Growth Through Export: Evidence from Iran's Manufacturing Plants

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Does export boost the long-term growth rate of a firm? If yes, how large is that increase in a developing economy? We incorporate a dataset from the manufacturing plants of Iran as a developing economy for 2004-12 to address this question. Using Panel Data Fixed Effect Estimation and Propensity Score Weighting method, we examine whether export can affect a plant's growth. To test this *learning to grow* hypothesis, we consider the plants' value-added, sales, investments, total payments and employment, in addition to productivity measures. Our findings reveal that exporters are not only more productive than non-exporters, but they also register higher growth. Additionally, we find that this growth is a short-term phenomenon and disappears in the second year, which indicates that export does not have a permanent growth effect. Results are qualitatively robust.

Keywords: International Trade, Export, Plants' Growth, Productivity, Propensity Score Weighting

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1. Introduction

Does export help firms grow? If so, is it a long- or short-term effect? In this paper, using a dataset from the manufacturing plants of Iran as a developing economy, we find evidence of the short-term growth effects of export on the firms' performance, based on the learning by exporting hypothesis.

It is well established that at least two mechanisms explain the better performance of exporters: selection and learning. The first emphasizes that more productive firms choose to enter the export market, while the latter specifies that firms improve their performance by undertaking export. Referred to as learning-by-exporting, this is consistent with the highly competitive environment of international markets. Many studies endeavor to identify the causality from either channel, which still requires further investigation.

Our paper departs from the current literature by testing the learning to grow hypothesis for a developing country. Our results indicate that the learning-by-exporting drives a spot growth of 17% for sale, 19% for total factor productivity (TFP) and 10% for labor productivity. Similar estimations in a developed country, such as Sweden, indicate a lower effect (about 2-3%), albeit in the same direction (Hansson and Lundin, 2004). Similar to our results, Blalock and Gertler (2004) report that the learning-by-exporting is much larger for firms in a developing economy like Indonesia. Notwithstanding, their focus is on the *level* of output. We test these patterns for both level and *growth*.

Our methodology is based on the Propensity Score Weighting. First, the probability of being an exporter is estimated in a binary choice model (e.g. logit), using the lag of plants' characteristics, e.g., labor, sale, and productivity, all at *t-1* and fixed effects for industry and year. The likelihood of becoming an exporter (propensity score) is extracted from this regression. Next, we trim data along four dimensions: always exporters, exporters who exit from the export market, new exporters with a high likelihood of exporting, and domestic plants with a low likelihood of exporting.

Next, the propensity scores are re-calculated and used for weighting the observations[5]. We show that the difference between the covariates of the two groups (treated and control) significantly declines when this methodology is employed, which makes the export choice similar to a random assignment, improving the arguments for a better identification by eliminating the selection.

Finally, by using the Panel Data Fixed Effect and Weighted Least Squares estimations, we test the effect of exporting on the firms' growth in size and productivity. For size, we use the plants' employment, value added, sales, investment, and total payments. For productivity, we employ TFP, value added per labor, sales per labor, investment per labor and total payment per labor. Besides, we test many variations in the model and control variables, and find that the results are qualitatively robust and stable.

We document the following facts in support of the learning to grow hypothesis: Entry into the export market has a positive impact on the manufacturing plants' performance, especially in the plants' short-term growth. More specifically, exporting has a positive level and growth effect on exporters. However, the growth effect is not permanent. We show that a plant's performance increases after becoming an exporter, both in terms of level and growth, but this is just a spot growth effect and it disappears in the following years.

The rest of the paper is organized as follows: We review the literature in section 2, describe the data and its features in section 3, specify our empirical strategy in section 4, and discuss the results in section 5. Conclusion forms the last section of this study.

2. Literature Review

The performance of exporters is well-documented in the literature of international trade. Exporters are on average larger in size variables like employment, sales, production, investment, and payments, in addition to being more productive. Bernard and Jenson (1995) lead the pack in

[5] An alternative is matching based on this score, which is well documented in the literature.

outlining these facts using the data of US manufacturing firms. Following their seminal work, several strands of studies use data from different countries and show the same facts[6].

In theory, the existence of fixed costs of entry[7] prohibits the less productive firms to enter foreign markets (Melitz, 2003). This is consistent with an established empirical fact about the *selection* of better performing firms in the export market, although a more interesting issue is to address the learning-by-exporting hypothesis.

Keller (2004) reviews different mechanisms on the international diffusion of technology and mentions two mechanisms. First, the trading of intermediate goods triggers a flow of knowledge from the producing country to the importing country. Second, it leads to the spillover of R&D from one country to others. Empirically, the latter is more substantial than the former. Nevertheless, these two channels are strong enough to motivate empirical researches on the learning-by-exporting hypothesis.

