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# How Inward FDI Shapes the Dynamics of Exports and R&D Activities: Evidence from Tunisian Manufacturing Firms

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**Abstract:**
Foreign Direct Investment (FDI) can inject technology and knowledge into host-country economies, potentially influencing their firms' R&D investments and export capacities; as a result, these firms may engage in more or less R&D (exports), potentially shaping the interaction between the two strategies. This paper investigates whether and when these strategies are complementary and reinforce each other, or whether they are substitutes, and should not be jointly pursued, as well as how combining the two strategies may lead to synergies positively affecting growth. Using four different clusters of firms, the findings suggest that R&D and exports positively reinforce each other in a dynamic virtuous circle to boost exports for firms with no foreign participation, whereas substitutability effects emerge for R&D activity, primarily for firms with foreign participation.

**Keywords:** manufacturing industry, exports, R&D investment, foreign participation, complementarities, substitutability effects, Multiple Imputation, Tunisia

**JEL classification :** F140, L250, L63, L67, O55, O32

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## 1. Introduction

A bulk of the literature has investigated the relationship between FDI, exports, and innovation. This literature has mainly focused on the relationship between two activities at a time: innovation and exports, FDI and exports, and FDI and innovation. In the innovation-export and FDI-export links, a number of studies (Golovko and Valentini [39]; Roper and Love [97], Helpman et *al*. [50], Ma et *al*. [74]; Clausing [24]; Pfaffermayer [91]) have explored the nature of the interaction between the two activities, which could either complement or crowd out one another. Two strategies are complementary if one activity increases the benefits of the other and engaging in one activity lowers the costs of engaging in another: firms that export are more likely to engage in innovation (FDI), and vice versa. Other studies have suggested that because the successful implementation of these two strategies depends on the concurrent use of limited organizational resources (such as qualified personnel and liquidity), exports and innovation (FDI) may represent alternative growth strategies, which should not be carried out jointly.

In the export-innovation link, there are compelling reasons to believe that exports and innovation could have a positive relationship. Superior productivity and the self-selection of more productive firms into exports could be attributed to innovation. As a result, by increasing productivity, innovation has the potential to alleviate the burden of export-related costs [22]. Exporting firms, on the other hand, can gain access to more internal financial resources as well as external financing for innovation investments [103, 105]. Exporting firms, according to Salomon and Shaver [103], can stabilize their cash flows because business cycles are not perfectly correlated across national markets. A steady cash flow may allow for greater access to internal financial resources for innovation investments. Furthermore, because of reduced liquidity constraints, exporting can provide greater assurances to external sources of funds that the firm will be able to service its obligations more effectively [105].

The nature of the interaction between exports and innovation has been documented in a large body of empirical literature, but the results are not always clear-cut. According to some studies, the two strategies should be carried out jointly; Golovko and Valentini [39] and Esteve-Pérez and Rodríguez [32] use data from Spain to support this claim. Lileeva and Trefler 69]; Girma et *al*. [37]; and Mattoussi and Ayadi [84], brought evidence for the dichotomy between the two activities, and this complementarity explains the higher performance levels (sales growth) of Canadian, Irish, and Tunisian manufacturing firms, respectively. These findings suggest that innovative firms that enter foreign markets and have the opportunity to learn by exporting and producing higher-quality innovations will be able to gain even more market power and, as a result, increase their sales even more.

Another line of empirical research, including Roper and Love [97] and Kumar [64] was more consistent with a trade-off between both strategies, which compete for finite internal resources and need prioritizing over time. According to Roper and Love [97], exports and innovation may be perceived, as substitute strategies in the case of German manufacturing firms where innovation levels were high but the proportion of sales ascribed to new products was low. These businesses must decide whether to focus solely on domestic product development or to devote fewer resources to innovation and more to developing new export markets. Similarly, Kumar [64] finds a negative association between product diversification and international diversification in the short run for US firms. He claims that short-run constraints such as replicating and transferring tacit, causally ambiguous competencies [114, 82, 83] and absorptive capacity [27, 119] limit diversification along the two dimensions, forcing firms to trade-off growth along the two dimensions, resulting in a negative relationship. Thus the relationship between growth along the two dimensions provides important insight into whether short-run constraints play a more influential role in strategic choices compared to incentives to expand such as economies of scope.

Two strands of literature were used to investigate the FDI-export link. In the first strand, the theory suggests a dual link between trade flows and outward FDI, with the two strategies exhibiting substitutability or complementarity effects. According to Helpman et *al*. [50], the nature of the interaction between FDI and exports is determined by the type of FDI, which can be horizontal or vertical. Horizontal FDI occurs when multinational enterprises (MNEs) establish a subsidiary in each country of interest, either to save on transportation or simply to be closer to the final customer. Horizontal FDI typically takes place between countries with similar factor endowment, income, and technological capabilities. In general, the model suggests that horizontal FDI is likely to occur between developed countries.
According to the theoretical literature on this type of outward FDI, there is a substitution relationship between FDI and exports. Markusen [79], states that a multinational enterprise (MNE) chooses FDI to serve foreign markets over exports if the additional fixed costs of establishing a new plant in a foreign country are lower than the fixed costs of exporting. Another reason to engage in horizontal FDI is to save money on trade costs like tariffs and transportation [50]. As noted by Brainard [18], firms face the proximity-concentration trade-

off: they have to decide between maximizing proximity to local markets and avoiding transport costs (via outward FDI) or concentrating production to achieve economies of scale.

Vertical FDI ont he other hand, occurs when MNEs locate each stage of the manufacturing process in a different country to take advantage of lower factor prices. Helpman [49] suggests that there are complementarities between trade flows of final goods from foreign affiliates to parent firms and intra-firm transfers of intermediate goods from parent firms to foreign affiliates. In general, the model suggests that vertical FDI is likely to occur between developed and developing countries. Complementarity has compelling reasons: for example, a firm's presence in a foreign market with one product may increase total demand for the entire line of products [70]. Another reason for complementarity could be that a manufacturer's investment may increase input exports from the home market to the host market.

Carr et *al*. [20] and Markusen [79] attempted to combine horizontal and vertical FDI motivations in a model known as the knowledge-capital model (KK). Horizontal FDI predominates in countries with similar factor endowments and high trade costs, whereas vertical FDI predominates in countries with different factor endowments and low trade costs. Liu et *al*. [71] also propose a pendulum gravity model that demonstrates the complexity of the outward FDI-export link. As a result, depending on the stage of development of outward FDI, the two strategies can be complementary or substitute. In the early stages of FDI, a complementary relationship is more likely, but as FDI matures, it becomes a substitute for exports.

As can be seen, the theoretical arguments do not presuppose a clear relationship between outward FDI and exports. Tariffs, the type of goods, and the type of FDI all influence whether a substitution or complementary relationship exists. Similarly, the empirical evidence on this relationship varies and is inconclusive. Several studies, including Ma et *al*. [74] found a substitution relationship between outward FDI and exports for Japaneese firms. Other studies, on the other hand, such as Brainard [18], and Clausing [24], supported the idea that overseas production supplements rather than replaces exports for the U.S. manufacturing industries; Co [26] for Japanese industries, and Pfaffermayer [91] for Austrian industries.

The second body of literature examines the dual relationship between inward FDI and host-country export capacity, with inward FDI regarded as one of the primary driving forces of international trade. According to Moran et *al.* [86], if inward FDI is supported by adequate public policies, it can be an important driver for the development of local businesses and contribute to the host country's competitiveness by promoting the transfer of new knowledge and technology among economies and spreading spillovers to local firms, which can help the host country gain competitive advantages and integrate international markets. The existence of a training effect is primarily related to the nature of local firms' links with foreign firms, as well as the absorptive capacity of local firms.

Seen from the theoretical perspective and earlier empirical studies, the results of the relationship between innovation and (inward) FDI are not always clear-cut. On the one hand, inward FDI can stimulate host-country innovation activity via spillover channels such as reverse engineering, skilled labor turnovers, demonstration effects, and supplier-customer relationships [23, 32, 125]. However, it cannot be taken for granted that FDI promotes innovation; in fact, FDI may stifle innovation. Several studies have found that foreign companies may be poorly embedded in a local innovation system for a variety of reasons. Multinational parents with access to more advanced technologies may be enticed to transfer older technologies to domestic firms, and they may also limit knowledge spillover to non-affiliated firms in order to protect their ownership advantage [107].

Porter and Siggelkow [92] have emphasized that the nature of interaction between a firm's strategic activities may not just be an inherent property of the activities themselves, but also a function of the other decisions a firm makes. In other words, a firm's choice of other activities may also influence whether and how two activities interact—whether they are complementary and reinforce each other, or whether they are substitutes. In this context, we will investigate the role of inward FDI in shaping the dynamics of exports and R&D activities– when the two strategies complement each other and when they compete. We also explore whether complementarities between the two strategies improve firm growth. All of this occurs in the context of a developing country with a subcontracting regime, where strict contractual arrangements can either benefit or constrain firms' strategic choices.

The study is based on three firm-level datasets derived from accounting, industrial, and export flow surveys conducted on Tunisian firm-level data from 2016 to 2018. Despite the best efforts of the interview team, we have a problem with missing data due to (item) non-response. We use the Multiple Imputation (MI) technique to account for missing units and correct for potential bias caused by non-random sample selection. We distinguish four groups of firms using both export and FDI differentials. The first and second clusters consist of any exporting firm (differentiating exporters from non-exporters) without and with foreign ownership, respectively. The third and fourth clusters include firms that are fully exporting (exporting 100% of their output) without and with foreign involvement, respectively.

Econometric findings gave support for the learning by exporting hypothesis for R&D activity in the cluster of any exporting firms with no foreign participation. There is also compelling evidence for the self-selection effect for most clusters, in particular for the R&D activity. Findings also suggest that complementarities between the two strategies prevail for exporting activity primarily in the clusters of firms with no foreign ownership; whereas, substitutability effects emerge primarily for R&D activity, particularly for clusters of firms with foreign participation, with substitutability being more pronounced for firms exporting their entire output than others. The findings are also consistent with the complementary effect having a positive impact on firm growth for fully exporting firms with foreign ownership.

Our paper differs from the majority of the existing empirical literature in two ways. To begin, no paper (with the exception of Mattoussi and Ayadi [84]) has come close to considering the differential exporter characteristics that may shape firm export behavior, particularly in economies with subcontracting regimes, where subcontractors who export their entire production may benefit or be bided by contractual export arrangements. Second, none of these papers has investigated into the role of inward FDI in shaping the interaction between trade flows and R&D investments, which can be complementary and reinforce each other or crowd out one another, with complementarity being more prevalent in firms with no foreign participation and substitution being more prevalent in firms with foreign participation.

This paper is structured as follows. Section 2 sketches out the materials and methods used in the study: they include a description of the dataset and an overview of the basic descriptive statistics, as well as the methodology for investigating the dynamics of exports and R&D and whether the presence of complementarities between the two strategies would positively affect firm growth. Section 3 presents and discusses our econometric analysis, and Section 4 concludes.

## 2. Materials and Methods:

### 2.1. Data and Summary Statistics

Our empirical analysis draws on three firm-level datasets derived from the annual accounting, industrial, and export flow surveys of Tunisian manufacturing firms conducted between 2016 and 2018. Datasets collected by the Institut National de la Statistique in Tunisia contain missing values due to (item[2]) non-response. According to sample statistics, only 90% of the observations were complete; thus 10% of the data contained

[2] Item non-response, occurs when a sample member responds to some of the survey questions but fails or refuses to provide answers for particular items [67, 75].

missing values (so many respondents will be excluded from the analytic sample due to their missing values). Scrutiny of our missingness mechanism revealed that the data are missing at random[3] (MAR) [98], implying that complete cases are not a random sample (missingness diagnosis appears in the appendix). Indeed, observed variables predict missingness - the likelihood of a specific value being missing is determined solely by observed data. That is why we use the Multiple Imputation (MI) method, in which an imputation model, i.e. a model for the distribution of the missing values given the observed data, is specified. To create a complete set of data, the missing values are replaced with values generated at random by this model. The entire procedure is repeated independently M times, resulting in M imputed datasets. The analysis model is fitted to each of these in turn and the estimated parameters are averaged over the datasets.

There is no agreement on how many imputations should be used. Standard MI texts suggest that small numbers of imputed datasets, on the order of three to five imputations, produce excellent results [99, 106]. Recently, the consensus has shifted towards higher values of M. White et *al*. [123], for example, propose a rule of thumb that M should be at least equal to the percentage of incomplete cases in the dataset, implying that we should run 10 imputations in our study. Stata, on the other hand, recommends 20 imputations, and Graham et *al.* [42] contend that a higher number of imputations is even better because it may yield increased power. In the light of all this we choose to follow stata and perform 20 imputations[4].

We impute using the chained equations approach (MICE[5]) (also known as full conditional specification) [98, 118, 123] for the following reasons. Data with missing values do not account for a very large proportion of observations (only 10 percent of the data contain missing values). The missing pattern is arbitrary, with datasets containing different variable types ranging from continuous to binary. Furthermore, continuous variables have skewed distributions. White et *al.* [123] discuss two approaches to dealing with such variables: transformation to normality and Predictive Mean Matching (PMM). Instead of regressing, we use the PMM technique[6] in this case. The rationale for this choice is that PMM can be a useful alternative when the normality of the residuals is not guaranteed. It is also an easy-to-use and versatile method that is less prone to model misspecification than other methods. Furthermore, imputations are realistic because they are based on values

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[3] Multiple imputation is becoming the standard route to estimating models with missing covariate data under a missing-at-random assumption [98].

[4] Econometric estimates using data with 10 imputations are qualitatively similar to those using data with 20 imputations.

[5] Multiple imputation under chained method tends to be mostly indicated when the variables are highly skewed, or there are too many count or categorical variables in the model [98, 123].

[6] Marshall et *al.* [81] used the Predictive Mean Matching method in a simulation study that addressed skewed data and concluded that this method "produced the least biased estimates and better model performance measures."

observed elsewhere. Additionally, imputations outside of the observed data range will not occur, avoiding the issues associated with meaningless imputations (e.g., negative capital or sales). The method also works best with large samples and provides imputations that possess many characteristics of the complete data [62].

Our data include information on the status of exports and R&D investment as well as sales, financial resources, and direct and indirect foreign ownership of firms. We also have information on the number of employees and the number of years the company has been in business. The literature uses R&D expenditures as a common measure of firms' technological and innovation activities, and we use the same strategy here. The firm's innovator status is defined as a 1 if it reports positive R&D expenditures and a 0 if it does not. It is important to note that companies can spend money on R&D even if they are not innovating.

In our analysis, we use four firm clusters and both the export and foreign participation differentials. We first differentiate firms based on their exporting behavior, resulting in two groups of firms. In the first group (referred to as any exporting firms), we distinguish exporters (including partially and fully exporting firms) from non-exporters. In the second group (referred to as fully exporting firms), we distinguish firms exporting 100 percent of their output from partially exporting firms and non-exporters. Following that, each of these two groups is distinguished by the presence or absence of foreign capital in the capital of its firms. The four clusters are as follows. The first and second clusters are made up of any exporting firms without and with foreign participation, respectively. While, the third and fourth clusters include fully exporting firms without and with foreign participation, respectively.

The rationale for the exporting differential (see, Mattoussi and Ayadi [84]) is driven by a peculiarity of the Tunisian manufacturing sector: nearly 70% of exports come from the offshore sector, which is primarily composed of subcontractors that may benefit from various advantages such as technology transfer and export guarantees or be bid by strict contractual arrangements.

The primary reason for the FDI differential is the opportunities for exporting, as well as for innovation, managerial expertise, and technological transfer that foreign firms may provide to (subsidiary) firms. These opportunities may enable (subsidiary) firms to benefit from the available stock of knowledge and financial resources to carry out their own R&D activities [32] and enhance export capabilities [86], or they may obstruct these activities because (subsidiary) firms are very likely to become the most technologically advanced, and thus the least likely to have higher returns from the R&D activity (exports). Furthermore, lumping together partially and fully exporting firms (firms without and with foreign participation) may obscure the true characteristics of fully exporting firms (resp. whether and how foreign participation may shape the dynamics of exports and R&D activities).

Table 1 displays the variable definitions as well as summary statistics. Table 2 summarizes the firms' export and R&D status in the final sample. Approximately 70 percent of the firms are exporters (about 45 percent of the firms export 100 percent of their output), with the proportion of exporting firms increasing from 70.14 percent in 2016 to 70.68 percent in 2018 (with the proportion of firms exporting their entire production increasing from 44.84 percent in 2016 to 44.96 percent in 2018). R&D activities are reported by approximately 23.4 percent of firms in the sample, ranging from 24.4 percent in 2016 to 23.1 percent in 2018.

