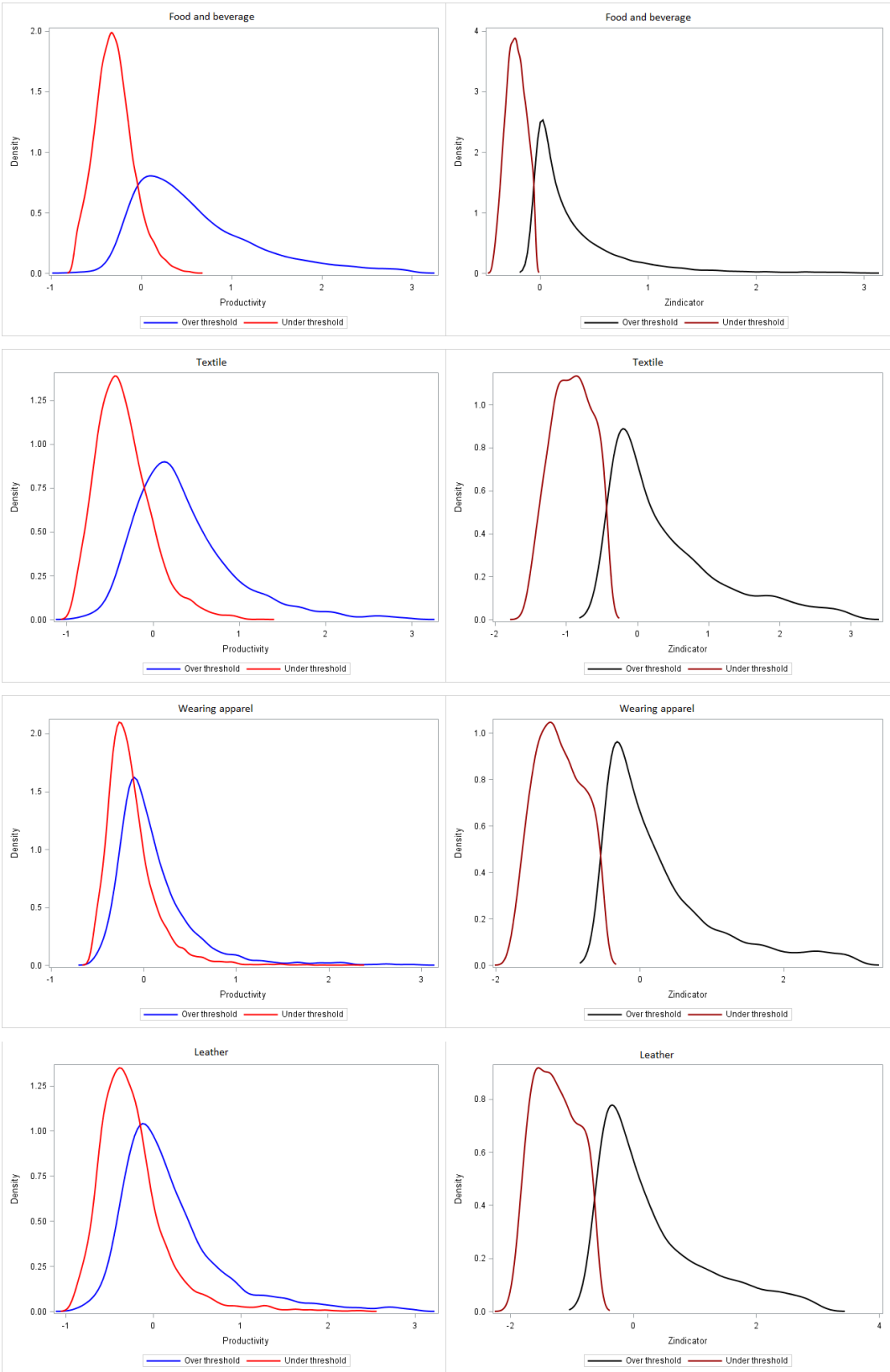
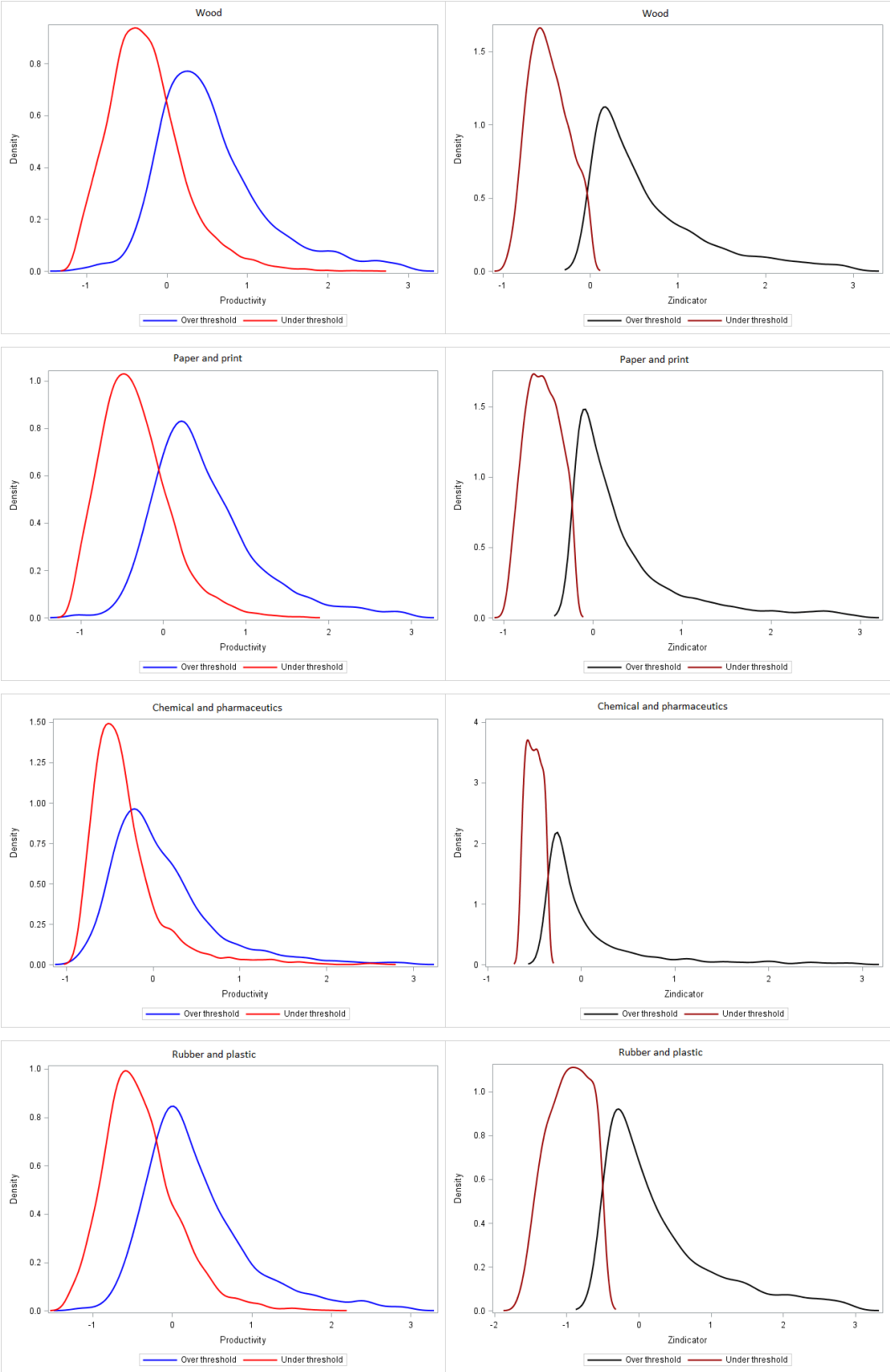