In order to identify the learning effect, the endogenous selection of better performing firms to the export market should be controlled. Wagner (2002) employs the matching technique[8] (introduced by Rosenbaum and Rubin, 1983) and shows that the *learning* causes the exporters' performance to improve. He also shows that the effect is pronounced if the firm increases the number of destinations. Other scholars who follow Wagner (2002) and use the same matching technique to test for the learning hypothesis include Greenaway and Kneller (2007), Girma et al. (2004), Arnold and Hussinger (2005), and Yasar and Rejesus (2005).

The learning-by-exporting effect has been confirmed for several countries. For example, Sjöholm (1999) shows it for Indonesian firms, Baldwin and Gu (2003) for Canadian firms, Hansson and Lundin (2004) for Swedish firms, Van Biesebroeck (2005) for 200 firms of low-income countries in Africa, Greenaway and Kneller (2007) for firms in the UK, and Atkin et al.

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[6] See Clerides et al. (1998), Giles and Williams (2000), Roberts and Tybout (1997), Bernard and Wagner (1998) and Wagner (2002) for German firms, Delgado et al (2001) for Spanish firms, Isgut (2001) for Colombian firms, Bernard and Jensen (1999) and Bernard et al (2007) for US firms, Madanizadeh and Heidari (2016) for Iranian plants.

[7] The well-known iceberg cost of trade is well documented by the Obstfeld and Rogoff (2000) and Melitz (2003), as the initiators of the afterwards trade literature. The iceberg costs are equivalent to tariff and nontariff costs in the real worls.

[8] It is well known that OLS estimation is biased due to selection issue and the simultaneous decision between exporting and enhancing performance. This is why different studies use IV or matching techniques to control for the selection.

(2017) for rug exporters in Egypt. The latter relies on an exogenous random intervention to reduce matching frictions between a subset of Egyptian firms and US buyers.

As another example, De Loecker (2007) uses a similar methodology, matching, and finds that the productivity of new exporters in Slovenia is on average 8.8% higher than their counterparts. He also reports a sustainable productivity gap between exporters and domestic producers. He uses Olley and Pakes (1996) method to measure a firm's productivity.

In a more recent work, De Loecker (2013) relaxes the assumption on exogeneity of export status when estimating the firms' production function. His method reduces the bias in the estimation of the effect of learning by exporting, and confirms a significant learning effect among Slovenian firms. This is consistent with the finding of Damijan et al. (2010), which reports a causal relation from exporting to innovation among Slovenian firms. Damijan and Kostevc (2015) confirm a similar causality from export to innovation for Spanish firms. They show that the effect is pronounced among small and medium firms, as well as those which are closer to technological frontiers. Similarly, Kaoru et al. (2015) report a causal relation from export to higher productivity among Japanese firms.

The learning-by-exporting hypothesis is not entirely confirmed. Clerides et al. (1998), in an influential study, find no evidence of improvement in production costs after starting to export for plants in Colombia, Mexico and Morocco. In a survey, Wagner (2007) reviews the literature on learning-by-exporting. He reviews 33 countries (45 studies) and finds a robust causality from performance to export. However, the reverse causality is not necessarily significant.

Similarly, Tabrizy and Trofimenko (2010) reject the learning hypothesis among Indian firms; and Eliasson et al. (2012) report the same finding for Swedish small- and medium-sized enterprises. Hayakawa et al. (2012) survey different studies to categorize channels between the firms' better performance and globalization (which includes export and foreign direct investment). They confirm a significant decline in cost of export, which yields a selection of better performing firms in the global market, though the learning effect is not identified.

Gupta et al. (2018) report evidence of improving productivity before exporting, but not afterwards. One explanation about the failure of learning-by-exporting hypothesis might be the heterogeneity of the learning among firms. Using a panel of Swedish firms, Lööf et al. (2015)

find that only persistently innovative exporters and those with a large volume of exports thrive in a competitive environment.

Other scholars have also studied different aspects of learning-by-exporting. Crespi et al. (2008) report an interesting finding about the learning effect for those who had exported in the past. They find that firms with prior learning are more likely to grow faster. Fernandes and Isgut (2006) report a spot learning effect for Columbian exporters.

In this study, we employ propensity score technique for weighting. An alternative approach is matching[9] (Wagner, 2002). Similar to De Loecker (2007), we consider the endogeneity of labor and capital selection for the estimation of TFP, for which we follow the method of Olley and Pakes (1996), Levinsohn and Petrin (2003) and Wooldridge (2008). Our findings indicate a spot effect of learning, which is similar to what Fernandes and Isgut (2006) report for the *level* of TFP in Colombian firms, while ours is about *growth*.

3. Data Description

This study benefits from a recently available[10] dataset of Iranian manufacturing plants, namely *Iran's Manufacturing Plants Data Bank*. It is annually collected by the Statistical Center of Iran, which surveys Iran's manufacturing plants. It includes information on production and nonproduction employees, wages and other payments, sales, value-added, capital measures, management structure, energy consumption, and exports. This study reviews the survey from 2004 to 2012.