Table 2 shows some variation in export and R&D over time, as well as significant variation in each of these activities across firms in different exporting categories (partially exporting firms versus fully exporting firms) and across firms in the same export category when considering the FDI differential. We focus on reporting statistics for the latter category of firms, which is of interest for our study to examine how FDI would shape the interaction between export and R&D activities. In the category of any exporting firms, 13.69 percent of firms with no foreign participation report R&D activities (37.61 percent report export), whereas only 1.04 percent of firms with foreign ownership undertake R&D (32.89 percent export). For the class of fully exporting firms, 1.80 percent of firms with no foreign participation engage in R&D ( 19.60 percent export), whereas only 0.4 percent of firms with foreign ownership carry out R&D (25.26 percent export).

This dataset provides an appropriate setting for testing the impact of inward FDI on the interaction between export and R&D activities, as well as whether the presence of complementarities between the two strategies improves firm performance. First, the data allows for the tracking of firms and their export, R&D, and whether they have foreign ownership or not over a three-year period. Second, exporting firms account for a large proportion of the sample and exhibit some variation in their exporting behavior over time, as well as significant variation in export across firms in the same export class when the FDI differential is taken into account. Third, we have data on R&D activity, and when the FDI differential is considered, the sample shows some variation in R&D over time as well as a significant variation across firms in the same export class.

Table 3 displays a transition matrix, which shows the probability that a firm will adopt a given strategy in a specific year, given the strategy it was following in the previous year. Several patterns are clear.

First, there is significant persistence in some activities. Of firms with no foreign participation (resp. with foreign participation) that did not export or conduct R&D in previous periods, 78.86 percent (resp. 79.92 percent) are in the same category in subsequent periods. Firms without (resp. with) foreign participation that export but do not carry out R&D have an 81.96 percent (resp. 90.51 percent) chance of remaining in that category the following year. As a result, there is a strong persistence in exports.

Second, firms with no (resp. with) foreign participation that do not export but invest in R&D have a probability of 65.33 percent (resp. 65.47percent) to remain in the same category the following year. This suggests the persistence in R&D investments.

Third, of firms with no foreign participation (resp. with foreign participation) and doing both R&D and exports in previous periods, 84.34 percent (resp. 51.25 percent) will continue to do both activities in subsequent periods. These statistics indicate that there are complementarities between exports and R&D decisions.

Fourth, 38.56 percent of firms with foreign participation that did both activities in previous periods will abandon R&D in subsequent periods. These statistics may suggest that in some cases, one activity crowds the other out. In the presence of foreign participation, exports, in particular, tend to crowd R&D out.

Overall, the statistics indicate that while export and R&D strategies tend to be persistent, they also show significant variation across firms in different exporting categories (partially exporting firms versus fully exporting firms) and across firms in the same export category when considering the FDI differential. Trade flows and R&D investment, in particular, may complement or compete with one another, and as such, they should be modeled jointly. Furthermore, they assert that foreign involvement may influence how these various strategies interact with one another.

**2.2. Exporting, investment in R&D, and firm performance: Methods and conceptual framework**

2.2.1 Modelling exporting and R&D activities

Our exporting model relates the likelihood of firm i exporting in period t to the 1-year lags in exports, R&D, and other firm characteristics such as capital intensity, size, age, and labor productivity. The probit specifications for the first, second, third, and fourth clusters of firms are shown in equations (1), (2), (3), and (4), respectively:

$$\text{Prob}(ANYEXPNOFP_{i,t} = 1) = \Phi(ANYEXPNOFP_{i,t-1}, RD_{i,t-1}, Z_{i,t-1}) \quad (1)$$

$$\text{Prob}(ANYEXPWFP_{i,t} = 1) = \Phi(ANYEXPWFP_{i,t-1}, RD_{i,t-1}, Z_{i,t-1}) \quad (2)$$

and

$$\text{Prob}(TOTEXPNOFP_{i,t} = 1) = \Phi(TOTEXPNOFP_{i,t-1}, RD_{i,t-1}, Z_{i,t-1}) \quad (3)$$

$$\text{Prob}(TOTEXPWFP_{i,t} = 1) = \Phi(TOTEXPWFP_{i,t-1}, RD_{i,t-1}, Z_{i,t-1}) \quad (4)$$

where $ANYEXPWFP_{i,t-1}$ and $ANYEXPNOFP_{i,t-1}$ represent lagged exports for any exporting firms (including partially and fully exporting firms) with and without foreign participation, respectively; $TOTEXPWFP_{i,t-1}$ and $TOTEXPNOFP$i,t-1 represent lagged exports for fully exporting firms with and without foreign participation, respectively; $RD_{i,t-1}$ is the lagged R&D investment; $Z_{i,t-1}$ is a vector of lagged control variables capturing the above-mentioned firm characteristics; and t and i are time and firm indices, respectively. We include the 1-year lagged values of both exports and R&D to control for the possible persistence in the innovation and exporting activities. Furthermore, the inclusion of a lagged dependent variable allows for the capture of state dependence as well as the resolution of serial correlation issues [14, 29, 60, 87]. Previous export participation accounts for sunk costs, primarily at the start of the activity but also as the activity progresses [13]. Such sunk costs may include the cost of packaging, improving product quality, establishing marketing channels, and gathering demand information. Furthermore, firms that sell their products in a foreign country may be at a disadvantage when compared to domestic firms because they must typically bear additional transportation and administrative costs. All these costs act as a barrier to entry and have the potential to induce state dependence. Regarding R&D, the greater the firm's prior investment in R&D, the more likely its products and/or services will become innovative and competitive, positively influencing exports and thus gaining a competitive advantage [21, 66].

We also assume that the likelihood of exporting is affected by lags in firm size, age, capital intensity, and labor productivity. The age of a firm (measured in years in business) has an ambiguous effect on exports. On the one hand, because firms' resources and capabilities accumulate over time and age, older firms are more likely to have the necessary resources (financial and knowledge) to export. Firms can gain expertise in entering new foreign markets from experience and this lowers the fixed costs of entering any additional new markets in the coming years [109]. A similar argument can be made for the number of products exported. If a company successfully exports one good and learns how to adapt it to customer preferences or legal regulations in a foreign market, how to prepare a user manual in a foreign language, how to set up a distribution network, and so on, the fixed costs of exporting any other goods are reduced, and the company will begin to export more goods in the future [120]. On the other hand, if younger firms are more proactive, flexible, and aggressive, age and exports may have a negative relationship [32]. Because it is difficult to predict which effect will be dominant a priori, the coefficient sign is uncertain.

The relationship between firm size and export performance is examined in current literature, but the empirical results seem inconsistent [77]. Competitive advantages can be found in both large and small firms [85]. Firm size may have a fixed-cost interpretation because exporting is typically associated with fixed costs that are prohibitively expensive for small businesses. These costs are thought to include product compliance research, distribution networks, advertising, and so on. Firm size can affect export behavior in the search for economies of scale and scope to spread costs across expanded markets [32, 34, 35, 77]. Larger firms can also take advantage because of the significance of R&D expenditure, their capacity for taking risks, and the potential for price discrimination [89]. Smaller firms, on the other hand, should not be viewed as less competitive, they have different competitive advantages, which are associated with niche products that are cutting-edge technologically or unique in their market [85]. The competitiveness of small firms is more dependent on the quality of their products and on how easily they can enter and exit foreign markets [17].

Labor productivity is used as a proxy of firms' efficiency, to capture a potential self-selection process by which certain firms choose to enter export markets because they are relatively efficient. We also include the vector of year dummies to control for macroeconomic conditions that are common to all firms, as well as a set of sector dummies intended to correct industry-specific factors.

We follow Girma et *al*. [36], and Aw et *al*. [7] in assuming that the determinants of R&D activity are the same as those used to determine export status. The innovation equation is represented as a probit regression of firm i's R&D activity in period t on the 1-year lagged R&D, exports, and other firm characteristics (the same characteristics used for the exporting equation). The estimation procedures for the first, second, third, and fourth clusters of firms are provided by equations (5), (6), (7), and (8), respectively:

$$\text{Prob}(RD_{i,t} = 1) = \Phi(ANYEXPNOFP_{i,t-1}, RD_{i,t-1}, Z_{i,t-1}) \quad (5)$$

$$\text{Prob}(RD_{i,t} = 1) = \Phi(ANYEXPWFP_{i,t-1}, RD_{i,t-1}, Z_{i,t-1}) \quad (6)$$

And

$$\text{Prob}(RD_{i,t} = 1) = \Phi(TOTEXPNOFP_{i,t-1}, RD_{i,t-1}, Z_{i,t-1}) \quad (7)$$

$$\text{Prob}(RD_{i,t} = 1) = \Phi(TOTEXPWFP_{i,t-1}, RD_{i,t-1}, Z_{i,t-1}) \quad (8)$$

Where $Z_{i,t-1}$ is the control variable vector used in the exporting equation. The main variable of interest in this equation is lag in exports, as its coefficient indicates whether exporting firms are more or less likely to be innovators than non-exporters. Previous export participation captures a potential learning-by-exporting effect, in which the stock of knowledge accumulated externally through exports may lead exporters to improve their knowledge base, thereby increasing their innovative capacity and ability to create higher-quality innovations [39]. Is state dependence also expected in the case of innovation? According to Peters [90], there is a "success breeds success" effect in which previous successful innovations stimulate subsequent successful innovations as a result of increased market power and/or broader technological opportunities. State dependence may also have a fixed cost interpretation. R&D involves fixed and sunk costs, which are thought to include the costs of establishing R&D divisions, researching promising technologies, searching for people capable of performing these activities, and so on. These costs are likely to be lower for firms that have previously carried out R&D. Labor productivity is included to capture a selection process resulting from the direct effect of the firm's productivity on the profitability of R&D investment.

Firm size appears to be an important determinant of R&D, but its impact on stimulating subsequent R&D is unclear. On average, larger firms may have more financial resources to carry out R&D [39] because they have better access to credit markets and/or a larger set of non-financial resources (managerial, scale economies). Small firms, on the other hand, may have more favorable conditions for innovation to flourish, as they may have more flexible management structures that allow them to adapt to changing competitive environments [32]. The effect of age on subsequent innovation is unclear. Older firms can accumulate resources, managerial knowledge, and the ability to deal with uncertainty [51, 68], as well as a reputation and market position, all of which help facilitate relationships and contacts. Mature firms may also benefit from their previous investments in innovation because of learning effects, which enable these firms to innovate more effectively by building on previous routines and capabilities [68]. Younger companies, on the other hand, are less affected by organizational inertia and are not burdened by rigid routines that stifle innovation, allowing them to respond more quickly and easily to useful new knowledge [46, 47, 56]. Younger companies may also need to invest more in R&D to survive and grow [25, 110].The sign of the coefficient is unknown because it is impossible to predict which effect will dominate a priori.

In the subsequent analysis, we investigate the dynamics of exports and R&D decisions to see if they complement or crowd each other out. Specifically, we examine whether the presence of complementarity between the two strategies fosters the adoption of both export and R&D activities, or whether the two strategies compete and should not be jointly pursued. Following Aw et *al.* [7], Girma et *al*. [36], Golovko and Valentini [39], and Esteve-Pérez and Rodríguez [32], we estimate a seemingly unrelated bivariate probit model to test the direct effect of the decision to export on the R&D decision, and vice versa. The model allows for correlation between the error terms [32], which may result from the potential high serial correlation and the correlation between export and R&D decisions.

In this model, we replace the simple exports and R&D dummies with a vector of mutually exclusive dummy variables $D_1$ (for the two clusters of any exporting firms) and $D_2$ (for the two clusters of fully exporting firms) that captures the combination of previous exports and R&D decisions [39]:

$D_1=\{RDNOFPONLY_{i,t-1}, RDWFPONLY_{i,t-1}, ANYEXPNOFPONLY_{i,t-1}, ANYEXPWFPONLY_{i,t-1}, RDANYEXPNOFP_{i,t1}, RDANYEXPWFP_{i,t-1}\}$.

And

$D_2$={$TOTEXPNOFPONLY_{i,t-1}$,$TOTEXPWFPONLY_{i,t-1}$,$RDTOTEXPNOFP_{i,t-1}$, $RDTOTEXPWFP_{i,t-1}$}.

These dummies distinguish the following mutually exclusive cases:

(1) firms that both export and conduct R&D: $RDANYEXPNOFP_{i,t1}$, and $RDANYEXPWFP_{i,t-1}$ for clusters of any exporting firms, and $RDTOTEXPNOFP_{i,t-1}$, and $RDTOTEXPWFP_{i,t-1}$ for clusters of fully exporting firms.

(2) firms that only export: $ANYEXPNOFPONLY_{i,t-1}$, and $ANYEXPWFPONLY_{i,t-1}$, for clusters of any exporting firms, and $TOTEXPNOFPONLY_{i,t-1}$, and $TOTEXPWFPONLY_{i,t-1}$, for clusters of fully exporting firms.

(3) firms that only carry out R&D: $RDNOFPONLY_{i,t-1}$, and $RDWFPONLY_{i,t-1}$ for clusters of any exporting firms.

The model given by equations (9)–(10), equations (11)–(12), equations (13)–(14)equations (15)–(16) for the first, second, third, and fourth clusters of firms, respectively, relates probabilities of firm i investing in R&D and exporting in period t to lagged dummies capturing the combination of R&D and exports and to lagged firm characteristics:

$$\text{Prob}(R\&D_{i,t} = 1) = \Phi(ANYEXPNOFPONLY_{i,t-1}, RDNOFPONLY_{i,t-1}, RDANYEXPNOFP_{i,t-1}, Z_{i,t-1}) \quad (9)$$

$$\text{Prob}(ANYEXPNOFP_{i,t} = 1) = \Phi(ANYEXPNOFPONLY_{i,t-1}, RDNOFPONLY_{i,t-1}, RDANYEXPNOFP_{i,t-1}, Z_{i,t-1}) \quad (10)$$

$$\text{Prob}(R\&D_{i,t} = 1) = \Phi(ANYEXPWFPONLY_{i,t-1}, RDWFPONLY_{i,t-1}, RDANYEXPWFP_{i,t-1}, Z_{i,t-1}) \quad (11)$$

$$\text{Prob}(ANYEXPWFP_{i,t} = 1) = \Phi(ANYEXPWFPONLY_{i,t-1}, RDWFPONLY_{i,t-1}, RDANYEXPWFP_{i,t-1}, Z_{i,t-1}) \quad (12)$$

$$\text{Prob}(R\&D_{i,t} = 1) = \Phi(TOTEXPNOFPONLY_{i,t-1}, RDTOTEXPNOFP_{i,t-1}, Z_{i,t-1}) \quad (13)$$

$$\text{Prob}(TOTEXPNOFP_{i,t} = 1) = \Phi(TOTEXPNOFPONLY_{i,t-1}, RDTOTEXPNOFP_{i,t-1}, Z_{i,t-1}) \quad (14)$$

and

$$\text{Prob}(R\&D_{i,t} = 1) = \Phi(TOTEXPWFPONLY_{i,t-1}, RDTOTEXPWFP_{i,t-1}, Z_{i,t-1}) \quad (15)$$

$$\text{Prob}(TOTEXPWFP_{i,t} = 1) = \Phi(TOTEXPWFPONLY_{i,t-1}, RDTOTEXPWFP_{i,t-1}, Z_{i,t-1}) \quad (16)$$

The coefficients of the dummies in vectors $D_1$ and $D_2$ indicate whether prior R&D/exporting status influences subsequent decisions to undertake R&D/exporting. The two strategies complement each other if the effect of lagged exporting on current exporting (or R&D) is greater if the firm did R&D in previous periods than if it did not. Similarly, if the effect of lagged R&D on current exports (or R&D) is greater if the firm also exported in previous periods than if it did not. We can expect firms coupling the two activities to be more likely to continue R&D or export than firms that only carry out R&D (exporting). Alternatively, the two strategies may be perceived as substitutes when they compete for finite organizational internal resources and need prioritizing over time, which would suggest that one strategy crowds out the other.

### 2.2.2 The impact of exports and R&D on firm performance

In this section, we investigate the impact of the independent and joint decisions to export and conduct R&D on firm performance. Our data include manufacturing firms from various industries, so we measure organizational size growth in terms of sales in accordance with Weinzimmer et *al*. [122] and Golovko and Valentini [39]. There seems to be a growing consensus, according to Delmar et *al*. [31], that if only one indicator is to be chosen as a measure of firm growth, the most preferred measure should be sales.

We regress sales growth on the exclusive combinations of exporting and R&D activities, together with the control variables that might influence growth. In the clusters of any exporting firms, the lagged choices of R&D and export distinguish three cases: firms that carried out both exporting and R&D (*RDANYEXPNOFPi,t-1*, *RDANYEXPWFPi,t-1*), firms that only exported (*ANYEXPNOFPONLYi,t-1*, *ANYEXPWFPONLYi,t-1* ), and firms that only conducted R&D (*RDNOFPONLYi,t-1*, *RDWFPONLYi,t-1*). The omitted or base case is a firm that did not engage in any of these activities. However, because fully exporting firms are unable to perform either R&D exclusively or neither of the two activities, there are only two cases that are distinguished by the lagged decisions of R&D and export in these clusters: firms that combined the two activities (*RDTOTEXPNOFPi,t-1*, *RDTOTEXPWFPi,t-1*), and firms that only exported (*TOTEXPNOFPONLYi,t-1*, *TOTEXPWFPONLYi,t-1* ).