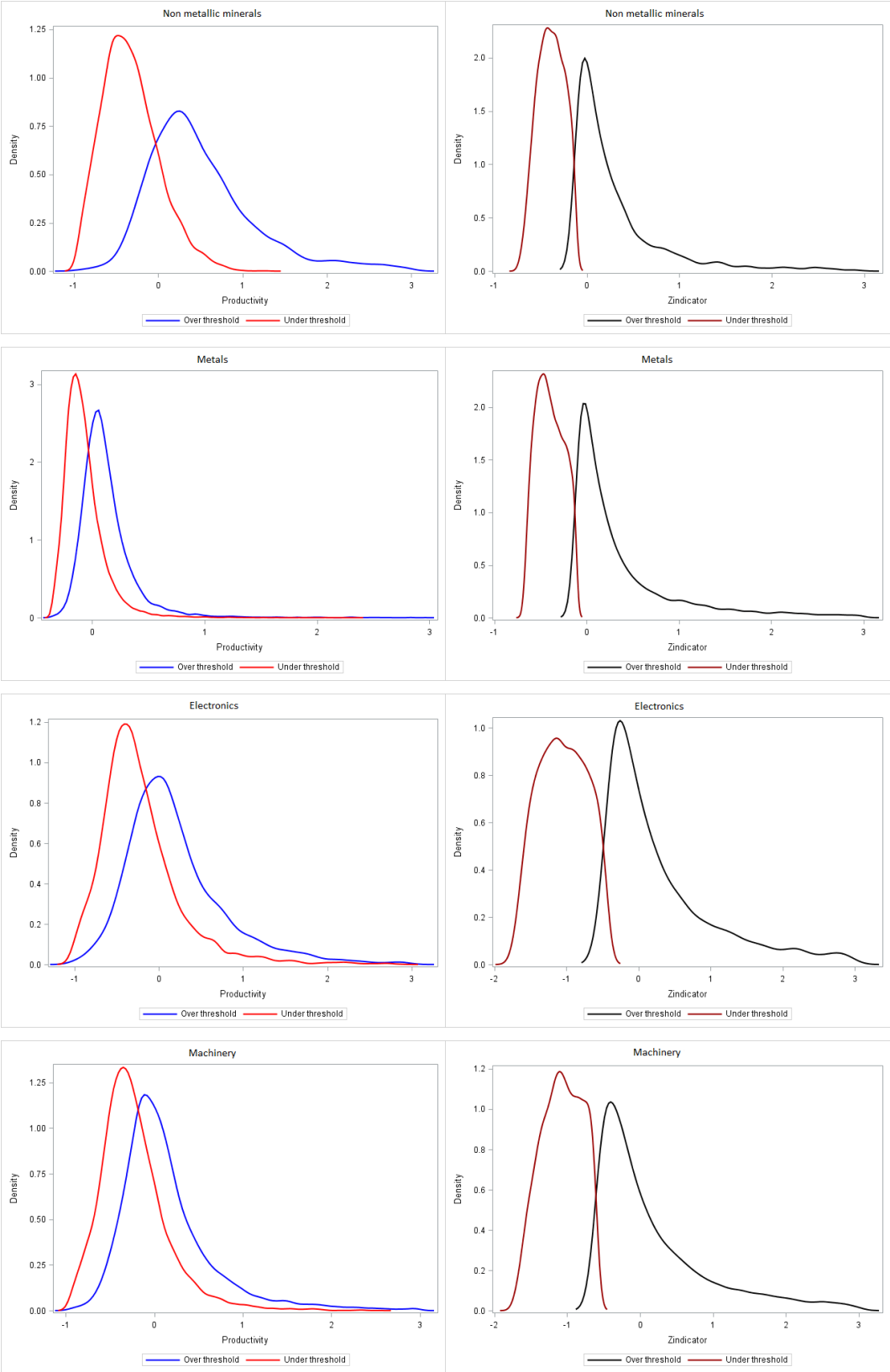