[9] It is notable that the use of propensity score in the data pre-processing is criticized by King and Nielsen (2018). They report increase in "imbalance, inefficiency, model dependence, research discretion, and statistical bias" in studies which incorporate propensity scores to re-order the data. Though, they recommend full blocking and other matching methods for the purpose of causal inferences.

[10] Several other (ongoing) studies are using this datasets; e.g., Rahmati and Karimirad (2017), Esfahani and Yousefi (2017), Birjandi-Feriz and Yousefi (2017), Rahmati and Pilehvari (2018), Mahmoudzadeh et. al (2018), Esfahani and Amini Behbahani (2018).

For cleaning, we exclude observations with missing industry, zero or missing labor, zero sampling weight[11], and 20 observations with anomalies in fuel usage[12]. The remaining dataset includes 129,951 observations with 26,558 distinct plants.

To pursue a comparison, we need to define two groups of treated and control groups. Here, treatment pertains to export market entry while plants with only domestic sales are considered as the control group. For a valid comparison, we exclude 2,969 observations concerning lifetime exporters (established exporters) and 2,637 observations regarding those who have exited the export markets. The reason is that they don't have any counterpart in the control group. In other words, we focus on plants that have entered the foreign market within the years of this study, as well as domestic plants.

The next step of cleaning is to trim the data. We need to exclude observations for which export status is well predicted by past characteristics. In other words, their export status is predictable rather than being a random assignment. Thus, if those are included in a regression for a comparison of performance, the error is more likely to be correlated with export status. This is the idea behind data trimming.

For the purpose of trimming, we run logit regressions of export status on plants' characteristics at *t-1*, and obtain probability of export status for each plant based on its characteristics. Then, observations within the control (treated) group with very low (high) probability of being exporters are excluded from the data. It corresponds to $p<0.01 \mid p>0.7$ in the Panel A of Figure 1, where propensity scores for the two groups of exporter and others are shown. The excluded observations are, in other words, those for which there is no counterpart in the other group. For example, an exporting plant with a very high predicted p-score would stand in the right end of the diagram where there is no domestic plant.

Data trimming is repeated until we make sure that outliers are excluded, while not losing much data[13]. The second round is the same as the first one. We re-estimate the p-scores and drop observations which are less likely to have a counterpart in the other group.

[11] Sampling weight is assigned by the Center of Statistics in Iran and zero weight corresponds to plants which are exited.
[12] Our approach for the exclusion of anomalies is the same as the Esfahani and Yousefi (2017).
[13] There is no specific method of identifying how many rounds are needed.

The final dataset (after cleaning and trimming) encompasses 111,707 plant-years, with 25,826 individual plants. There are 2,107 distinct plants (equivalent to 4,717 plant-year) involved in exports. The rest are domestic sellers.

For each plant, we observe total sale and exports, production, reported capital, labor, energy usage in each form of electrical, natural gas, gasoil, etc. Some variables are obtained through calculations: TFP, total energy usage, and calculated capital. Details are as follows.

For TFP, the first step of our analysis is to estimate total factor productivity at the level of plants. Productivity has to be estimated using observable factors, such as inputs and outputs. In this paper, we use the method employed by Wooldridge (2008). It is a more efficient version of the Levinson and Petrin (2003) and Olley and Pakes (1996). More specifically, we assume a Cobb-Douglas production function, and construct the TFP measure from the residual of each observation in the logarithmic form of the equation. We employ a semi-parametric estimation technique to get consistent estimates of TFP. Olley and Pakes (1996) developed an estimator that uses investment as a proxy for these unobservable shocks.

Levinsohn and Petrin (2003) introduced an estimator that used intermediate inputs as proxies, arguing that intermediates may respond more smoothly to productivity shocks. They proposed using intermediate input proxies, truncating all the zero investment plants. Therefore, we used raw material as the proxy[14]. The average estimated value of the logarithm of total factor productivity is 13, while its within and cross variances are 0.67 and 1.8, respectively.

In our final dataset, we follow Esfahani and Yousefi (2017) and calculate the real value of capital through investment. Alternatively, we could use the reported book value of capital. Nevertheless, the book value is likely to be misreported due to tax issues or other reasons.

As Esfahani and Yousefi (2017) show, the estimated production function is the decreasing return to scale under book value while it is constant return under the calculated value of capital. For calculation, we add up eight different items (i.e. machines, durable devices, land, etc.) in the survey. The missing values of each item are replaced by zero and the total is reported as the amount of capital. The initial value of capital is the first value of reported capital in the dataset.

[14] Our method is consistent with Pilevari and Rahmati (2018) and Esfahani and Yousefi (2017) who estimate TFP for Iranian Industrial plants (same dataset) using Levinsohn-Petrin method.