We follow Golovko and Valentini [39] and estimate sales growth using a fixed-effects model to control for the possible endogeneity of exports and R&D decisions [45, 104]. This model allows controlling for time-invariant unobserved firm heterogeneity. Each firm has its own individual characteristics that may influence the exporting and R&D variables (for example, the firm's business practices, organizational structure or managerial capabilities may influence these firm's strategic choices). The fixed-effects model removes the effect of those time-invariant characteristics so we can assess the net effect of the predictors that vary over time on the outcome variable (specifically, that the predictors of interest in our analysis all vary over time).

Finally, to account for serial correlation, which in particular may arise for the independent variables R&D and export are serially correlated (this is likely to be the case, as these two variables show some persistence over time), we use firm-level clustered standard errors. The models for the first, second, third, and fourth clusters are given by equations (17), (18), (19,) and (20), respectively:

$$Salesgrowth_{i,t} = \mathrm{f}(ANYEXPNOFPONLY_{i,t-1}, RDNOFPONLY_{i,t-1}, RDANYEXPNOFP_{i,t-1}, Z_{i,t-1}) \quad (17)$$

$$Salesgrowth_{i,t} = \mathrm{f}(ANYEXPWFPONLY_{i,t-1}, RDWFPONLY_{i,t-1}, RDANYEXPWFP_{i,t-1}, Z_{i,t-1}) \quad (18)$$

and

$$Salesgrowth_{i,t} = \mathrm{f}(TOTEXPNOFPONLY_{i,t-}, RDTOTEXPNOFP_{i,t-1}, Z_{i,t-1}) \quad (19)$$

$$Salesgrowth_{i,t} = \mathrm{f}(TOTEXPWFPONLY_{i,t-}, RDTOTEXPWFP_{i,t-1}, Z_{i,t-1}) \quad (20)$$

Where $Z_{i,t-1}$ is the same vector of control variables used previously. In this model, previous export participation ($ANYEXPNOFPONLY_{i,t-1}$, $ANYEXPWFPONLY_{i,t-1}$, $TOTEXPNOFPONLY_{i,t-1}$ and $TOTEXPWFPONLY_{i,t-1}$) is included in the model to capture efficiency gains (learning) from exporting. There is support for the learning-by-exporting hypothesis whenever these variables significantly and positively affect sales growth. We content that exports and R&D have a complementary effect on firm growth, when the return in terms of sales growth from undertaking one activity increases if a firm also undertakes the other. There is empirical evidence for this effect whenever the parameters estimates of $RDANYEXPNOFP_{i,t-1}$ and $RDANYEXPWFP_{i,t-1}$ (for the first and second clusters of firms) and $RDTOTEXPNOFP_{i,t-1}$ and $RDTOTEXPWFP_{i,t-1}$ (for the third and fourth clusters of firms) are positive and statistically significant.

## 3. Empirical Results and Discussion

In this section, we present the findings of univariate and bivariate models that account for independent and joint decisions to export and carry out R&D. We then report on whether the presence of complementarities between the two strategies would boost firm sales growth. Our empirical findings should be interpreted as indicating only partial correlations rather than causation.

Tables 4 and 5 show the average marginal effects (estimated using probit) for the exporting and innovation equations, respectively. All of the specifications listed below allow for a quadratic effect on labor productivity (as the linear and quadratic terms of labor productivity are not independent of each other, calculations of the marginal effects are thus performed accordingly).

### 3.1. Estimates of exporting activity (Exporting equation)

3.1.1. Any exporting firms with no foreign participation

Lagged exports increase the likelihood of current exports. The average marginal effect is 1.0213, implying that firms that exported previously are 102.13 percentage points more likely to export in the current period than firms that did not. This is consistent with the sunk-cost interpretation, which implies the existence of high entry and exit costs in the export market. The existence of sunk costs has two interconnected consequences. For starters, it raises entry barriers because firms that enter export markets must make enough money to cover the fixed costs of entry. Second, substantial sunk costs imply substantial exit costs. When a company stops exporting, its knowledge of the export market rapidly deteriorates, and it loses the expertise gained over years of exporting. Those who have already incurred startup costs are therefore more likely to continue exporting during this period. The combination of sunk costs and uncertainty, should induce persistence in exporting status [108].

Lagged R&D has a positive impact on current exports. Investing in R&D allows a company to develop more innovative and competitive products and/or services, resulting in a competitive advantage and positive effects on exports [21, 66]. Conducting R&D has also been identified as a relevant factor in explaining exporters' higher productivity when compared to non-exporters, implying that productivity gains allow firms to afford the costs associated with exporting and enable them to achieve a greater ability to meet international market demand, making exporting more profitable [39, 72].

Firm age predicts current exports fairly well because older firms may be endowed with more resources (financial and knowledge) that enhance exporting capacities. This is consistent with the findings of Majocchi et *al.* [77], who use firm age as a proxy for the duration of firms' internationalization experience, implicitly assuming that age and internationalization experience are both positively related to the extent or intensity of firms' international engagement.

Labor productivity and exports have a nonlinear relationship, with export sales increasing only after a certain threshold is reached (as labor may need some learning phase to take its full effect for productivity gains to be taduced into an increased scale of production and sales). This finding is consistent with the self-selection hypothesis, which holds that more productive firms choose to enter export markets because they are relatively efficient [13, 43]. The remaining control variables are statistically insignificant.

3.1.2. Any exporting firms with foreign participation

Exports in previous periods positively affect exports in subsequent periods. Lagged R&D reduces the likelihood of current exports. We provide an explanation in the absorptive capacity line. Cohen and Levinthal [27] show in a seminal publication that R&D serves two distinct purposes: it generates innovation and/or increases the firm's absorptive capacity that shapes the extent to which firms can benefit from technological knowledge available in global and local networks [11, 38]. Firms in host countries, must recognize the value of new, external knowledge grafted from FDI inflows, assimilate it, and apply it to the local context. Because R&D and exports are both expensive activities, firms may devote more resources to R&D (to improve absorptive capacity) at the expense of developing export capabilities (rival utilization of limited organizational resources).

Firm size has a positive impact on current exports because large firms may produce and sell on a large scale or have lower fixed costs associated with exporting than small firms. Coherently, Helpman et *al*. [50], Madsen and Servias [76], and Hindinis [52] point out that larger companies have a better chance of exporting and succeeding in transportation. Large firms, according to Hirsch and Adar [54], can also afford to take on more risks than small firms, because they benefit from economies of scale in foreign marketing. As a result, large firms demand a lower risk premium from foreign marketing than small ones. Large firms, therefore, tend to export a greater proportion of their output. These theoretical constructs are confirmed by empirical analysis of a sample of several hundred firms from six industries in Denmark, Holland, and Israel. The data show that, with a few exceptions, firm size is indeed positively correlated with the export-to-sales ratio.

The coefficient of *AGE_1* is negative and statistically significant. This is consistent with the findings of Kirpalani & McIntosh [61], as well as Love et *al*. [73]. Love et *al*. [73] criticize studies that use firm age as a proxy for a firm's internationalization experience, arguing that this is more likely to be related to the potential for learning [58] than to export performance. Firm age, on the other hand, may be associated with sclerotic thinking, inflexibility, and the management team's or the firm's overall inability to change strategy and/or behavior. The coefficients of the remaining control variables are insignificant.

3.1.3. Fully exporting firms with no foreign participation

There is strong statistical support for the positive impact of lagged exports on current exports. The average marginal effect decreased (from 1.0213 to 0.496) in comparison to the first cluster and decreased (from 0.895 to 0.496) in comparison to the second one. This could be attributed to strict contractual arrangements governing fully exporting firms (mostly subcontractors), who are required to export exactly what is mandated by the contracts, and where international demand may be lower this year than last.

R&D is reducing current exports. Similarly, we provide an explanation alongside the absorptive capacity approach as for the previous cluster, except that fully exporting firms, primarily subcontractors, obtain new knowledge from their parent firm (the contractor) rather than FDI flows. Subcontractors can obtain technologies from their parent companies, according to Urata and Kawai [115], and parent companies frequently press subcontractors to improve their technological capabilities through flexible relationships. In most developing countries, subcontracting relationships with large enterprises, particularly transnational corporations (TNCs) and their joint ventures and corporate affiliates, are regarded as an important source of technological progress for SMEs. Furthermore, according to the knowledge-based literature, it is critical for the parent company to improve the absorptive capacities of the subcontractors themselves [16, 28].

Additionally, Gorodnichenko et *al.* [40] state that domestic corporations' absorptive capacity is determined by their level of technology/efficiency and skilled workers/human capital. Because technological competence increases firm productivity, subcontractors are more likely to be productive than non-subcontractors. According to Nishiguchi [88], a multi-tier subcontracting system based on specialization and SMEs is viewed as a factor in improving firm efficiency and competitiveness in Japanese manufacturing. All of the preceding arguments may imply that the companies in this cluster are more likely to be productive than other domestic firms, as well as to have skilled workers and/or better human capital. These firms may be better able to absorb, internalize, and apply the knowledge potentially provided by their parent companies, implying that they will be able to more easily adapt this technology and knowledge to the local environment. As a result, they would devote fewer resources to R&D, as opposed to the second cluster.

Firm size positively affect current exports. There is little support for self-selection, possibly because contractual arrangements may well mask most of the effect of efficiency on exporting. The coefficients of the remaining variables are statistically insignificant.

3.1.4. Fully exporting firms with foreign participation

There is strong statistical support for the positive impact of lagged exports on current exports. The average marginal effect increased (from 0.496 to 0.6208) in comparison to the third cluster. This could be due to foreign participation in these firms' capital, as they may have better access to financial resources, knowledge, and technology, allowing them to produce and sell at a larger scale. Consistently Moran et *al*. [86], point out that if inward FDI is supported by appropriate public actions, it can be a significant driver of local economic development and contribute to the host country's competitiveness by facilitating the transfer of new knowledge and technology among economies and allowing the host country to gain competitive advantages in international markets.

Lagged R&D reduces current exports. The average marginal effect increases in absolute value when compared to the third cluster (from 0.05004 to 0.1122). This is because, in addition to knowledge and technology grafted from parent firms, this cluster's firms benefit from FDI knowledge. In order to adapt this knowledge and technology to the local business environment, they should devote more resources to R&D than the third cluster. The average marginal effect is somewhat smaller when compared to the second cluster (it decreases in absolute value from 0.1274 to 0.1122). This cluster (primarily made up of subcontractors) is more likely than the second to have a higher absorptive capacity because its firms' in-house knowledge is supplemented by new knowledge and technology grafted from their parent firms, for whom it is critical to improve the absorptive capacities of their subcontractors [16, 28]. These firms may be more efficient than those in the second cluster at adjusting external knowledge brought in by FDI. As Cohen and Levinthal [27] state, companies require strong internal technological capability to facilitate the adoption and assimilation of new technologies. Wallin [121] also showed that increased external knowledge diversity benefits firms in the medium-high tech and medium-low tech sectors of Swedish manufacturing exporters only if they have some internal knowledge to boost their absorptive capacity. As a result, these firms may devote fewer resources to R&D for this purpose than the second cluster.

Firm age negatively affects exports (the arguments offered for the second cluster still apply here).The other control variables are statistically insignificant.

### 3.2. Estimates of R&D activity (Innovation equation)

#### 3.2.1. Any exporting firms with no foreign participation

Lagged R&D investment has a positive impact on current R&D, lending credence to the true state dependence on R&D activity. This finding can be interpreted as "success breeds success" [90] or as having fixed and sunk costs interpretation. These costs are thought to include the costs of establishing R&D divisions [5].

The positive and statistically significant coefficient of lagged exports provides compelling evidence for the learning by exporting effect. Exposure to international markets can further stimulate innovation by increasing competitive pressure on firms and promoting technological transfer from destination markets, improving a company's technological (but also marketing) knowledge, and laying the groundwork for the development of additional knowledge [12, 124]. Integrating international markets can also boost a company's ability to innovate by allowing it to hire more qualified technologists and gain access to skilled technical expertise [59]. Furthermore, according to Kotabe et *al*. [63], internationalization can reduce costs associated with innovation: highly internationalized firms can access many markets around the world, buy materials and R&D from the cheapest available sources, and locate their R&D and other departments in the most productive regions, potentially achieving higher returns from innovation.

Firm age predicts current R&D fairly well because older firms are more likely to be more seasoned and endowed with more resources (financial and human) to carry out R&D, which may be undertaken for two reasons: to generate innovation and/or to increase the firm's absorptive capacity. Several studies have found that absorptive capacity is path-dependent and cumulative, so mature firms will have more experience identifying and exploiting external knowledge [27].

The relationship between labor productivity and R&D is nonlinear, with labor productivity increasing R&D only after a certain threshold (Labor may require some learning phase to generate efficiency gains, which will also require time to translate into a larger scale of R&D). This captures the self-selection process by which more efficient firms conduct R&D activities.
The average marginal effect of the *ELECT* and *ENER_MIN_MISCEL* sector dummies are positive and significant, indicating that these sectors are the most involved in R&D activity compared to the remaining sectors. The coefficients of the remaining control variables are insignificant.

3.2.2. Any exporting firms with foreign participation

The coefficient of lagged R&D is positive and significant at less than a 1 percent confidence level (not reported). Furthermore, the average marginal effect is slightly smaller when compared to firms in the first cluster. A host of factors may account for this decline. First, firms with foreign participation may start with relatively high average R&D because the firm's base knowledge may be supplemented by FDI-brought external knowledge [32], implying that there may be less clear returns to R&D in terms of innovation. Second, R&D activity in developing countries is focused on building up a firm's absorptive capacity more than the development of its own innovations. Firms may then prioritize adapting new technologies and knowledge to local conditions over innovating.

The nonlinear effect of labor productivity on R&D persists. Furthermore, the coefficients of *PRODUCTIVITY_1*'s linear and quadratic terms are smaller than those of the first cluster. Similarily to the interpretation above, FDI as a potential source for knowledge and technology injection into host country economies may allow local firms to experiment with relatively high average R&D, implying that there are less clear returns to labor productivity in terms of R&D.

There is no support for the learning by exporting effect. Firm age increases R&D investment (The arguments made for any exporting firms with non-foreign participation may still apply here). The average marginal effect of the *ELECT*, *AGROFOOD*, *TEXTILE*, and *ENER_MIN_MISCEL* sector dummies is positive and significant, indicating that these industries are more involved in R&D than the other sectors. The remaining control variable coefficients are insignificant.

3.2.3. Fully exporting firms with no foreign participation

A 1-year lagged R&D increases the likelihood of current R&D. The average marginal effect is somewhat larger than in the first two clusters, implying a twofold interpretation. First, fully exporting firms (primarily subcontractors) must meet the high-quality product standards demanded by multinational parents in order to meet the needs of a more sophisticated demand in foreign markets. This is consistent with Baudry (2007), who shows that subcontractors use coordination mechanisms that are no longer limited to price mechanisms but require practices and tools that reveal a subcontractor's ability to deliver goods in due quality and on time, as well as to innovate. ubcontractors are no longer only expected to produce but are also frequently pushed to generate the technological knowledge that drives new product and process development. Evenhough, in most cases, subcontractors are rarely in charge of product design, because it is too specific or risky to be subcontracted. Subcontractors may have no incentive to innovate in either process or product because of the nature of this interfirm relationship. Nontheless, subcontractors may be able to improve their processes as a result of passive learning effects. Second, fully exporting firms have to invest more in R&D to increase absorptive capacity, which influences how much the firm can benefit from technological knowledge and spillovers grafted from multinational parents [11, 38].

Firm age increases current R&D. There is no support for the hypothesis of learning by exporting. This finding does not imply that fully exporting firms lack export-based learning; rather, it stems from the peculiarity of Tunisian manufacturing firms, which may be primarily subcontractors (70 percent of exports come from the offshore sector with relatively long exporting experience. Hence, they are likely to experience a gradual decline in the scope for learning. Bingham & Davis [15] state that a firm should expect a decrease in the learning ratio as it gains more export experience, owing to the decreasing rate of the learning sequence. Younger firms, according to Hashai and Almor [48], begin exploring the acceptance of their goods in foreign markets and continue to exploit their advantages based on the knowledge gained during their first international activities. However, when a company starts to export and enters a new stage, it shifts its focus to the exploitation of prior knowledge rather than the exploration of new knowledge.

The average marginal effect of the *ELECT*, *AGROFOOD,* and *ENER_MIN_MISCEL* sector dummies is positive, suggesting that these sectors are more involved in R&D than the other sectors. The remaining findings are similar to those of the second cluster.