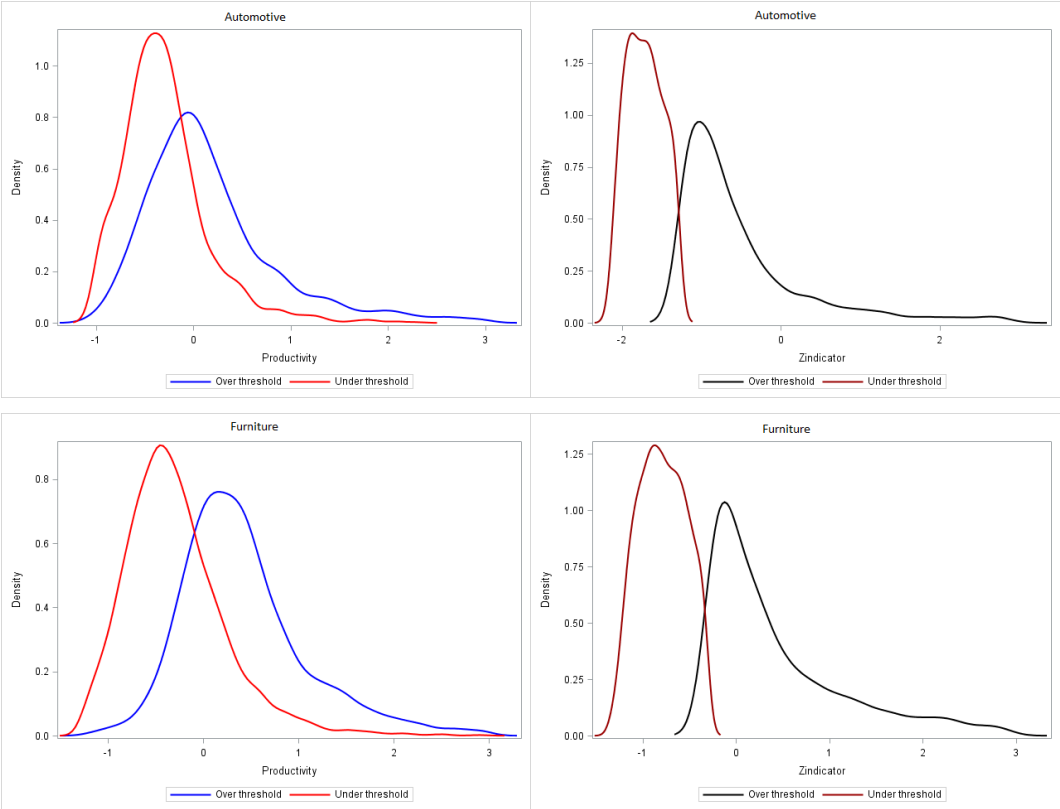
Appendix A. Kernel density graphs of labour productivity and *Z* indicator for firms over and under the export threshold