In cases where no amount is reported for the initial years, we employ the same methodology, albeit backward. Each investment item is deflated by its corresponding price index; corresponding price index is obtained from the Central Bank of Iran.

Energy intensity is defined as the ratio of energy consumption to value added. Energy productivity is the inverse of energy intensity. Besides, energy could be in different forms, i.e. electricity, oil, diesel and gas, which need to be transformed into a unique unit, e.g. British Thermal Unit (BTU). After unitization, different values of energy can be added to calculate total energy consumption.

There are 28 observations for which total energy consumption is zero. We replace the zero values by the average observed throughout the operation of the corresponding plant. The average value of the logarithm of energy usage (in BTU) in our dataset is 22, with a cross variance of 1.5 and a within variance of 0.6. Finally, we define a dummy for private management. In our final dataset, there are 1,190 plants with state management, some of which have been privatized during the period of our data.

Table 1 shows statistics of our main variables. We use logarithmic transformation for value added, sale, investment, and capital. The average values of these variables are, respectively, 27, 86, 2.9 and 34 billion rials, in constant 2011. The distribution of all these non-logarithmic nominal measures are skewed towards small firms. The median of these variables, respectively, are 4.8, 11, 0.093 and 9 billion rials, in constant 2011. The logarithmic counterparts are shown in the table.

4. Empirical Strategy

We are interested in the average treatment effect within the treatment group (ATT), if the (counter) factual performance of plant *i* at time *t* is indicated by ($y^0_{i,t}$) $y^1_{i,t}$,:

$$\begin{aligned} ATT &= E\{y^1_{i,t+s} - y^0_{i,t+s} \mid export_{i,t} = 1\} \\ &= E\{y^1_{i,t+s} \mid export_{i,t} = 1\} - E\{y^0_{i,t+s} \mid export_{i,t} = 1\} \end{aligned} \quad (1)$$

Here, y could be a measure of performance (in level or growth), $export$ is a dummy variable that becomes one at the time of first export. The issue is that $E\{y^0_{i,t+s} | export_{i,t} = 1\}$ is not observed (it is a counterfactual outcome). With appropriate weighting, one could replace this counterfactual value with a factual outcome of non-exporters: $E\{y^0_{i,t+s} | export_{i,t} = 0\}$.

Rosenbum and Rubin (1983) show that under CIA[15], the method of Propensity Score matching could be a solution to this problem. Girma et al. (2004) uses CIA and measures the impact over new exporters:

$$ATT \cong E\{y^1_{i,t+s} | export_{i,t} = 1\} - E\{y^0_{i,t+s} | export_{i,t} = 0\} \quad (2)$$

We continue by explaining how to obtain propensity scores and to implement them in a comparison between exporters (treated) and domestic firms (control). Our methodology is referred to as propensity score weighting.

1) Obtaining propensity score

At each time t, the probability of decision to export can be assumed as a function of the past period (t-1) characteristics and performances:

$$P(export_{i,t} = 1) \quad (3)$$
$$= F(X_{i,t-1}, exchange\ rate_{t-1}, industry\ dummies_i, time\ dummies_t)$$

Where, P denotes the probability of exporting, $export_{i,t}$ is a dummy for the export status of plant *i* at time *t*, $X_{i,t-1}$ is the vector of plants' characteristics at time t-1; i.e., labor, sale, productivity, payment to labor, dummy for private management. Dummies for each year and industry (in 2 digits of ISIC[16] codes) are controlled. Exchange rate controls for aggregate shocks to the currency valuation, which incentivizes export.

We use logit specification to estimate the parameters of the above model and predict the probability of becoming an exporter.

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[15] Conditional Independence Assumption: if one can control for observable differences in characteristics between the treated and non-treated group, the outcome that would result in the absence of treatment is the same in both cases. This identifying assumption for matching, which is also the identifying assumption for the simple regression estimator, is known as the Conditional Independence Assumption (CIA).

[16] The International Standard Industrial Classification.

In the next step, we incorporate the above-mentioned estimated probabilities (called propensity scores) to weigh observations in our main regression, which uses a fixed effect model. A standard within estimator[17] excludes fixed effects of each observation. Thus, each plant's weight should be unique (and not change over time). Otherwise, a within estimator does not exclude fixed characteristics. As a result, each plant's weight is defined as the average p-score over all observed years[18]. This method also helps us overcome the following data issue: not all plants are observed in all years, therefore, the number of observations in the logit model drops far below the total number of observations. By using average p-scores, we are able to prevent significant data losses.

Estimated weights (or, probability of being exporter) are used to weight observations in each group: exporters and non-exporters. To elaborate, let's consider a plant with the estimated probability of exporting=0.8>>0; it means that the explanatory variables (through the Logit model) predict a very high probability of exporting for this plant. If this plant is an exporter in the data, we say that there is a little room for unobserved random forces which are caused its exporting status=1. Thus its weight should be a low value ($\frac{1}{0.8}$). If this plant is a domestic one, its weight would be higher amount: $\frac{1}{1-0.8}$.