3.2.4. Fully exporting firms with foreign participation

Lagged R&D positively affects current R&D. In comparison to the third cluster, the average marginal effect is slightly smaller (it reduces from 0.5305 to 0.4697). Due to the additional technology and knowledge grafted from FDI, firms in this cluster are likely to be more cutting-edge technologically than those in the previous cluster. These companies are probably more R&D-intensive to begin with, so there are less clear returns on R&D in terms of investment in R&D.

The marginal effect in the first cluster is twice as large as the marginal effect in the second cluster (it increases from 0.1274 to 0.4697). The same arguments put forth for the previous cluster still hold true. Firm age increases investment in R&D. The remaining findings are qualitatively similar to those from the second cluster, and it is possible that the same reasoning and justifications still apply.

**3.3. Estimates of the interaction between exports and R&D activities**

Tables 6 and 7 summarize the estimates of the interplay between exporting and R&D activities for the four clusters of firms.

3.3.1. Any exporting firms with no foreign participation

Firms that do both activities are more likely to continue exporting (carrying R&D) in the current period than firms that did neither activity or previously exported (performed R&D) only (*RDANYEXPNOFP_1* has a larger coefficient than *ANYEXPNOFPONLY_1* and *RDNOFPONLY_1*). The results suggest that exports and R&D complement each other to increase export sales and R&D investment. Complementarities prevail for both activities, because through innovation, firms can enter new geographical markets with novel and improved products, increasing the success of exports (e.g., Hitt et *al*. [55]). Furthermore, participating in export markets can help firms learn more and improve their innovation performance. Exporting firms may have access to knowledge sources not available in their domestic market, which they can then use to produce more and higher-quality innovations (e.g.[, Alvarez & Robertson [4]). Exports and R&D can thus create a virtuous, mutually reinforcing circle, producing more clear returns in terms of export and R&D activities.

The outcomes for the remaining control variables are almost identical to those depicted by Tables 4 and 5. *AGE_1* has a positive impact on both exports and R&D. *SIZE_1* reduces the incentives to invest in R&D in the bivariate model (but has no impact in the univariate model)
The sector dummies *ELECT* and *ENER_MIN_MISCEL* positively affect R&D decisions. *PRODUCTIVITY_1* has a nonlinear relationship with R&D. These findings corroborate the majority of the findings of the independent decisions of exporting and R&D.

3.3.2. Any exporting firms with foreign participation

Firms combining both activities in previous periods are more likely to continue exporting (conducting R&D) in subsequent periods compared to firms that did neither activity or only exported (innovated) in previous periods, albeit the coefficient of *RDANYEXPWFP_1* is slightly smaller than that on *ANYEXPWFPONLY_1* for the exporting activity, and the coefficient of *RDANYEXPWFP_1* is smaller than that of *RDWFPONLY_1* for the innovation activity, bringing little evidence for the potential of export-R&D complementarity to boost export sales or R&D investment. However, *RDWFPONLY_1* reduces export sales for the exporting equation and *ANYEXPWFPONLY_1* reduces R&D investment for the innovation equation, supporting the trade-off between the two strategies that should not be pursued jointly.

Prior literature on inward FDI posits that being a part of a foreign company may facilitate the process of becoming an exporter, as FDI may allow the transfer of new knowledge, technology, and managerial practises, among local economies and spreading spillovers to local firms, which may help the host country companies gain competitive advantages and integrate international markets [8, 86]. Following that, because FDI recipients are more technologically advanced than non-FDI recipients, they may prioritize developing export capacities over R&D. Domestic firms receiving FDI, on the other hand, may need to invest more in R&D in order to assimilate and apply the external know-how brought by FDI to the local context, because R&D activity in developing countries is focused on increasing a firm's absorptive capacity rather than developing its own innovations.

The results for the remaining control variables are nearly the same as those shown in Tables 4 and 5. *AGE_1* boosts R&D while decreasing exports. *SIZE_1* increases exports while reducing R&D; The *AGROFOOD*, *TEXTILE*, *ELECT*, and *ENER_MIN_MISCEL* sector dummies have a positive impact on R&D decisions in the bivariate model (but only the *AGROFOOD* and *TEXTILE* sector dummies increase the incentives to invest in R&D in the univariate model). *PRODUCTIVITY_1* has a nonlinear relationship with R&D. These findings support the majority of the findings from independent decisions to export and carry out R&D.

### 3.3.3. Fully exporting firms with no foreign participation

In this cluster, firms involved in both activities continue to export more than firms that exported only in previous periods. *TOTEXPNOFPONLY_1* and *RDTOTEXPNOFP_1* both have positive and significant coefficients, with *RDTOTEXPNOFP_1* having a slightly larger coefficient than *TOTEXPNOFPONLY_1*. Overall, the results are consistent with complementarities of export and R&D activities in increasing export sales.

As for the R&D activity, firms that previously exported only have fewer incentives to invest in R&D in subsequent periods (the coefficient of *TOTEXPNOFPONLY_1* is negative and statistically significant), suggesting that exports and R&D are alternative strategies and they should not be carried jointly. There are two possible explanations for the displacement of R&D by exports. First, firms that export their entire output engage in a large scale of production and sales to face increased international demand. Alternatively, fully exporting firms (mostly subcontractors) may be bid on under strict export arrangements, limiting the firm's ability to diversify along both strategies, exports and R&D. In both cases, these companies must increase their exporting capacity, which they can afford by foregoing R&D. This finding is consistent with Kumar [64 who showed that short-run constraints are a source of a negative association between product diversification and international diversification for US firms.

Second, due to the external knowledge and technology grafted from the parent firms, fully exporting firms are very likely to be cutting-edge technologically (compared to others), inducing them to devote more resources to developing exports rather than R&D activities, as further increases in the scale of innovation for firms starting with a high average R&D may produce less clear returns in terms of investment in R&D.

Substitutability effects are stronger in this cluster than in the second cluster. The coefficient of *TOTEXPNOFPONLY_1* is somewhat larger in absolute value than the coefficient of *ANYEXPWFPONLY_1* (it rises from 0.7358 to 0.9105). This is probably because fully exporting firms produce and sell on a large scale compared to others.

The results for the remaining control variables are as follows: *AGE_1* increases the incentives to invest in R&D while reducing those to export. *SIZE_1* boosts exports and reduces R&D. *PRODUCTIVITY_1* increases the incentives to invest in R&D only after a certain threshhold. The *ELECT*, *AGROFOOD*, *TEXTILE*, and *ENER_MIN_MISCEL* sector dummies have all a positive impact on R&D in the univariate model, but only the *ELECT* sector dummy positively affects R&D in the bivariate model. These findings corroborate some of the findings of the independent activities to export and invest in R&D.

3.3.4. Fully exporting firms with foreign participation

The coefficient of *RDTOTEXPWFP_1* is somewhat smaller compared to that of *TOTEXPWFPONLY_1*, giving little support for the complementary effect of the two strategies on boosting exports. Export advantages, such as export guarantees, which benefit fully exporting firms (primarily subcontractors), have the potential to obscure the majority of the effect of the complementarity mechanism on increasing export sales. *TOTEXPWFPONLY_1*, on the other hand, has a negative impact on R&D, providing compelling evidence for the trade-off between R&D and exports - exports are likely to crowd R&D out. This finding is supported by similar results for the second and third clusters, and the same intuition and arguments may still apply.

Substitutability has a greater impact in this cluster than in the third. The coefficient of *TOTEXPWFPONLY_1* is larger in absolute value than the coefficient of *TOTEXPNOFPONLY_1* (it increases from 3.0745to 3.12405). This is because FDI may provide host-country firms with a better understanding of foreign markets, more relationships, and contacts, thereby increasing their export opportunities in terms of quantity and destinations. Substitutability is also stronger here than in the second cluster. The coefficient of *TOTEXPWFPONLY_1* is twice as large in absolute value as the coefficient of *ANYEXPWFPONLY_1* (it rises from 2.9579 to 3.12405). This is due to the fact that fully exporting firms have more opportunities and involvement in international markets than firms that only partially export. In both cases, firms in this cluster are more likely to be involved with international markets, which encourages them to increase their export sales in order to meet high international demand, which they can only do by foregoing R&D.

The results for the remaining control variables are as follows: *AGE_1* reduces the incentives to export while increasing those to invest in R&D; *SIZE_1* increases exports while decreasing R&D (but has no impact on either activity in the univariate models). *PRODUCTIVITY_1* has a positive impact on R&D in the bivariate model (but has no impact on R&D in the univariate model). The *ELECT*, *TEXTILE*, *AGROFOOD*, and *ENER_MIN_MISCEL* sector dummies boost R&D in the bivariate model, but only the *ELECT*, *TEXTILE*, and

*ENER_MIN_MISCEL* sector dummies increase R&D in the univariate model. These findings back up the majority of independent activities' efforts to export and invest in R&D.

### 3.4. Estimates of the growth regression

Table 8 depicts the estimates of the independent and combined impact of exporting and R&D decisions on sales growth. We examine whether the complementarity of the two strategies positively affects firm growth.

#### 3.4.1. Any exporting firms with no foreign participation

The positive, albeit insignificant, coefficient of *RDANYEXPNOFP_1* provides no evidence that coupling R&D and exports influences firm growth. There is little support for the hypothesis of learning by exporting. Labor productivity has a nonlinear effect on growth, increasing sales growth only after a certain threshold is reached (as labor may need some learning phase to realize its full potential and for productivity gains to be translated into an increased scale of production and sales). Many researchers have studied the relationship between labor productivity and firm performance, concluding that labor productivity leads to additional revenues, which results in higher profits and improved corporate performance [2, 33, 93, 101]. The remaining control variables are statistically insignificant.

#### 3.4.2. Any exporting firms with foreign participation

There is no evidence that combining R&D and exports increases firm growth (the *RDANYEXPWFP_1* coefficient is positive but insignificant). Labor productivity continues to have a nonlinear effect on firm performance. Furthermore, the coefficients of the linear and quadratic terms of *PRODUCTIVITY_1* are smaller in absolute value than those of the first cluster, indicating that foreign ownership boosts the productivity of affiliate firms in developing countries through advanced technology, business practices, and modern management [30, 37]. These firms are likely to begin with a relatively large scale of production and sales, implying that labor productivity will produce less obvious sales returns. The remaining control variables are statistically insignificant.

#### 3.4.3. Fully exporting firms with no foreign participation

There is little evidence that coupling R&D and export activities positively affects sales growth. There is also no support for the learning by exporting effect. This finding does not imply that there are no efficiency gains from exporting for these firms; rather, it stems from the unique characteristic of the Tunisian manufacturing sector, in which firms exporting 100 percent of their output may be primarily subcontractors with relatively long exporting experience. Hence, their learning opportunities are likely to dwindle over time.

Labor productivity has a nonlinear effect on sales growth, and the coefficients of the linear and quadratic terms of *PRODUCTIVITY_1_* are slightly smaller in absolute value than in the previous two clusters, possibly, because partially exporting firms (a sub-category of any exporting firms) should put more effort into increasing productivity in order to catch up with fully exporting firms and increase further their scale of sales in foreign markets. An alternative interpretation is alongside the large scale of production and sales fully exporting firms (which export 100 percent of their output) can start with, meaning that labor productivity will produce less clear returns in terms of sales. The remaining control variables are insignificant.

3.4.4. Fully exporting firms with foreign participation

The positive and statistically significant coefficient of *RDTOTEXPNOFP_1* directly suggests that coupling R&D and export activities may lead to synergies positively affecting growth. This indicates that the return from R&D increases as firms export, and vice versa. The two activities complement one another in terms of knowledge acquisition, cost reduction, and increased firm profits. Exporting firms that also perform innovation activities can increase their sales volume by selling new and improved products in export markets, and therefore either engaging in a larger scale of production and sales or getting better prices [32, 39, 69]. On the other hand, innovative firms that enter export markets have the opportunity to gain knowledge through exporting (learning by exporting) and subsequently produce better goods. Thus, these firms will be able to boost their sales in both domestic and international markets, again either by raising prices or profiting from increased demand, or both.

The coefficient of *TOTEXPWFPONLY_1* is not significantly different from zero, suggesting that the combination of both activities—rather than the optimization of export on its own—really matters in explaining the growth of the firms in our sample [39]. Labor productivity increases sales growth only after a certain threshold. We have similar results and intuition as the previous cluster. The other control variables are statistically insignificant.

## 4. Conclusions

The exports-FDI, exports-innovation, and innovation-FDI links have all been widely studied in the literature. The theoretical discussions and empirical studies in the first two links were primarily concerned with determining whether the two strategies in each link complement or crowd out one another. In this study, we go one step further and investigate whether and how (inward) FDI shapes the dynamics of exports and R&D, as well as whether coupling the two activities positively affects firm growth.

Our empirical analysis relied on firm-level data from Tunisian manufacturing industries from 2016 to 2018. These data are drawn from accounting, industrial, and exporting flow surveys. We identified four types of firms using the export and FDI differentials: (i) The first and second clusters consist of any exporting firms (including partially and fully exporting firms) without and with foreign participation; respectively (ii) The third and fourth clusters of firms are made up of fully exporting firms without and with foreign participation, respectively.

The analysis provided evidence for the learning by exporting effect in the first cluster of firms' R&D activity. In turn, there is strong support for self-selection for most clusters, in particular for the R&D activity. The findings corroborated complementarities between the two strategies for the exporting activity primarily for clusters of firms with no foreign participation, whereas, a strategic trade-off between both strategies emerges for the R&D activity, primarily for clusters with foreign ownership. Furthermore, the mutually reinforcing effect of exports and R&D fosters sales growth for fully exporting firms with foreign participation.

We believe that our research sheds some light on the role of foreign participation in shaping the dynamics of exports and R&D in developing countries with a subcontracting regime. First, our findings suggest that the exporting behavior of fully exporting firms (primarily subcontractors) in our sample, and more broadly in the country as a whole, may either mask or obstruct the interaction between R&D and exports because exporting behavior appears to be driven more by strict export arrangements than by efficiency considerations. Second, foreign participation proved important in shaping the interplay between exports and R&D activities, with findings indicating that the two activities complement each other primarily for clusters of firms with no foreign participation, whereas a strategic trade-off between these activities emerges mainly for clusters of firms with foreign participation, particularly for the R&D activity. Third, firm performance improvements do not necessarily come from optimizing exports or R&D on their own; but rather from their combination. Furthermore, the complementarity mechanism positively affects firm growth only for fully exporting firms with foreign ownership, suggesting that FDI is a key contextual variable that influences the extent to which combining R&D and exports increases firm sales growth. This is most likely because FDI has the potential to stimulate both exports (in terms of quantity or quality or both) and R&D, implying that the functioning of the virtuous circle at the basis of the complementarity between R&D and exports comes into play to boost sales growth only after certain levels of exports and R&D have been reached. This suggests that there are critical sizes for exports and R&D activities above which the complementarity mechanism is effective at boosting firm growth.

In accordance with the "absorptive capacity" argument [27], Aw et *al*. [7] and Wallin [121] have shown that increased external knowledge diversity (resulting from learning from exporting) benefits domestic firms only if they have some internal knowledge and R&D activities. Second, a high export level may indicate a large scale of production of the same good, exporting to a variety of destinations, or a combination of all of these, potentially increasing the scope for learning and the opportunities to bring new knowledge and technology to local economies.