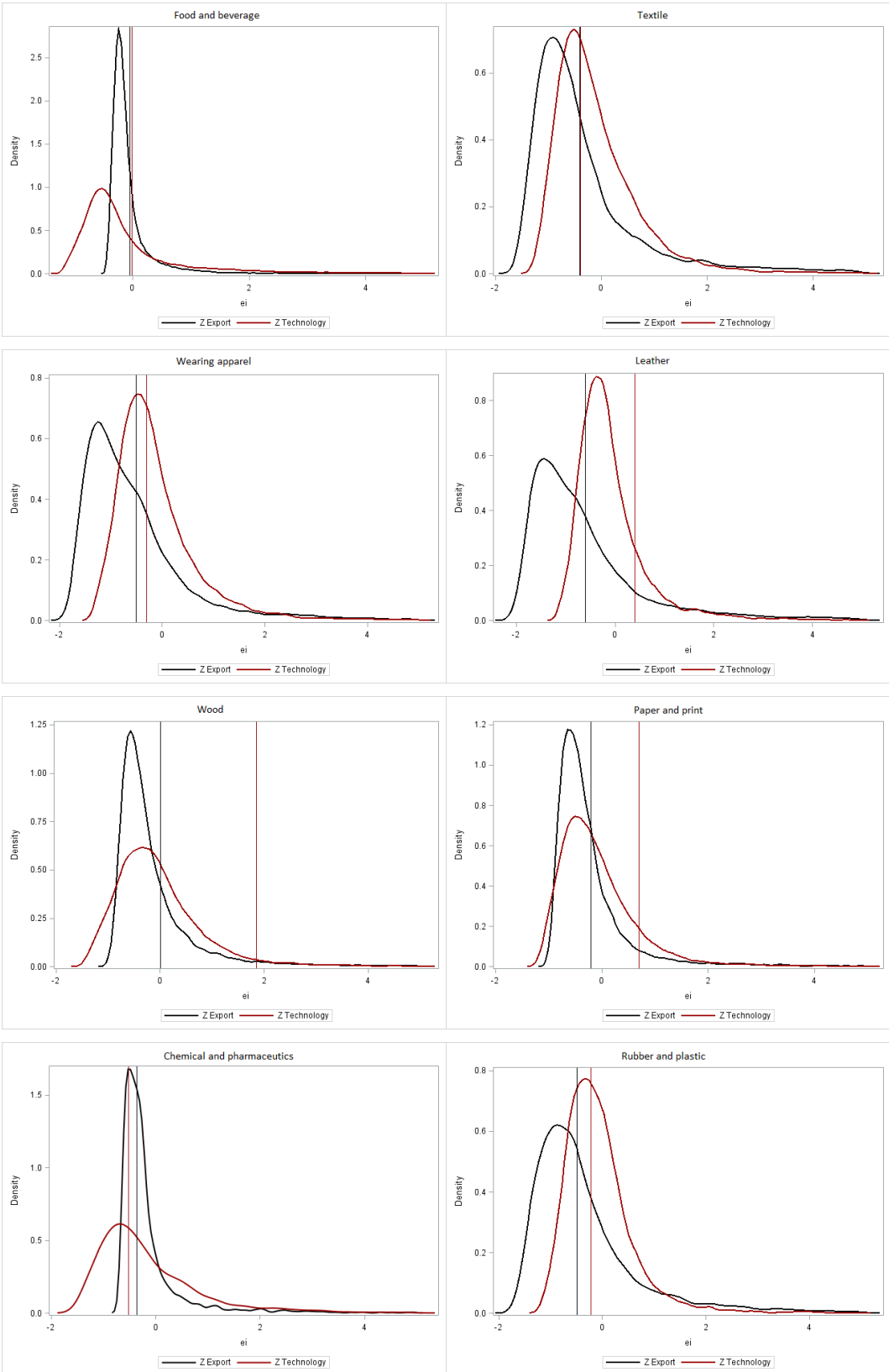


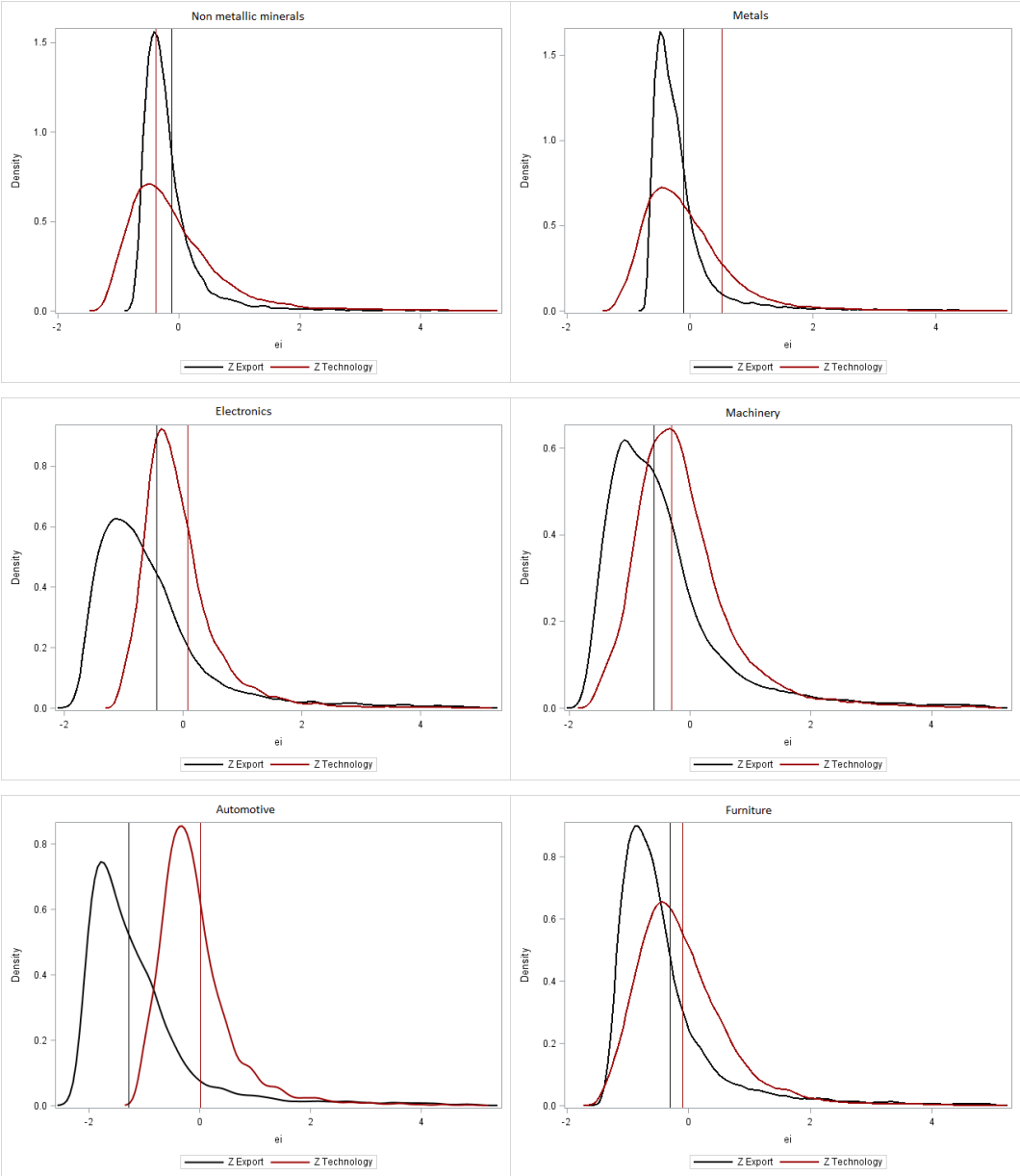

Wood
Density
Productivity
Over threshold
Under threshold
Wood
Density
Zindicator
Over threshold
Under threshold
Paper and print
Density
Productivity
Over threshold
Under threshold
Paper and print
Density
Zindicator
Over threshold
Under threshold
Chemical and pharmaceutics
Density
Productivity
Over threshold
Under threshold
Chemical and pharmaceutics
Density
Zindicator
Over threshold
Under threshold
Rubber and plastic
Density
Productivity
Over threshold
Under threshold
Rubber and plastic
Density
Zindicator
Over threshold
Under threshold


Non metallic minerals
Density
Productivity
Over threshold
Under threshold
Non metallic minerals
Density
Zindicator
Over threshold
Under threshold
Metals
Density
Productivity
Over threshold
Under threshold
Metals
Density
Zindicator
Over threshold
Under threshold
Electronics
Density
Productivity
Over threshold
Under threshold
Electronics
Density
Zindicator
Over threshold
Under threshold
Machinery
Density
Productivity
Over threshold
Under threshold
Machinery
Density
Zindicator
Over threshold
Under threshold