As mentioned before, the purpose of weighting is to reduce differences between the two groups of exporters and domestic plants. Kernel densities in Figure 2 indicate those differences, before (Panel A) and after weighting (Panel B). As the figures show, the distribution of firms' outcomes (i.e., labor, value added, sale) are more similar when we use weighting. Here, we employ the average of propensity score weights over each firm's lifetime, which are used in the main regressions (fixed effect panel). Alternatively, we can employ the original propensity scores that may vary by firm-year. In that case, the distributions in Panel B become even closer.

2) Main model

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[17] $\beta_{within} = (\ddot{X}'\ddot{X})^{-1}\ddot{X}'\ddot{Y}$, where, $\ddot{X} = X - average(X)$.

[18] Reminding that the purpose of p-score weighting is to close the gap between the distributions of control and treated groups, it is notable that using the *average* p-scores does a good job in doing so. Figure 2 shows the gap is reduced after weighting by the average p-scores.

We incorporate weighted regressions to derive the main results. First, we use a simple Least Square framework to compare differences among the two groups of exporters and non-exporters. Results for this specification are reported in Table 2.

$$Performance_{i,t} = \alpha\, Export_{i,t} + X'\beta + \varepsilon_{i,t} \qquad (4)$$

Here, *industry* indicates dummies for four-digit ISIC codes and *X* is a vector of explanatory variables; i.e., log (labor)[19], dummy for private management (vs. state), dummies for industry and year, and constant term. Weights are propensity scores obtained from the first stage Logit regression. These specifications do not control the plants' fixed characteristics.

To exclude plants' fixed effects, we use a weighted fixed effect panel model. In the following specification, we measure changes in the level of performance:

$$Performance_{i,t} = \alpha\, Export_{i,t} + X'\beta + d_i + \varepsilon_{i,t} \qquad (5)$$

Here, the dependent variable is the outcome of interest, and the right-hand side variables are *export* status (1 for exporting) and a vector of explanatory variables; e.g. log (labor), dummy for private management, year dummies, and constant term. Moreover, fixed characteristics of each plant is excluded through demeaning. Thus, controlling the industry dummies is redundant.

The impact of export on growth variables is captured in Model (6). In the left-hand side, we use the first differenced dependent variable ($\Delta x_t = x_t - x_{t-1}$), while the variables in the right-hand side are similar to (5):

$$\Delta Performance_{i,t} = \alpha\, Export_{i,t} + X'\beta + d_i + \varepsilon_{i,t} \qquad (6)$$

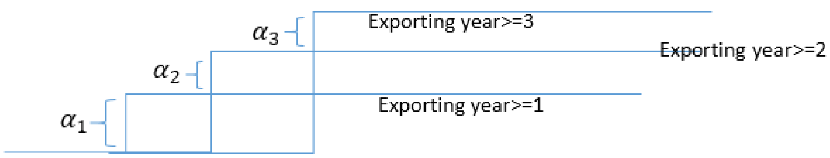
Again, we use fixed effect panel regression, weighted by the average of p-score for each plant during its lifetime. Other explanatory variables are similar to the specifications (4-5).

Finally, we track the learning effect in different years. For this purpose, a model of distributed lags is used:

[19] It is worth mentioning that for regressions with *labor* as the dependent variable, we are not controlling the log(labor) as the explanatory variable.

$$Performance_{i,t} = \alpha_1\ Exportingyear_{i,t} \geq 1 + \alpha_2\ Exportingyear_{i,t} \geq 2 + \alpha_3\ Exportingyear_{i,t} \geq 3 + X'\beta + d_i + \varepsilon_{i,t} \quad (7)$$

Here, *X* could be either size or productivity measures, the dummy variable *exporting year≥1* is one in all the years of an exporting plant's operation. *Exporting year≥2* is only one for those who export for more than one year, and *exporting year≥3* is one for plants exporting for more than three years. It is worth noting that exiters are excluded from the final dataset, therefore we don't observe plants that frequently enter and exit the export market. A schematic of this model of distributed lags is as below:



The first variable (exporting year>=1) becomes one in the first year of export and remains one forever. The second variable becomes one in a year after becoming an exporter. Thus, the estimated coefficient of the first variable (α_1) is the effect of exporting that rises in the first year and persists. The α_2 is a share of learning effect that rises in the second year, after controlling the effect from the first year. Thus, ceteris paribus, estimate of α_2 is the lagged effect of exporting. Similarly, the estimate of α_3 can be interpreted as the second lag of the effect of export.

5. Results

In this section, first, we show the superiority of exporters over non-exporters in our dataset for a developing country like Iran. Next, we discuss the results of the propensity score matching model, showing the learning effect of export on the plants.