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## Table 1. Empirical variable definitions and summary statistics

| Variable | Description | Observations | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|---|
| ***Firm characteristics*** | | | | | | |
| *AGE_1* | Years in operation (lagged) | 100079 | 20.7046 | 13.8064 | 1 | 144 |
| *CAPITAL_1* | Financial resources, in constant (2004) US dollars (lagged) | 100079 | 3.30e+07 | 4.09e+08 | 21969 | 2.54e+10 |
| *PRODUCTIVITY_1* | Value-added per employee, in constant (2004) US dollars (lagged) | 100079 | 98465.16 | 901011.4 | 0.0022 | 5.86e+07 |
| *SALES* | Total sales, in constant (2004) US dollars | 100080 | 15.2276 | 3.7417 | 0.15 | 213.8845 |
| *SIZE_1* | Number of employees (lagged) | 100079 | 218.176 | 546.149 | 2 | 9950 |
| ***Exports*** | | | | | | |
| *ANYEXPNOFP* | Dummy: 1 if firm is an exporter with no foreign participation; 0 otherwise | 100080 | 0.2398 | 0.4269 | 0 | 1 |
| *ANYEXPWFP* | Dummy: 1 if firm is an exporter with foreign participation; 0 otherwise | 100080 | 0.3185 | 0.4659 | 0 | 1 |
| *TOTEXPNOFP* | Dummy: 1 if firm exports 100% of its output and has no foreign participation; 0 otherwise | 100080 | 0.196 | 0.397 | 0 | 1 |
| *TOTEXPWFP* | Dummy: 1 if firm exports 100% of its output and has foreign participation; 0 otherwise | 100080 | 0.2426 | 0.4345 | 0 | 1 |

## Table 1/Continued

| Variable | Description | Observations | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|---|
| ***R&D*** | | | | | | |
| *RD* | Dummy: 1 if firm has positive R&D expenditures; 0 otherwise | 100080 | 0.2336 | 0.4231 | 0 | 1 |
| ***Exports and R&D combined*** | | | | | | |
| *ANYEXPNOFPONLY_1* | Dummy (lagged): 1 if *ANYEXPNOFP*=1 | 100079 | 0.2398 | 0.4269 | 0 | 1 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | and *RD*=0; 0 otherwise | | | | | |
| *ANYEXPWFPONLY_1* | Dummy (lagged): 1 if *ANYEXPWFP*=1 and *RD*=0; 0 otherwise | 100079 | 0.3185 | 0.4659 | 0 | 1 |
| *RDANYEXPNOFP_1* | Dummy (lagged): 1 if *ANYEXPNOFP*=1 and *RD*=1; 0 otherwise | 100079 | 0.1363 | 0.3431 | 0 | 1 |
| *RDANYEXPWFP_1* | Dummy (lagged): 1 if *ANYEXPWFP*=1 and *RD*=1; 0 otherwise | 100079 | 0.0104 | 0.1014 | 0 | 1 |
| *RDNOFPONLY_1* | Dummy (lagged): 1 if *ANYEXPNOFP*=0 and *RD*=1; 0 otherwise | 100079 | 0.0973 | 0.2964 | 0 | 1 |
| *RDWFPONLY_1* | Dummy (lagged): 1 if *ANYEXPWFP*=0 and *RD*=1; 0 otherwise | 100079 | 0.2232 | 0.4164 | 0 | 1 |
| *RDTOTEXPNOFP_1* | Dummy (lagged): 1 if *TOTEXPNOFP*=1 and *RD*=1; 0 otherwise | 100079 | 0.01798 | 0.1329 | 0 | 1 |
| *RDTOTEXPWFP_1* | Dummy (lagged): 1 if *TOTEXPWFP*=1 and *RD*=1; 0 otherwise | 100079 | 0.00399 | 0.06309 | 0 | 1 |

## Table 1/Continued

| Variable | Description | Observations | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|---|
| *TOTEXPNOFPONLY_1* | Dummy (lagged): 1 if *TOTEXPNOFP*=1 and RD=0; 0 otherwise | 100079 | 0.17806 | 0.3825 | 0 | 1 |
| *TOTEXPWFPONLY_1* | Dummy (lagged): 1 if *TOTEXPWFP*=1 and RD=0; 0 otherwise | 100079 | 0.2486 | 0.4322 | 0 | 1 |
| ***Sector*** | | | | | | |
| *ELECT* | Dummy: 1 electric, mechanical and electronics sector; 0 otherwise | 100080 | 0.1768 | 0.3815 | 0 | 1 |
| *TEXILE* | Dummy: 1 if textile sector; 0 otherwise | 100080 | 0.4358 | 0.4958 | 0 | 1 |
| *ENER_MIN_MISCEL* | Dummy: 1 if other sector; 0 otherwise | 100080 | 0.3049 | 0.4604 | 0 | 1 |
| *AGROFOOD* | Dummy: 1 if agrofood sector; 0 otherwise | 100080 | 0.0895 | 0.2855 | 0 | 1 |

Source: Compilation of variables and calculations are made by the authors.

## Table 2. Export and R&D status (expressed in percent) during the sample period, 2016-2018

| | 2016 | 2017 | 2018 | Total |
|---|---|---|---|---|
| **Exporters** | | | | |
| Any exporting firms with no foreign participation | 37.59 | 37.71 | 37.53 | 37.61 |
| Any exporting firms with foreign participation | 32.55 | 32.97 | 33.15 | 32.89 |
| Fully exporting firms with no foreign participation | 19.54 | 19.66 | 19.60 | 19.60 |
| Fully exporting firms with foreign participation | 25.30 | 25.12 | 25.36 | 25.26 |
| **Firms carrying out R&D** | | | | |

| | | | | |
|---|---|---|---|---|
| Any exporting firms with no foreign participation | 14.69 | 12.77 | 13.43 | 13.63 |
| Any exporting firms with foreign participation | 1.38 | 0.78 | 0.96 | 1.04 |
| Fully exporting firms with no foreign participation | 2.46 | 1.20 | 1.74 | 1.80 |
| Fully exporting firms with foreign participation | 0.78 | 0.12 | 0.30 | 0.40 |

Source: Authors' calculations.

## Table 3. Transition matrix for for exports and R&D activities

| Status year t-1/Status year t | No exports, no R&D, and no foreign participation | No exports and no R&D, but foreign participation | Exports, but no R&D, and no foreign participation | Exports and foreign participation, but no R&D | R&D, but no exports and no foreign participation | R&D and foreign participation, but no exports | Exports and R&D, but no foreign participation | Exports, R&D, and foreign participation |
|---|---|---|---|---|---|---|---|---|
| **No exports, no R&D and no foreign participation** | 0.7886 | 0.0066 | 0.0414 | 0.0151 | 0.131 | 0.0046 | 0.0126 | 0.0001 |
| **No exports and no R&D, but foreign participation** | 0.0485 | 0.7992 | 0.0118 | 0.0317 | 0.0027 | 0.1046 | 0.0015 | 0.00 |
| **Exports, but no R&D and no foreign participation** | 0.03 | 0.0003 | 0.8196 | 0.0794 | 0.0035 | 0.0001 | 0.0646 | 0.0026 |
| **Exports and foreign participation, but no R&D** | 0.0081 | 0.0035 | 0.0592 | 0.9051 | 0.0025 | 0.0001 | 0.0082 | 0.0133 |
| **R&D, but no exports and no foreign participation** | 0.3152 | 0.0007 | 0.0114 | 0.0099 | 0.6533 | 0.00 | 0.0093 | 0.0003 |

## Table 3/Continued

| Status year t-1/Status year t | No exports, no R&D, and no foreign participation | No exports and no R&D, but foreign participation | Exports, but no R&D, and no foreign participation | Exports and foreign participation, but no R&D | R&D, but no exports and no foreign participation | R&D and foreign participation, but no exports | Exports and R&D, but no foreign participation | Exports, R&D, and foreign participation |
|---|---|---|---|---|---|---|---|---|
| **R&D and foreign participation, but no exports** | 0.0726 | 0.2613 | 0.0019 | 0.0057 | 0.0028 | 0.6547 | 0.0009 | 0.00 |
| **Exports and R&D, but no foreign participation** | 0.0174 | 0.0004 | 0.1102 | 0.0205 | 0.0066 | 0.0001 | 0.8434 | 0.0014 |
| **Exports, R&D, and** | 0.0192 | 0.00 | 0.0625 | 0.3856 | 0.001 | 0.00 | 0.0192 | 0.5125 |

**foreign participation**

Source: Authors' calculations.

## Table 4. Exporting Equation-Marginal effects (Univariate probit estimation)

| **Independent variable** | ***Exporters vs. non-exporters*** | | ***Fully exporting firms vs. others*** | |
|---|---|---|---|---|
| | Firms with no foreign participation | Firms with foreign participation | Firms with no foreign participation | Firms with foreign participation |
| ***ANYEXPNOFP_1/ ANYEXPWFP_1/ TOTEXPNOFP_1 /TOTEXPWFP_1*** | 1.0213$^{***}$ (0.02315) | 0.8955$^{***}$ (0.0235) | 0.4963$^{***}$ (0.0135) | 0.6208$^{***}$ (0.02054) |
| ***R&D_1*** | 0.04701$^{*}$ (0.0175) | -0.1274$^{***}$ (0.02307) | -0.05004$^{***}$ (0.01136) | -0.1122$^{***}$ (0.01903) |
| ***SIZE_1*** | 7.44e-07 (7.02e-06) | 0.00002$^{*}$ (8.97e-06) | 0.00001$^{*}$ (7.47e-06) | 4.46e-06 (7.41e-06) |
| ***AGE_1*** | 0.00068$^{**}$ (0.00034) | -0.00235$^{***}$ (0.00043) | -0.00036 (0.00024) | -0.00219$^{***}$ (0.00037) |
| ***CAPITAL_1*** | -2.90e-12 (8.74e-12) | -2.61e-11 (2.12e-11) | -6.20e-11$^{**}$ (2.51e-11) | -2.37e-11 (1.81e-1) |
| ***PRODUCTIVITY_1*** | 2.72e-08$^{*}$ (1.59e-08) | -1.43e-08 (1.71e-08) | 8.94e-09 (8.52e-09) | -1.39e-08 (2.92e-08) |
| ***PRODUCTIVITY_1 squared*** | -5.68e-16$^{**}$ (2.82e-16) | 4.07e-16 (3.23e-16) | -1.87e-16 (1.44e-16) | 4.55e-16 (2.41e-15) |
| ***TEXTILE*** | 0.08224 (0.06108) | 0.03396 (0.05317) | 0.00429 (0.02230) | 0.0414 (0.0432) |
| ***AGROFOOD*** | 0.0838 (0.0629) | -0.0616 (0.05646) | -0.01798 (0.02466) | -0.0355 (0.0463) |
| ***ELECT*** | 0.07230 (0.0615) | 0.0348 (0.05556) | -0.00868 (0.02219) | 0.0477 (0.04515) |
| ***ENER_MIN_MISCEL*** | 0.01653 (0.06071) | -0.04305 (0.05404) | -0.04166$^{*}$ (0.02283) | -0.0439 (0.0442) |
| ***YEAR 2016*** | 0.01686 (0.0207) | -0.0125 (0.0198) | 0.01109 (0.0119) | 0.0029 (0.01481) |
| ***YEAR 2017*** | 0.0173 (0.0192) | 0.00902 (0.0174) | 0.01196 (0.0105) | -0.0036 (0.01325) |
| **No. of observations** | 100079 | 100079 | 100079 | 100079 |

Note: Heteroscedasticity-Robust standard errors ’clustered within a firm) are in parentheses; *, **, and *** denote variables significant at 10%, 5%, and 1%, respectively.

Source: Authors’ calculations.

**Table 5: Innovation Equation—Marginal effects (Univariate probit estimation)**

| Independent variable | *Exporters vs. non-exporters* | | *Fully exporting firms vs. others* | |
|---|---|---|---|---|
| | Firms with no foreign participation | Firms with foreign participation | Firms with no foreign participation | Firms with foreign participation |
| ***ANYEXPNOFP_1/ ANYEXPWFP_1/ TOTEXPNOFP_1 /TOTEXPWFP_1*** | $0.06671^{***}$ (0.00954) | $-0.1655^{***}$ (0.0136) | $-0.0704^{***}$ (0.0132) | $-0.1927^{***}$ (0.0158) |
| ***R&D_1*** | $0.51706^{***}$ (0.0209) | $0.4687^{***}$ (0.0167) | $0.53052^{**}$ (0.01506) | $0.4697^{***}$ (0.01606) |
| ***SIZE_1*** | -0.000012 (7.95e-06) | -7.99e-06 (6.91e-06) | -9.93e-06 (7.70e-06) | -0.00001 (6.56e-06) |
| ***AGE_1*** | $0.00108^{***}$ (0.00031) | $0.00056^{*}$ (0.00031) | $0.00122^{***}$ (0.00032) | $0.00052^{*}$ (0.0003) |
| ***CAPITAL_1*** | 5.13e-12 (8.26e-12) | 3.17e-12 (7.27e-12) | 4.39e-12 (7.89e-12) | 3.12e-12 (7.15e-12) |
| ***PRODUCTIVITY_1*** | $6.67e\text{-}08^{*}$ (3.46e-08) | $3.86e\text{-}08^{*}$ (2.32e-08) | 3.92e-08 (2.68e-08) | 3.44e-08 (2.27e-08) |
| ***PRODUCTIVITY_1 squared*** | -1.34e-14 (9.58e-15) | $-5.32e\text{-}15^{**}$ (2.61e-15) | -4.86e-15 (3.09e-15) | $-4.65e\text{-}15^{*}$ (2.49e-15) |
| ***TEXTILE*** | 0.04478 (0.03902) | $0.0783^{**}$ (0.0381) | 0.06317 (0.03946) | $0.0822^{**}$ (0.03891) |
| ***ELECT*** | $0.09078^{**}$ (0.0398) | $0.1196^{**}$ (0.0388) | $0.10194^{**}$ (0.0399) | $0.12377^{**}$ (0.0396) |
| ***ENER_MIN_MISCEL*** | $0.0855^{**}$ (0.0395) | $0.0896^{**}$ (0.0385) | $0.0854^{**}$ (0.0399) | $0.0880^{**}$ (0.0394) |
| ***AGROFOOD*** | 0.0609 (0.0406) | $0.0728^{*}$ (0.0398) | $0.0754^{*}$ (0.0410) | $0.0756^{*}$ (0.0405) |
| ***YEAR 2016*** | 0.0209 (0.01597) | 0.02235 (0.0151) | 0.02026 (0.01587) | 0.0219 (0.0151) |

**Table 5/Continued**

| **Independent variable** | *Exporters vs. non-exporters* | | *Fully exporting firms vs. others* | |
|---|---|---|---|---|
| | Firms with no foreign participation | Firms with foreign participation | Firms with no foreign participation | Firms with foreign participation |
| ***YEAR 2017*** | -0.01625 (0.01475) | -0.01716 (0.01413) | -0.01743 (0.0149) | -0.01620 (0.01407) |
| **No. of observations** | 100079 | 100079 | 100079 | 100079 |

Note. Heteroscedasticity-Robust standard errors (clustered within a firm) are in parentheses; *, **, and *** denote variables significant at 10%, 5%, and 1%, respectively.

**Table 6: Estimates of the interaction between exports and R&D activities — Bivariate probit estimation for any exporting firms**

| Independent variable | *Any exporting firms with no foreign participation* | | *Any exporting firms with foreign participation* | |
|---|---|---|---|---|
| | Exporting decision | R&D decision | Exporting decision | R&D decision |
| ***ANYEXPNOFPONLY_1/ ANYEXPWFPONLY_1*** | 2.7307*** (0.0781) | 0.01046 (0.0659) | 2.9579*** (0.0827) | -0.7358*** (0.0763) |
| ***RDANYEXPNOFP_1/ RDANYEXPWFP_1*** | 3.251*** (0.0947) | 2.5238*** (0.0762) | 2.8368*** (0.2493) | 1.3344*** (0.1977) |
| ***RDWFPONLY_1*** | -0.3616*** (0.1134) | 1.8027*** (0.0848) | -0.5273*** (0.0919) | 2.00619*** (0.07182) |
| ***SIZE_1*** | -0.000015 (0.00002) | -0.00006* (0.00003) | 0.000066** (0.00003) | -0.000034 (0.000029) |
| ***AGE_1*** | 0.00245** (0.00099) | 0.00531*** (0.00135) | -0.008007*** (0.00143) | 0.00226* (0.001365) |
| ***CAPITAL_1*** | -1.74e-11 (2.95e-11) | 1.93e-11 (3.22e-11) | -6.58e-11 (6.32e-11) | 1.32e-11 (3.15e-11) |
| ***PRODUCTIVITY_1*** | 8.82e-08** (4.48e-08) | 1.97e-07* (1.19e-07) | -6.17e-08 (5.77e-08) | 1.67e-07* (9.99e-08) |
| ***PRODUCTIVITY_1 squared*** | -1.82e-15** (7.92e-16) | 2.66e-14* (1.44e-14) | 1.62e-15 (1.11e-15) | -2.28e-14** (1.12e-14) |
| ***TEXTILE*** | 0.1626 (0.1796) | 0.10515 (0.17156) | 0.17246 (0.1775) | -2.28e-14** (1.12e-14) |
| ***ELECT*** | 0.1327 (0.1811) | 0.3022* (0.17416) | 0.17097 (0.1856) | 0.3272** (0.16101) |
| ***ENER_MIN_MISCEL*** | -0.01304 (0.17837) | 0.2968* (0.17434) | -0.0839 (0.1799) | 0.3713** (0.16278) |
| ***AGROFOOD*** | 0.1538 (0.1853) | 0.1801 (0.1780) | -0.1382 (0.1881) | 0.30227* (0.16838) |
| ***YEAR 2016*** | 0.03859 (0.0594) | 0.0751 (0.0647) | -0.01859 (0.06535) | 0.0959 (0.06557) |
| ***YEAR 2017*** | 0.0464 (0.0542) | -0.0842 (0.06016) | 0.01514 (0.05802) | -0.0696 (0.06084) |
| ***CONSTANT*** | -1.7386*** (0.18606) | -1.7876*** (0.1832) | -1.53105*** (0.1884 | -1.6856*** (0.1725) |

**Table 6/Continued**

| Independent variable | *Any exporting firms with no foreign participation* | | *Any exporting firms with foreign participation* | |
|---|---|---|---|---|
| | Exporting decision | R&D decision | Exporting decision | R&D decision |
| **Wald Chi$^2$ (p-value>chi$^2$)** | 23.0041 (0.0000) | _ | 34.3078 (0.0000) | _ |
| **No. of observations** | 100079 | 100079 | 100079 | 100079 |

Note. Heteroscedasticity-Robust standard errors (clustered within a firm) are in parentheses; *, **, and *** denote variables significant at 10%, 5%, and 1%, respectively.