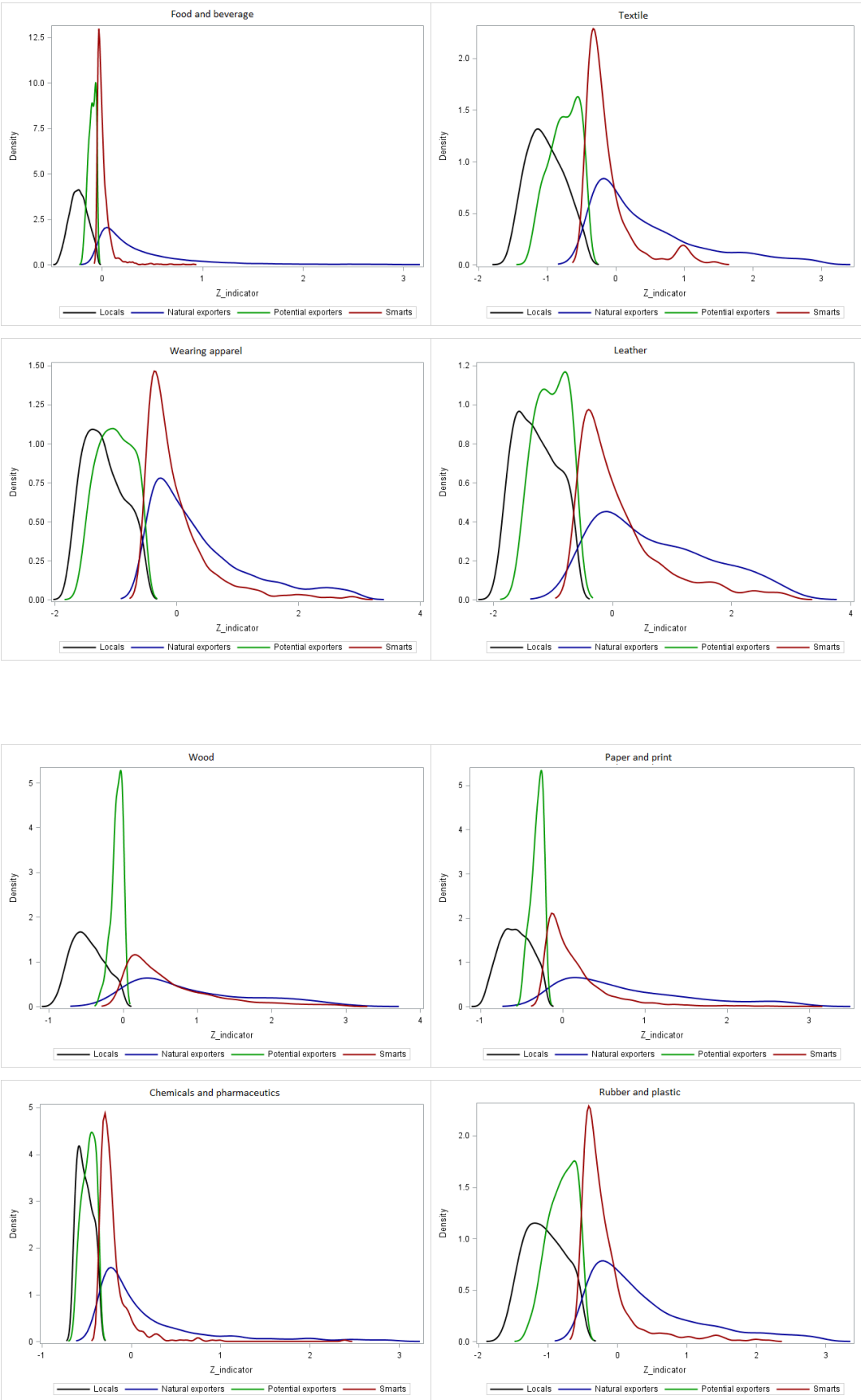

Automotive
Density
Productivity
Over threshold
Under threshold
Automotive
Density
Zindicator
Over threshold
Under threshold
Furniture
Density
Productivity
Over threshold
Under threshold
Furniture
Density
Zindicator
Over threshold
Under threshold

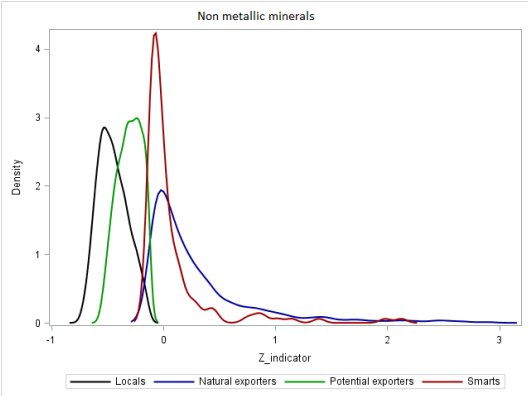
Appendix B. Kernel density graphs of the distribution Z indicator for exports and technology and the value of Z^t and Z^e for each industry