First, we document the significant differences of exporters and non-exporters in Table 2 (column 1) based on size and productivity. This column documents the regression results that confirm the positive correlation between export and different size and productivity measures. Sales, value added, labor, energy productivity, wage, and other payments of exporters are on average higher than those of non-exporters. For example, exporters turn out to have around twice more workers (100%), 140% more value added, 140% more sales, and 140% more investment.

Also they are approximately 50% more productive in terms of TFP and pay 71% more wages per labor. Finally, they use 27% more energy per labor[20].

In Table 3, we document the higher probability of exporting for larger and more productive plants, using a logit model. This model demonstrates the higher probability of a larger plant becoming an exporter depending on its observable states. Results in Table 3 indicate that, ceteris paribus, the probability of becoming an exporter increases by 0.1 percentage point (on a [0,1] scale) if a plant increases its labor force (at *t-1*) by 10%. Similar effects from a 10% increase in total sale, productivity, and payment to labor are respectively 0.06, 0.03, and 0.07 percentage points. These results confirm the selection mechanism adopted by more productive plants.

The next step is to quantify how weighting changes the results. Column 2 in Table 2 shows results for the Weighted Leas Squares regressions. Although the differences of the two types of plants are significant, the t-stats of the differences are now much less than the non-weighted case (column 1 in Table 2).

Panel A and B of Figure 2 support the same finding graphically. They show that after weighting and trimming, the distributions of different measures for exporters and non-exporters are pretty close, enabling us to compare them and find out what would happen to a plant after it becomes an exporter. This induced similarity makes the two groups (exporters and non-exporters) resemble each other.

Tables 4 and 5 convey the results of specifications (5-6) that show the effects of export on plants' performances. Each cell shows the coefficient α_1 for the related dependent variable on each column, which is the percentage change in the performance measure (on the LHS) if the plant becomes an exporter. As explained in Section 4, we employ weighted fixed effect specification.[21] Weights are average propensity scores of becoming exporters and employing the fixed effect model ensures the exclusion of fixed characteristics of each individual plant, e.g. management skills and political networks.

[20] In an oil producer country (i.e., Iran) which pays substantial energy subsidy to the industry, part of the export comparative advantage is due to cheap energy prices (Rahmati and Karimirad, 2017); thus, energy usage is higher among exporters compared to domestic sellers.

[21] For a weighted fixed effect panel model, coefficients can be obtained by employing a generalized least square model in a within model: $\hat{\beta}_{weighetd-FE} = \left(\ddot{X}'W\ddot{X}\right)^{-1}(\ddot{X}'W\ddot{Y})$, where, W is weighting matrix, and $\ddot{X}$ and $\ddot{Y}$ are demeaned values of X and Y. The variance of β can be obtained by $\sigma^2 E\left(\ddot{X}'W\ddot{X}\right)^{-1}/N$. Corresponding Stata command is *xtreg y x [aweight=W], fe.*

Panel A of Table 4 shows the impact of becoming an exporter on the size of the plants. We find that if a plant becomes an exporter, its employment rises by 12%. Controlled for the plant's labor, a new exporter's value added rises by 12%, its sales go up by 20.7%, and its energy usage (in BTU) rises by 11.3%. Payments to labor and investment also increase by 15% and 35% respectively.

The impact of becoming an exporter on *growth* of size is shown in Panel B of Table 4. Results for controlled labor size and management type (private vs. state) show export increases the value added growth rate by 11%, sales by 17%, total payments by 23%, investment by 28%, and energy consumption by 7.4%. The impact on employment growth is about 10%. If we control for the lagged value of log (labor), which is not shown in Table 4, employment growth increases to 11%. Overall, results in Table 4 confirm that becoming an exporter increases both the level and growth of size, meaning that export induces plants to become larger and grow faster.

The impact of export on productivity is documented in Table 5. Based on the results in Panel A, following their export market entry, plants become more productive in TFP by 15.7%. Their value added per labor increases by 12%, sale per labor increases by 20.7%, total payments per labor increases by 35%, investment per labor increases by 15%, and energy use per labor increases by 11%.

Panel B of Table 5 identifies the impact of export on productivity. We find that exporters' productivity (in TFP) grows 19% faster. Value added per labor and sales per labor growth are 10% and 15.9% respectively. Growth rates of total payments per labor and investment per labor are also higher by 26.9% and 22.8% respectively.

Table 6 shows the effect of distributed lags of the impact on plants' performance after export. In other words, we investigate how export affects plants' performance and growth rates over time. Results show that all of the growth effects of export occur in the first year of export. Interestingly, in all cases, two and three years after exporting, we observe negative growth in size and productivity. These results denote a spot impact of export. Therefore, our results identify short-term growth rather than a long-term one, as we observe that the plants' growth declines in the second and third year of export.