Source: Authors' calculations.

**Table 7. Estimates of the interaction between exports and R&D activities – Bivariate probit estimation for fully exporting firms**

| Independent variable | *Fully exporting firms with no foreign participation* | | *Fully exporting firms with foreign participation* | |
|---|---|---|---|---|
| | Exporting decision | R&D decision | Exporting decision | R&D decision |
| ***TOTEXPNOFPONLY_1 /TOTEXPWFPONLY_1*** | 3.0745$^{***}$ (0.089) | -0.9105$^{***}$ (0.0749) | 3.12405$^{***}$ (0.0862) | -1.5399$^{***}$ (0.0873) |
| ***RDTOTEXPNOFP_1/ RDTOTEXPWFP_1*** | 3.1635$^{***}$ (0.1896) | 0.6056$^{***}$ (0.1668) | 2.7788$^{***}$ (0.3424) | -0.6587$^{**}$ (0.3358) |
| ***SIZE_1*** | 0.00009$^{*}$ (0.000045) | -0.000106$^{*}$ (0.0000645) | 0.000036 (0.000036) | -0.00011$^{*}$ (0.000057) |
| ***AGE_1*** | -0.003004$^{**}$ (0.00141) | 0.00859$^{***}$ (0.00225) | -0.01132$^{***}$ (0.0018) | 0.0044$^{*}$ (0.00233) |
| ***CAPITAL_1*** | -3.59e-10$^{**}$ (1.52e-10) | 1.80e-11 (5.21e-11) | -1.08e-10 (8.43e-11) | 1.17e-11 (4.97e-11) |
| ***PRODUCTIVITY_1*** | 4.97e-08 (5.32e-08) | 3.55e-07$^{**}$ (1.67e-07) | -1.34e-07 (1.53e-07) | 3.03e-07$^{*}$ (1.62e-07) |
| ***PRODUCTIVITY_1 squared*** | -1.02e-15 (8.98e-16) | -4.10e-14 (2.53e-14) | 8.71e-15 (1.42e-14) | -3.85e-14$^{**}$ (1.69e-14) |

**Table 7/Continued**

| Independent variable | *Fully exporting firms with no foreign participation* | | *Fully exporting firms with foreign participation* | |
|---|---|---|---|---|
| | Exporting decision | R&D decision | Exporting decision | R&D decision |
| ***TEXTILE*** | 0.0225 | 0.2697 | 0.2076 | 0.4498$^{*}$ |

| | | | | |
|---|---|---|---|---|
| | (0.1482) | (0.2424) | (0.1954) | (0.2435) |
| ***ELECT*** | 0.0823 (0.1473) | $0.553^{**}$ (0.24289) | 0.19504 (0.202) | $0.7643^{***}$ (0.2435) |
| ***ENER_MIN_MISCEL*** | $-0.2663^{*}$ (0.1516) | 0.3967 (0.2445) | -0.1857 (0.1977) | $0.4606^{*}$ (0.2451) |
| ***AGROFOOD*** | -0.12103 (0.16104) | 0.3547 (0.2562) | -0.1374 (0.2086) | 0.3791 (0.2578) |
| ***YEAR 2016*** | 0.07406 (0.0722) | 0.0392 (0.0324) | 0.0395 (0.0702) | $0.0753^{**}$ (0.0332) |
| ***YEAR 2017*** | 0.0477 (0.0645) | -0.0307 (0.0264) | -0.03702 (0.0645) | -0.00835 (0.0266) |
| ***CONSTANT*** | $-1.8241^{***}$ (0.15925) | $-1.1942^{***}$ (0.2498) | $-1.7161^{***}$ (0.2097) | $-1.1353^{***}$ (0.2516) |
| **Wald Chi$^2$ (*p*-value>Chi$^2$)** | 21.9513 (0.0000) | _ | 67.7008 (0.0000) | _ |
| **No. of observations** | 100079 | 100079 | 100079 | 100079 |

Note. Heteroscedasticity-Robust standard errors (clustered within a firm) are in parentheses; *, **, and *** denote variables significant at 10%, 5%, and 1%, respectively.

**Table 8. Predictors of sales growth-Fixed effects estimation**

| Independent variable | *Any exporting firms with no foreign participation* | *Any exporting firms with foreign participation* | *Fully exporting firms with no foreign participation* | *Fully exporting firms with foreign participation* |
|---|---|---|---|---|
| ***RDNOFPONLY_1/ RDWFPONLY_1*** | 0.06102 (0.04116) | 0.07389 (0.04824) | _ | _ |
| ***RDANYEXPNOFP_1/ RDANYEXPWFP_1/ RDTOTEXPNOFP_1/ RDTOTEXPWFP_1*** | 0.39241 (0.33658) | 0.36816 (0.37397) | 0.06956 (0.04655) | $0.04977^{*}$ (0.02625) |
| ***ANYEXPNOFPONLY_1/ ANYEXPWFPONLY_1/ TOTEXPNOFPONLY_1/ TOTEXPWFPONLY_1*** | -0.0616 (0.07456) | 0.0581 (0.0431) | 0.0149 (0.0093) | 0.01963 (0.0229) |
| ***SIZE_1*** | -0.00002 (0.00002) | -0.00002 (0.00002) | $-0.00004^{**}$ (0.00002) | $-0.00004^{**}$ (0.00002) |
| ***AGE_1*** | -0.01292 (0.01238) | -0.01292 (0.01235) | -0.01263 (0.01235) | -0.01260 (0.01234) |
| ***CAPITAL_1*** | -2.26e-12 (2.32e-12) | -2.10e-12 (2.37e-12) | -3.03e-12 (2.11e-12) | -3.05e-12 (2.11e-12) |

| | | | | |
|---|---|---|---|---|
| ***PRODUCTIVITY_1*** | -6.15e-08** (2.53e-08) | -5.85e-08** (2.47e-08) | -5.64e-08*** (1.89e-08) | -5.61e-08*** (1.89e-08) |
| ***PRODUCTIVITY_1 squared*** | 1.03e-15** (4.25e-16) | 9.82e-16** (4.14e-16) | 9.47e-16*** (3.17e-16) | 9.42e-16*** (3.18e-16) |
| ***TEXTILE*** | -0.00037 (0.0358) | -0.00106 (0.0354) | -0.01294 (0.0214) | -0.01257 (0.02054) |
| ***ELECT*** | 0.01391 (0.0660) | 0.01776 (0.0675) | -0.03035 (0.0264) | -0.0345 (0.02513) |
| ***ENER_MIN_MISCEL*** | 0.0694 (0.0595) | 0.0659 (0.0575) | 0.0326 (0.02047) | 0.0266 (0.01806) |
| ***AGROFOOD*** | -0.04585 (0.0399) | -0.0501 (0.0432) | -0.01687 (0.0305) | -0.0164 (0.0301) |
| ***YEAR 2016*** | 0.02917 (0.0523) | 0.02952 (0.0526) | 0.0317 (0.0549) | 0.0318 (0.0549) |
| ***YEAR 2017*** | -0.0221 (0.0161) | -0.02075 (0.0158) | -0.0138 (0.0132) | -0.0133 (0.0132) |
| ***CONSTANT*** | 0.23842 (0.2468) | 0.2159 (0.267) | 0.2943 (0.2523) | 0.2947 (0.2529) |

**Table 8/Contiuned**

| **Independent variable** | ***Any exporting firms with no foreign participation*** | ***Any exporting firms with foreign participation*** | ***Fully exporting firms with no foreign participation*** | ***Fully exporting firms with foreign participation*** |
|---|---|---|---|---|
| $R^2$ within | 0.0033 | 0.0033 | 0.0007 | 0.0007 |
| No. of observations | 100079 | 100079 | 100079 | 100079 |

Note. Heteroscedasticity-Robust standard errors (clustered with a firm) are in parentheses;*,**,*** denote variables significant at 10%, 5%, and 1%, respectively.

Source: Authors' calculations

## Appendix: Multiple Imputation diagnostics

Imputation techniques require some diagnostics to help determine whether imputations are reasonable. A large number of studies have developed important diagnostics that can be used both before and after the imputation process [1, 19, 39, 77, 91, 108, 110, 114, 120]

Prior to the imputation process, the quantity and patterns of missing data, as well as the mechanism underlying missingness, must be investigated. These prognoses indicate whether or not the Multiple Imputation (MI) method should be used. Following imputation, we must compare the imputed and observed data distributions using frequency tables and graphical diagnostics, as well as check the model fit of the imputation model to the observed data (StataCorp, 2017).

## 1. Investigating quantity and patterns of missingness

### 1.1 Exploring missing-data quantity

We begin by investigating how many missing values there are in the variables. Table 1 displays the results. We should note that the variables *ANYEXP*, *TOTEXP*, *RD*, *CAPFOREIGN*, *TEXTILE*, *AGROFOOD*, *ELECT*, and MISCEL are not included in the output because they have no missing values. *LABPROD* has the most missing values (185), followed by *CAPITAL* (120 missing values) and *SALES* (111 missing values). *FIRMSIZE* and *FIRMAGE*, on the other hand, have fewer missing values.

**Table 1. Missing-data Quantity**

| Variable | Missing values | Observed values | Unique values | Min | Max |
|---|---|---|---|---|---|
| ***FIRMSIZE*** | 73 | 4931 | >500 | 2 | 9950 |
| ***FIRMAGE*** | 75 | 4929 | 96 | 1 | 144 |
| ***CAPITAL*** | 120 | 4884 | >500 | 21969 | 2.54e+10 |
| ***SALES*** | 111 | 4893 | >500 | 0.15 | 213.8845 |
| ***LABPROD*** | 185 | 4819 | >500 | 0.00223 | 5.86e+07 |

Source : Authors' calculations.

### 1.2. Exploring missing-data patterns

To select an appropriate imputation method, we must first examine the missing-data pattern. We investigate which missingness patterns exist and how frequently each pattern occurs. The patterns of co-occurrence of missing values across the variables in the analysis are shown in Table 2.

Table 2 shows, for the specified variables, each pattern of missing data that occurs, ordered by frequency (or percentage) of occurrence. The first two rows show that 4504 (90 percent) of the 5,004 firms had data for all variables in the analysis model. The most common pattern which has some missing values is when all variables are observed except *LABPROD* (n=135 and p=3%). The next most common pattern is one in which all variables are present except *CAPITAL* (n=105 and p=2%). The other most common pattern is one in which all variables are observed except *SALES* (n=95 and p=2%). Then we see that all of the other possible missingness patterns occur, albeit at lower frequencies

We can see that there are a total of 17 patterns for the specified variables. We would like to examine these tables for any patterns and the appearance of any set of variables that appear to be always missing together. As one can see this pattern is not monotone missing (as seen in longitudinal data when an individual drops out at a specific time point and all data after that is subsequently missing) (see Table 3). The missing-data pattern is *arbitrary* because it does not follow a regular pattern.

**Table 2. Missingness-value Patterns (1 means complete)**

| PATTERN | | | | | | |
|---|---|---|---|---|---|---|
| | | VARIABLES | | | | |
| **FREQUENCY** | **PERCENTAGE** | 1 | 2 | 3 | 4 | 5 |
| **4505** | 90% | 1 | 1 | 1 | 1 | 1 |
| **135** | 3 | 1 | 1 | 1 | 1 | 0 |
| **102** | 2 | 1 | 1 | 1 | 0 | 1 |
| **95** | 2 | 1 | 1 | 0 | 1 | 1 |
| **67** | 1 | 1 | 0 | 1 | 1 | 1 |
| **41** | <1 | 0 | 1 | 1 | 1 | 1 |
| **28** | <1 | 0 | 1 | 1 | 1 | 0 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **9** | <1 | 1 | 1 | 1 | 0 | 0 |
| **7** | <1 | 1 | 1 | 0 | 1 | 0 |
| **5** | <1 | 1 | 1 | 0 | 0 | 1 |
| **3** | <1 | 1 | 0 | 1 | 0 | 1 |
| **2** | <1 | 0 | 0 | 1 | 1 | 0 |
| **1** | <1 | 0 | 0 | 0 | 1 | 0 |
| **1** | <1 | 0 | 1 | 0 | 1 | 0 |
| **1** | <1 | 1 | 0 | 0 | 1 | 1 |
| **1** | <1 | 1 | 0 | 1 | 1 | 0 |
| **1** | <1 | 1 | 1 | 0 | 0 | 0 |
| **5,004** | 100% | | | | | |

Source : Authors' calculations.

Variables are: (1) *FIRMSIZE* (2) *FIRMAGE* (3) *SALES* (4) *CAPITAL* (5) *LABPROD*

**Table 3. An Example of a Monotone Pattern**

| | **Variable** | | |
|---|---|---|---|
| $\mathbf{X_1}$ | $\mathbf{X_2}$ | $\mathbf{X_3}$ | $\mathbf{X_4}$ |
| 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 0 |
| 1 | 1 | 0 | 0 |
| 1 | 0 | 0 | 0 |

Source : Authors' calculations.

## 2. Exploring missing data mechanism

The validity of MI rests, among other things, on assumptions about missing data mechanisms, i.e. the processes that underpin how missing data arose. Missing data mechanisms generally fall into one of three main categories [97]: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR).

Data are missing completely at random (MCAR) if the missingness is random and no processes are affecting the reason why the data is missing. There is no relationship between the pattern of missing data and the observed data or the missing data, i.e., there is no relationship between how the data is missing and data we do have (observed data) and do not have. In practice, an MCAR dataset is one that has less than 5% missing data for each variable.

Data are missing at random (MAR) if the pattern of missingness is related to the observed data but not to the missing data. A variable is said to be missing at random if other variables in the dataset (but not the variable itself) can be used to predict missingness on a given variable, e.g., Women are more likely to respond to survey questions than men. This means that gender predicts missingness on another variable. The MAR assumption is less restrictive than the MCAR assumption. Under this assumption, the probability of missingness does not depend on the true values after controlling for the observed variables.

Finally, if the value of the unobserved variable predicts missingness, the data is said to be missing not at random (MNAR). Income is a classic example of this: people with very high incomes are more likely to decline to answer questions about their income than people with more moderate incomes.

Understanding the missing data mechanism(s) present in the data is critical because different types of missing data require different treatments. When data are missing completely at random, analyzing only the complete cases does not result in biased parameter estimates. Multiple imputation and other modern methods, such as direct maximum likelihood, generally assumes that the data are at least MAR, implying that this procedure can also be used on data that are missing completely at random.

We now investigate which variables are predictive of missingness in each of the five variables, *LABPROD*, *FIRMSIZE*, *FIRMAGE*, *CAPITAL*, and *SALES*. For this purpose, we define a binary variable for each of these variables to indicate whether the variable is observed (=1) or missing (=0).

For the *LABPROD*, *FIRMSIZE*, *FIRMAGE*, *CAPITAL*, and *SALES* variables, the binary variables are *r_LABPROD*, *r_FIRMSIZE*, *r_FIRMAGE*, *r_CAPITAL*, and *r_SALES*, respectively. Next, we fit a logistic regression model for each of the five binary variables with all other variables as covariates (we could also have simply performed a chi-squared test). These findings are depicted in Table 4.

Column 1 of table 4 shows that we have strong evidence that *ANYEXP* and *TOTEXP* are independently associated with the likelihood of *LABPROD* being observed. Conditional on *ANYEXP* and *TOTEXP*, there is no evidence that *FIRMSIZE*, *FIRMAGE*, *CAPITAL*, *RD*, *CAPFOREIGN*, *ELECT*, *TEXTILE*, *AGROFOOD*, *MISCEL*, and *SALES* are associated with this probability.

In conclusion, we found strong evidence that the missing values in the *LABPROD* variable are not missing completely at random (MCAR) but rather missing at random (MAR), because the probability of this variable being missing is independently associated with the *ANYEXP*, and *TOTEXP* variables.

In column 2, there is strong support for the fact that *RD* is independently associated with the probability of *FIRMSIZE* being observed. Conditional on *RD* there is little evidence that *FIRMAGE*, *CAPITAL*, *TOTEXP*, *ANYEXP, ELECT*, *CAPFOREIGN*, *LABPROD*, *TEXTILE*, *AGROFOOD*, *MISCEL,* and *SALES* are associated with this probability. In the light of the above results, we conclude that data on *FIRMSIZE* are MAR given *FIRMAGE*, *CAPITAL*, TOTEXP, ANYEXP, *ELECT*, *CAPFOREIGN*, *LABPROD*, *TEXTILE*, *AGROFOOD*, *MISCEL* , *SALES*.