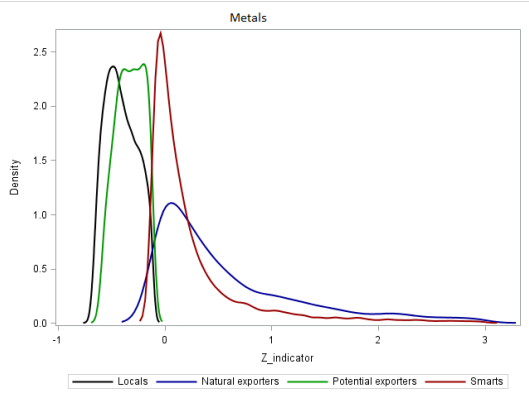


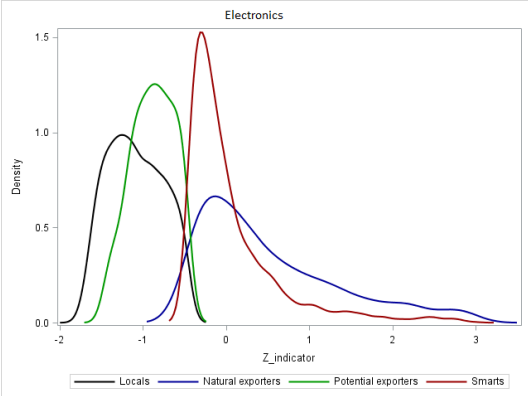

Non metallic minerals
Metals
Electronics
Machinery
Automotive
Furniture
Density
ei
Z Export
Z Technology

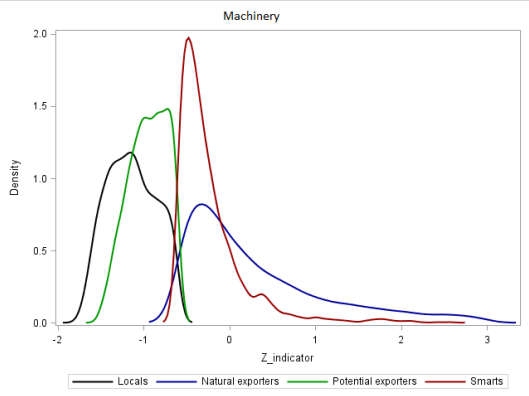
Appendix C. Kernel density graphs of the distribution of Z indicator and interaction between export threshold and technology line, by classes of firms

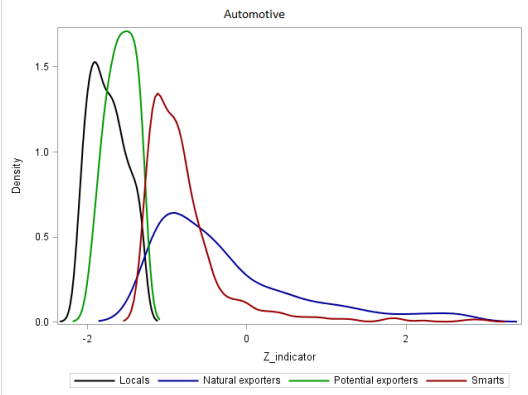


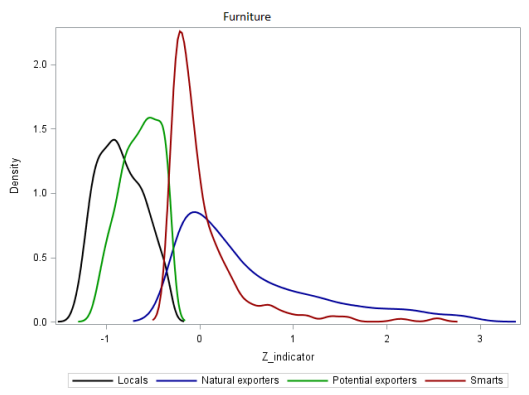

Non metallic minerals
Density
Z_indicator
Locals
Natural exporters
Potential exporters
Smarts


Metals
Density
Z_indicator
Locals
Natural exporters
Potential exporters
Smarts


Electronics
Density
Z_indicator
Locals
Natural exporters
Potential exporters
Smarts


Machinery
Density
Z_indicator
Locals
Natural exporters
Potential exporters
Smarts


Automotive
Density
Z_indicator
Locals
Natural exporters
Potential exporters
Smarts


Furniture
Density
Z_indicator
Locals
Natural exporters
Potential exporters
Smarts