In Table 7, we check for the robustness of our results on plants' performance. Panel A indicate sensitivity of size and Panel B regards productivity growth. For simplicity, first rows in both panels are the baselines. Second rows show the results of using fixed effect panel without weighting. The gaps between these rows and the benchmark show the proclivity of plants opting for exports. In the third row, we show that if the lag of the dependent variable is controlled, results are robust, though results in this row are marked by endogeneity.

Overall, the robustness of results confirms that the effect of learning-by-exporting on size and productivity growth is economically and statistically significant in the short run and not in the long run.

Conclusion

In this paper, we empirically test the hypothesis of learning to grow for exporters in a developing economy. We use the plant level panel data of Iranian manufacturing plants and show that becoming an exporter has a learning to grow effect, which is comparable to what is reported by other scholars using different datasets.

We realized that the impact is evident in the short run, but not in the long run. More specifically, we showed that a plant's number of workers, value added, sales, and total investment increase after it starts exporting, in terms of level and short-term growth. Also, plants' labor productivity and TFP match the export status, again both in terms of level and growth. Using the propensity score weighting method enables us to reduce the selection bias that exists in a simple OLS regression.

The results show that the learning impact of exporting stands in the short run, and it disappears after two to three years of export. Results are robust when the characteristics of plants and industries are controlled.

Nevertheless, many questions have remained unanswered in our study. The sources of learning require more studies to ascertain whether exporters benefit from a faster flow of know-how, devise a more efficient R&D process, or upgrade their raw materials to imported ones.

Another important issue concerns the heterogeneity of learning among plants. Is it associated with prior experience, age, or industry? Future studies might also address concerns regarding sources and heterogeneity, in addition to deciphering the effect into its components.

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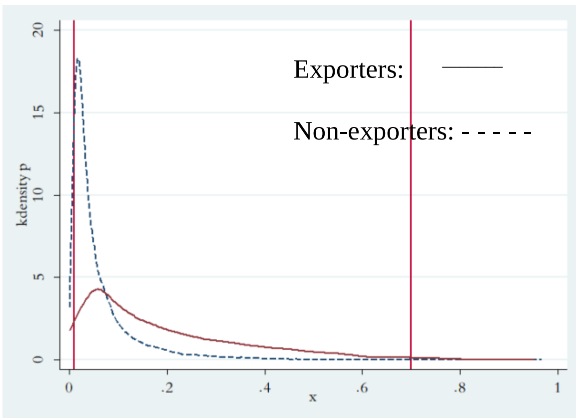
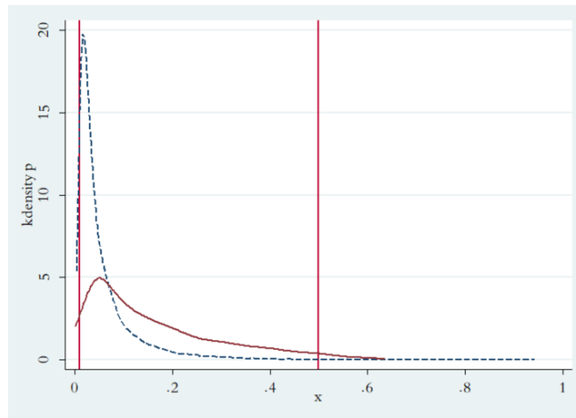
Figures and Tables

Figure 1. Kernel Densities for Estimated Probability of Decision to Export

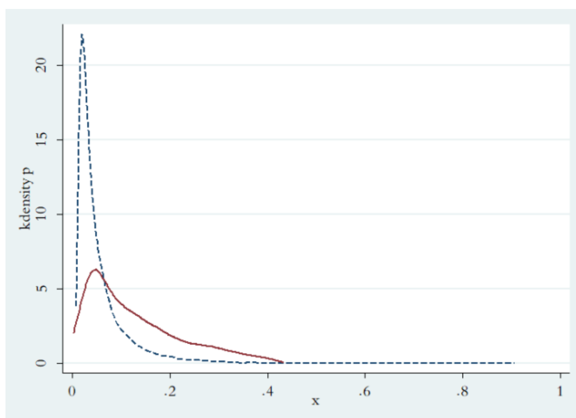
Panel a: All Data, with trimming observations with $p_a<0.01$ or $p_a>0.7$ and recalculating p