Column 3 shows that we have strong evidence that *ANYEXP*, *ELECT*, *TEXTILE*, *AGROFOOD,* and *MISCEL* are all independently associated with the likelihood of observing *FIRMAGE*. Conditional on *ANYEXP*, *ELECT*, *TEXTILE*, *AGROFOOD,* and *MISCEL* there is no evidence that *FIRMSIZE*, *CAPITAL*, *TOTEXP*, *RD*, *CAPFOREIGN*, *LABPROD*, and *SALES* are associated with this probability. In conclusion, there is strong support for the fact that the missing values in the *FIRMAGE* variable are MAR rather than MCAR.

Column 4 shows a high support for the fact that *LABPROD* is independently associated with the probability of *CAPITAL* being observed. Conditional on *LABPROD* there is no evidence that *FIRMSIZE*, *FIRMAGE*, *ANYEXP*, *TOTEXP*, *RD*, *ELECT*, *CAPFOREIGN*, *TEXTILE*, *AGROFOOD*, *MISCEL* and *SALES* are associated with this probability. In conclusion, we have found strong evidence that the missing values in the *CAPITAL* variable are MAR given *FIRMSIZE*, *FIRMAGE*, *ANYEXP*, *TOTEXP*, *RD*, *ELECT*, *CAPFOREIGN*, *TEXTILE*, *AGROFOOD*, *MISCEL* and *SALES*.

In column 5, there is strong evidence that *RD*, *TEXTILE*, and *AGROFOOD* are independently associated with the probability of *SALES* being observed. Conditional on *SALES* there is no evidence that *FIRMSIZE*, *FIRMAGE*, *ANYEXP*, *TOTEXP*, *LABPROD*, *ELECT*, *CAPFOREIGN*, *MISCEL* and *CAPITAL* are associated with this probability. In conclusion, we have found strong evidence that the missing values in the *SALES* variable are not MCAR. In particular, we have found that the probability of this variable being missing is independently associated with the *RD*, *TEXTILE*, and *AGROFOOD* variables.

In the light of our findings in the preceding sections, we conclude that using Multiple Imputation (MI) in our data is reasonable, as more than 5% of data are missing (10%), the missingness pattern is arbitrary and data are missing at random (MAR).

**Table 4. Investigation of Variables Predicting Missingness – Odd Ratios**

| Independent variable | *r_LABPROD* | *r_FIRMSIZE* | *r_FIRMAGE* | *r_CAPITAL* | *r_SALES* |
|---|---|---|---|---|---|
| ***FIRMSIZE*** | 0.9997 (0.0002) | _ | 1.001 (0.0008) | 0.999 (0.0002) | 1.0003 (0.00036) |
| ***FIRMAGE*** | 0.9912 (0.00616) | 0.985 (0.0094) | _ | 1.008 (0.0088) | 0.991 (0.0072) |
| ***CAPITAL*** | 1 (1.80e-09) | 1(1.54e-09) | 1 (8.00e-10) | _ | 1 (1.34e-10) |
| ***LABPROD*** | _ | 1 (9.42e-08) | 1 (6.56e-07) | 1.000003 (1.52e-06)* | 1.000001 (1.15e-06) |
| ***TOTEXP*** | 1.585 (0.357)** | 0.856 (0.399) | 1.153 (0.446) | 1.0503 (0.295) | 0.864 (0.2516) |
| ***ANYEXP*** | 0.443 (0.1148)*** | 1.183 (0.4825) | 2.224 (0.7627)** | 0.797 (0.226) | 0.689 (0.1997) |
| ***RD*** | 1.1946 (0.2957) | 0.523(0.193)* | 0.841 (0.257) | 0.698 (0.186) | 0.642 (0.1694)* |
| ***CAPFOREIGN*** | 0.8096 (0.162) | 1 (1.50e-09) | 0.856 (0.259) | 0.715 (0.166) | 1.329 (0.3367) |
| ***ELECT*** | 1.547 (1.1582) | 1.943(2.4106) | 15.402 11.557)*** | 1.246 (1.0196) | 2.721 (2.0846) |
| ***TEXTILE*** | 0.9302 (0.692) | 1.594 (1.972) | 6.223 (4.1303)*** | 1.0227 (0.834) | 4.2302 (3.231)* |
| ***MISCEL*** | 1.095 (0.824) | 1.151 (1.418) | 9.905 (6.5807)*** | 0.707 (0.5803) | 3.0176 (2.295) |

| | | | | | |
|---|---|---|---|---|---|
| ***AGROFOOD*** | 0.7486 (0.5807) | 6.2913 (9.887) | 19.018(16.2425)*** | 0.779 (0.679) | 4.864 (4.1248)* |
| ***YEAR*** | 0.939 (0.1018) | 0.826 (0.1615) | 1.11 (0.1692) | 1.064 (0.1315) | 1.039 (0.1328) |
| ***SALES*** | 1.0231 (0.0519) | 1.0736 (0.0967) | 1.005 (0.0365) | 1.003 (0.0324) | _ |

**Table 4/Continued**

| **Independent variable** | ***r_LABPROD*** | ***r_FIRMSIZE*** | ***r_FIRMAGE*** | ***r_CAPITAL*** | ***r_SALES*** |
|---|---|---|---|---|---|
| ***SALES*** | 1.0231 (0.0519) | 1.0736 (0.0967) | 1.005 (0.0365) | 1.003 (0.0324) | _ |
| ***CONSTANT*** | 4.55e+56 (9.95e+58) | 1.5e+168 (5.9e+170) | 1.13e-91 (3.48e-89) | 3.12e-53 (7.77e-51) | 8.86e-34 (2.28e-31) |
| **No. of observations** | 4640 | 4546 | 4572 | 4607 | 4600 |

Note: Standard errors are in parentheses:*, **, and *** denote variables significant at 10%, 5%, and 1%, respectively. Source: Authors' calculations.

## 3. Checking the imputation model

After performing an imputation, a useful initial check is to explore the imputed values that have been generated by the imputation model. This can be accomplished by displaying the imputed data graphically using plots such as kernel density plots, histograms, or boxplots. The imputed data can also be checked numerically by generating descriptive statistics like means and standard deviations. These graphical and numerical checks provide information about the distribution of imputed values and can help determine whether the imputed data are reasonable. We compute descriptive statics such as frequencies, means, and standard deviations, as well as kernel density plots for the observed data (labelled m=0) alongside the imputed data for the 20 imputations (labelled m=1 and m=20).

Tables 5 -11 show that we successfully imputed all of the missing values (frequencies of the five imputed variables are the same for the twenty imputations and they are higher than the frequencies of the observed data). All of the figures below show that there is no difference between the observed data and the imputed data distributions, as Kernel densities plots of the observed and imputed values for each variable are relatively similar (see the five figures below). Furthermore, the observed and imputed *FIRMSIZE*, *FIRMAGE*, *CAPITAL*, and *SALES* had similar means (for example, *FIRMESIZE* has an observed mean of 218.68 vs. the imputed means of 217.944 for m=1; 218.1896 for m=2; 218.264 for m=3; 218.0082 for m=4; 218.338 for m=5; 218.1457 for m=6; 218.2214 for m=7; 217.9816 for m=8; 218.1533 for m=9; 218.2446 for m=10; 218.2388 for m=11; 218.2124 for m=12; 218.1878 for m=13; 218.2144 for m=14; 218.3579 for m=15; 218.1884 for m=16; 218.0394 for m=17; 218.23 for m=18; 218.229for m=19; and 218.194 for m=20), and standard deviations (549.3129 for observed data vs. 545.983for m=1; 546.2072 for m=2; 546.2479 for m=3; 545.959 for m=4; 546.3166 for m=5; 546.1663 for m=6; 546.2373 for m=7; 546.0242 for m=8; 546.1537 for m=9; 546.2338 for m=10; 546.2514 for m=11; 546.1932for m=12; 546.2882 for m=13; 546.2613 for m=14; 546.3107 for m=15; 546.2653 for m=16; 546.104 for m=17; 546.2126for m=18; 546.323 for m=19; and 546.226 for m=20).

However, there were discrepancies between the observed and imputed means and standard deviations for the variable *LABPROD* (*LABPROD* has an observed mean of 99384.19 vs. 98780.37 for m=1; 98339.15 for m=2; 98266.35 for m=3; 98418.15 for m=4; 98702.9 for m=5; 97829.93 for m=6; 99098.95 for m=7; 98496.67 for m=8; 98546.15 for m=9; 98396.81 for m=10; 98607.61 for m=11; 98809.47 for m=12; 98376.87 for m=13; 98274.01 for m=14; 98764.36 for m=15; 98387.18 for m=16; 98323.89 for m=17; 98585.05 for m=18; 98134.35 for m=19; and 98147.73 for m=20. The variable has a standard deviation of 917859 for observed data vs. 901381.1for m=1; 901038.6for m=2; 900981.1 for m=3; 918293.4 for m=4; 901129.5 for m=5; 900910.2 for m=6; 901661.2 for m=7; 901091.7 for m=8; 900965.5 for m=9; 901007.2for m=10; 901215.3 for m=11; 901149.5for m=12; 900967.3 for m=13; 900993.5 for m=14; 901247 for m=15; 901016.5 for m=16; 901025.2 for m=17; 901053.8 for m=18; 900914.8 for m=19; and 901086 for m=20).

**Table 5: Frequencies, Means, and Standard Deviations of the Observed and Imputed Values for m=0, m=1, and m=2**

| Variable/Im -putation number | m=0 | m=1 | m=2 |
|---|---|---|---|

| | Freq. | Mean | St.Dev. | Freq. | Mean | St.Dev. | Freq. | Mean | St.Dev. |
|---|---|---|---|---|---|---|---|---|---|
| ***FIRMSIZE*** | 4931 | 218.68 | 549.3129 | 5004 | 217.944 | 545.983 | 5004 | 218.1896 | 546.2072 |
| ***FIRMAGE*** | 4929 | 20.698 | 13.8592 | 5004 | 20.7126 | 13.8054 | 5004 | 20.70024 | 13.83 |
| ***CAPITAL*** | 4884 | 3.31e+07 | 4.06e+08 | 5004 | 3.29e+07 | 4.01e+08 | 5004 | 3.27e+07 | 4.01e+08 |
| ***LABPROD*** | 4819 | 99384.19 | 917859 | 5004 | 98780.37 | 901381.1 | 5004 | 98339.15 | 901038.6 |
| ***SALES*** | 4893 | 15.2663 | 3.7744 | 5004 | 15.2633 | 3.7448 | 5004 | 15.2618 | 3.7409 |

Source : Authors' calculations.

**Table 6: Frequencies, Means, and Standard Deviations for Imputed Values for m=3, m=4, and m=5**

| **Variable/Imputation number** | **m=3** | | | **m=4** | | | **m=5** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Freq** | **Mean** | **ST.Dev** | **Freq** | **Mean** | **ST.Dev** | **Freq** | **Mean** | **ST.Dev** |
| ***FIRMSIZE*** | 5004 | 218.264 | 546.2479 | 5004 | 218.0082 | 545.959 | 5004 | 218.2456 | 546.3166 |
| ***FIRMAGE*** | 5004 | 20.6864 | 13.7825 | 5004 | 20.7292 | 13.8342 | 5004 | 20.69584 | 13.797 |
| ***CAPITAL*** | 5004 | 3.27e+07 | 4.01e+08 | 5004 | 3.28e+07 | 4.01e+08 | 5004 | 3.27e+07 | 4.01e+08 |
| ***LABPROD*** | 5004 | 98266.35 | 900981.1 | 5004 | 98418.15 | 901014.1 | 5004 | 98702.9 | 901129.5 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ***SALES*** | 5004 | 15.2618 | 3.7442 | 5004 | 15.26407 | 3.7422 | 5004 | 15.262 | 3.7421 |

Source : Authors' calculations.

**Table 7: Frequencies, Means, and Standard Deviations for Imputed Values for m=6, m=7, and m=8**

| **Variable/Imputation number** | **m=6** | | | **m=7** | | | **m=8** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Freq** | **Mean** | **ST.Dev** | **Freq** | **Mean** | **ST.Dev** | **Freq** | **Mean** | **ST.Dev** |
| ***FIRMSIZE*** | 5004 | 218.1457 | 546.1663 | 5004 | 218.2214 | 546.2373 | 5004 | 217.9816 | 546.0242 |
| ***FIRMAGE*** | 5004 | 20.68885 | 13.7827 | 5004 | 20.71663 | 13.804 | 5004 | 20.6844 | 13.8258 |
| ***CAPITAL*** | 5004 | 3.28e+07 | 4.01e+08 | 5004 | 3.27e+07 | 4.01e+08 | 5004 | 3.27e+07 | 4.01e+08 |
| ***LABPROD*** | 5004 | 97829.93 | 900910.2 | 5004 | 99098.95 | 901661.2 | 5004 | 98496.67 | 901091.7 |
| ***SALES*** | 5004 | 15.26228 | 3.7431 | 5004 | 15.26605 | 3.7399 | 5004 | 15.26313 | 3.7414 |

Source : Authors' calculations.

**Table 8. Frequencies, Means and Standard Deviations for Imputed Values for m=9, m=10 and m=11**

| **Variable/Imputation number** | **m=9** | **m=10** | **m=11** |
|---|---|---|---|

| | Freq | Mean | ST.Dev | Freq | Mean | ST.Dev | Freq | Mean | ST.Dev |
|---|---|---|---|---|---|---|---|---|---|
| ***FIRMSIZE*** | 5004 | 218.1533 | 546.1537 | 5004 | 218.2446 | 546.2338 | 5004 | 218.2388 | 546.2514 |
| ***FIRMAGE*** | 5004 | 20.72462 | 13.8013 | 5004 | 20.74361 | 13.8196 | 5004 | 20.68585 | 13.8032 |
| ***CAPITAL*** | 5004 | 3.29e+07 | 4.01e+08 | 5004 | 3.28e+07 | 4.01e+08 | 5004 | 3.27e+07 | 4.01e+08 |
| ***LABPROD*** | 5004 | 98546.15 | 900965.5 | 5004 | 98396.81 | 901007.2 | 5004 | 98607.61 | 901215.3 |
| ***SALES*** | 5004 | 15.26341 | 3.7436 | 5004 | 15.266 | 3.7404 | 5004 | 15.2663 | 3.7382 |

Source : Authors' calculations.

**Table 9. Frequencies, Means, and Standard Deviations for Imputed Values for m=12, m=13, and m=14**

| **Variable/Imputation number** | **m=12** | | | **m=13** | | | **m=14** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Freq** | **Mean** | **ST.Dev** | **Freq** | **Mean** | **ST.Dev** | **Freq** | **Mean** | **ST.Dev** |
| ***FIRMSIZE*** | 5004 | 218.2124 | 546.1932 | 5004 | 218.1878 | 546.2882 | 5004 | 218.2144 | 546.2613 |
| ***FIRMAGE*** | 5004 | 20.649 | 13.7939 | 5004 | 20.7664 | 13.8053 | 5004 | 20.6862 | 13.819 |
| ***CAPITAL*** | 5004 | 3.27e+07 | 4.01e+08 | 5004 | 3.82e+07 | 5.39e+08 | 5004 | 3.28e+07 | 4.01e+08 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ***LABPROD*** | 5004 | 98809.47 | 901149.5 | 5004 | 98376.87 | 900967.3 | 5004 | 98274.01 | 900993.5 |
| **SALES** | 5004 | 15.267 | 3.7408 | 5004 | 15.262 | 3.7403 | 5004 | 15.2647 | 3.746 |

Source : Authors' calculations.

**Table 10. Frequencies, Means, and Standard Deviations for Imputed Values for m=15, m=16, and m=17**

| **Variable/Imputation number** | **m=15** | | | **m=16** | | | **m=17** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Freq** | **Mean** | **ST.Dev** | **Freq** | **Mean** | **ST.Dev** | **Freq** | **Mean** | **ST.Dev** |
| ***FIRMSIZE*** | 5004 | 218.3579 | 546.3107 | 5004 | 218.1884 | 546.2653 | 5004 | 218.0394 | 546.104 |
| ***FIRMAGE*** | 5004 | 20.72422 | 13.8146 | 5004 | 20.6928 | 13.7895 | 5004 | 20.7058 | 13.7991 |
| ***CAPITAL*** | 5004 | 3.27e+07 | 4.01e+08 | 5004 | 3.28e+07 | 4.01e+08 | 5004 | 3.26e+07 | 4.01e+08 |
| ***LABPROD*** | 5004 | 98764.36 | 901247 | 5004 | 98387.18 | 901016.5 | 5004 | 98323.89 | 901025.2 |
| ***SALES*** | 5004 | 15.2655 | 3.740 | 5004 | 15.2652 | 3.7409 | 5004 | 15.2626 | 3.7381 |

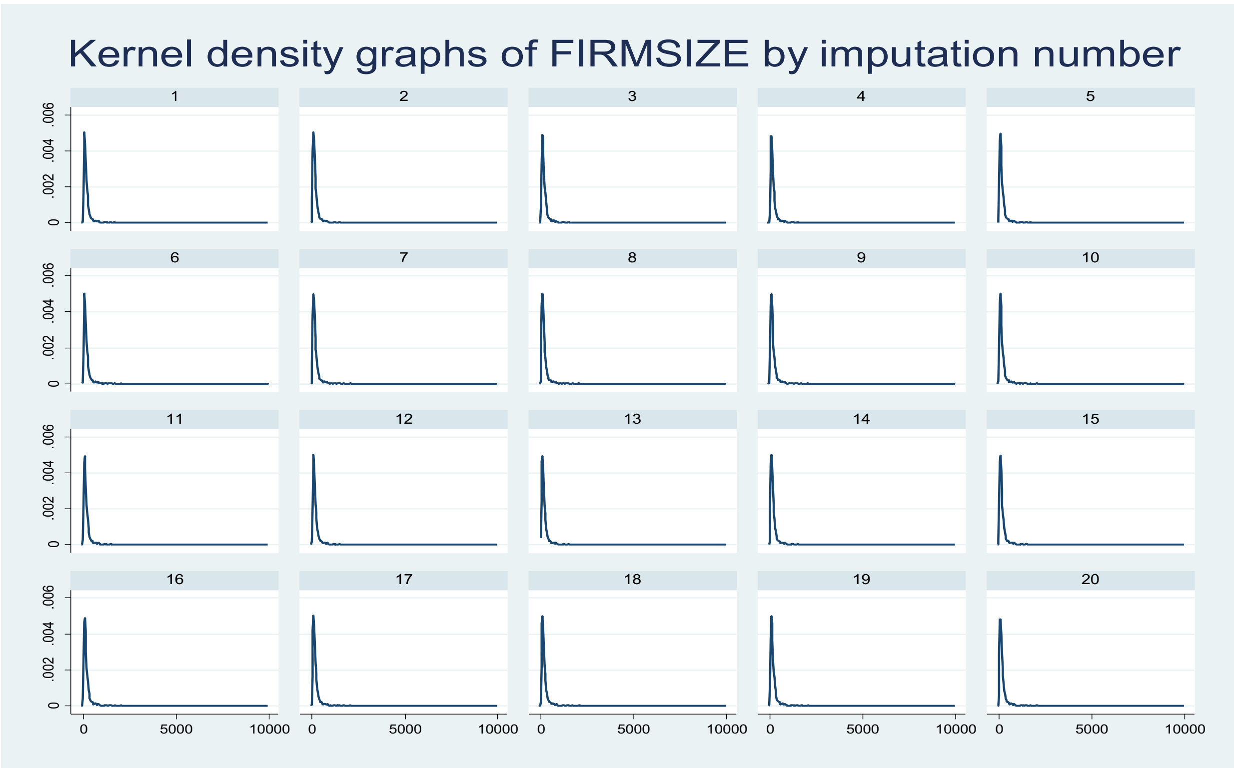
Source : Authors' calculations.

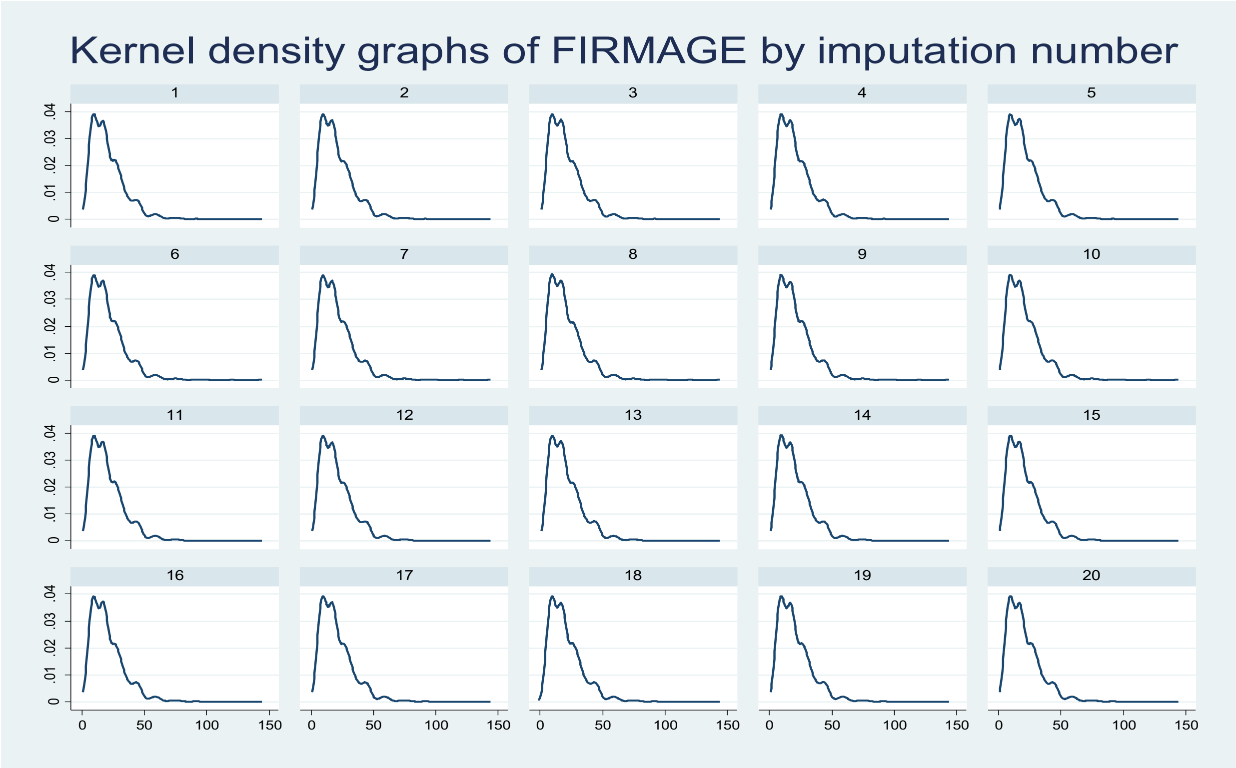
**Table 11. Frequencies, Means, and Standard Deviations for Imputed Values for m=18, m=19, and m=20**

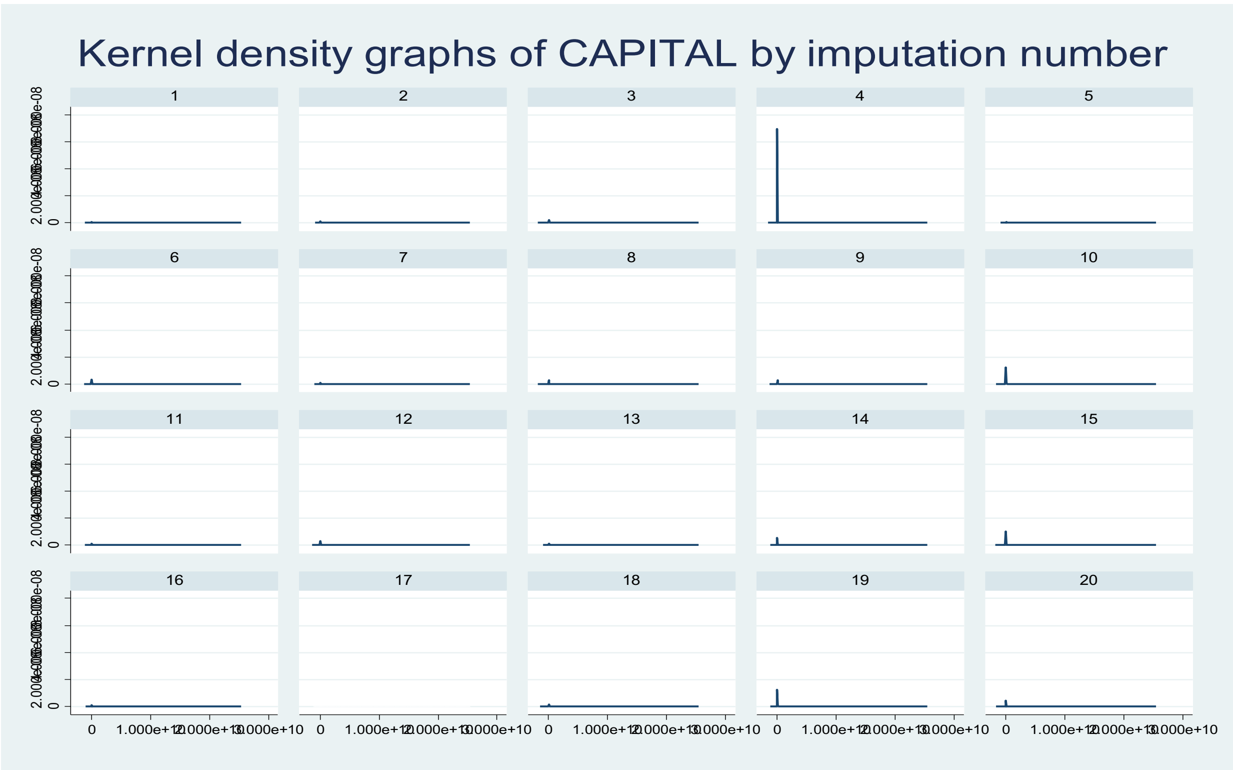
| **Variable/Imputation number** | **m=18** | **m=19** | **m=20** |
|---|---|---|---|

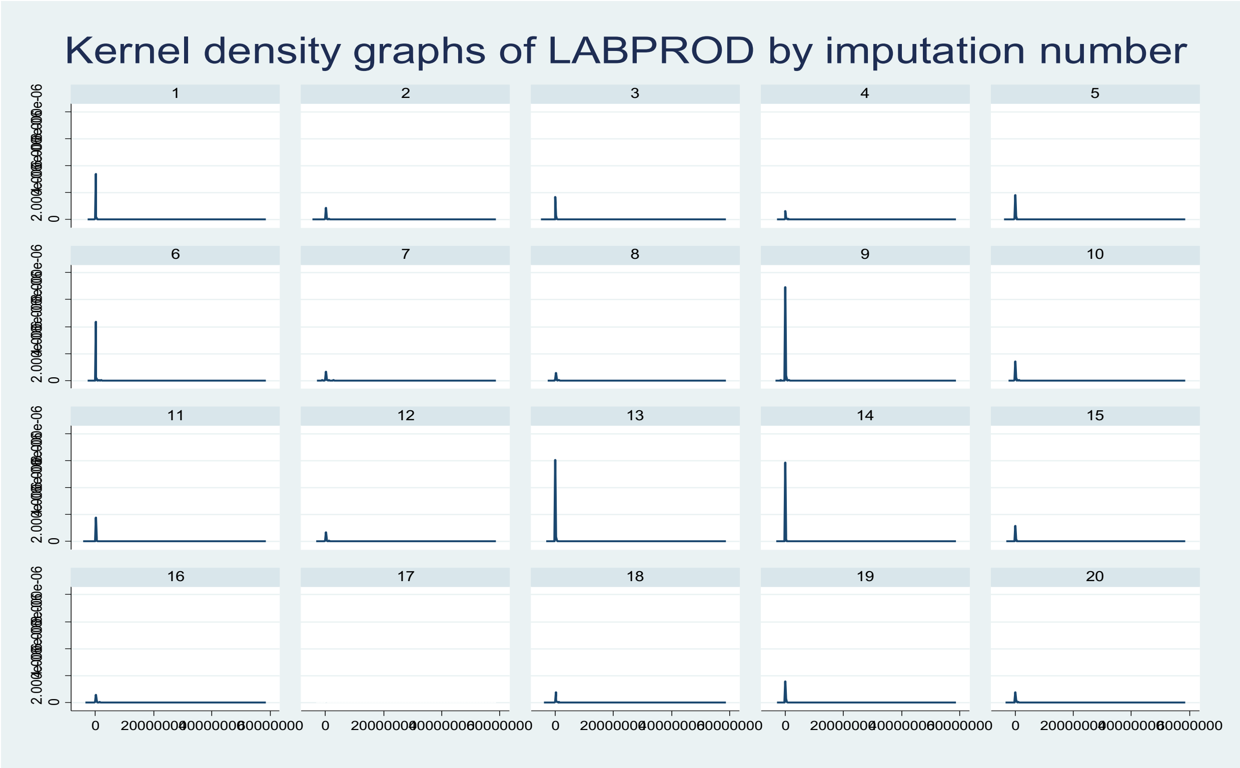
| | Freq | Mean | ST.Dev | Freq | Mean | ST.Dev | Freq | Mean | ST.Dev |
|---|---|---|---|---|---|---|---|---|---|
| ***FIRMSIZE*** | 5004 | 218.23 | 546.2126 | 5004 | 218.229 | 546.323 | 5004 | 218.194 | 546.226 |
| ***FIRMAGE*** | 5004 | 20.6836 | 13.8031 | 5004 | 20.7048 | 13.8206 | 5004 | 20.7084 | 13.8026 |
| ***CAPITAL*** | 5004 | 3.27e+07 | 4.01e+08 | 5004 | 3.27e+07 | 4.01e+08 | 5004 | 3.28e+07 | 4.01e+08 |
| ***LABPROD*** | 5004 | 98585.05 | 901053.8 | 5004 | 98134.35 | 900914.8 | 5004 | 98147.73 | 901086 |
| ***SALES*** | 5004 | 15.2578 | 3.747 | 5004 | 15.268 | 3.7456 | 5004 | 15.265 | 3.7415 |

Source : Authors' calculations.




Kernel density graphs of FIRMAGE by imputation number


Kernel density graphs of CAPITAL by imputation number


Kernel density graphs of LABPROD by imputation number
1
2
3
4
5
6
7
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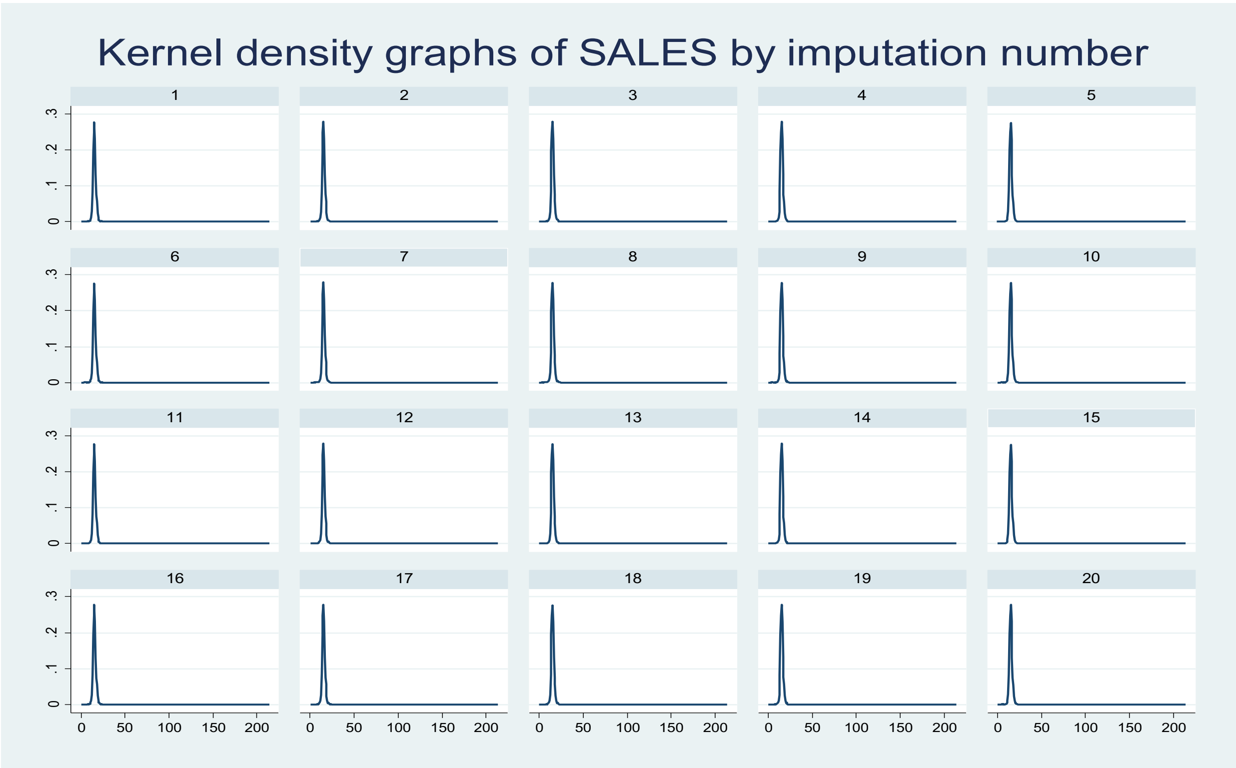
11
12
13
14
15
16
17
18
19
20
0
20000000
40000000
60000000


Kernel density graphs of SALES by imputation number
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
0
.1
.2
.3
0
50
100
150
200