Panel B: Trimming observations with $p_b<0.01$ or $p_b>0.5$ and recalculating p



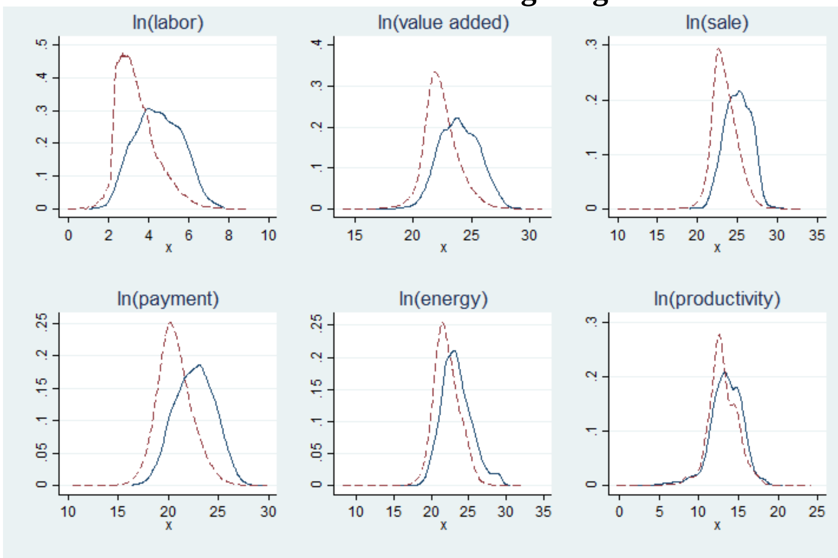
Panel C: Final Trimmed data



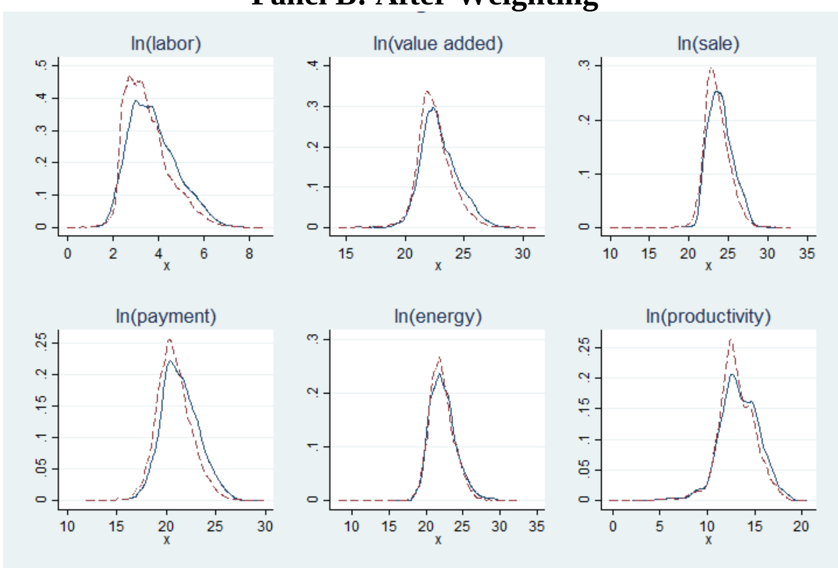
Note: Diagrams show kernel densities for the probability of exporting (exporters: solid line, non-exporters: dashed line), estimated in a logit model of export decision on plants' characteristics at t-1. The horizontal axis indicates probability of being an exporter at *t*, conditioned on observable outcomes at *t-1*. All data (before trimming) is shown in Panel A. 7897 observations, including exporters with pscore>0.7 and nonexporters with pscore<0.01 are dropped. Results is shown in Panel B. In next step, we again run the logit model and obtain pscores. Then, 4743 observations, including exporters with pscore>0.5 and nonexporters with pscore<0.01 are excluded. Results are shown in Panel C.

Figure 2. Distribution of Variables for the Control and Treated Groups

Panel A: Before Weighting



Panel B: After Weighting



Exporters: ———

Non-exporters: - - - - -

Note: Diagrams show kernel densities among exporters (solid) and domestic plants (dashed). Panel A is without weighting. Panel B shows weighted densities. Weights are averaged over lifetime of each plant. The original dataset is Iran's Manufacturing Plants Data Bank, 2004-2012.

Table 1: Data Description, 2004-2012

Pane A: Statistics

VARIABLES, in logarithms	mean	Standard Deviation	min	max	25th percentile	median	75th percentile
Logarithm of value added, in constant rial 2011	22.5	1.5	14	31.2	21.5	22.3	23.3
Logarithm of sale, in constant rial 2011:	23.4	1.6	10.1	32.8	22.4	23.3	24.4
Logarithm of labor (# of employed labor)	3.5	1.0	0.0	8.9	2.7	3.3	4.0
Logarithm of physical capital (calculated), in constant rial 2011:	23.0	1.4	11.6	31.2	22.2	22.9	23.7
Logarithm of investment, in constant rial 2011:	19.5	2.1	-1.0	29.5	18.1	19.4	20.8
Energy consumption (sum over usage of different energy types, BTU)	22.1	1.8	8.1	32.6	20.9	22.0	23.2
Logarithm of total payment to labor (wage+ other payments), in constant rial 2011	20.7	1.8	10.5	30.0	19.5	20.6	21.8
Logarithm of productivity	13	1.89	-0.24	24.2	11.9	12.9	14.3

Panel B: Aggregate Statistics per Industries for Selective Year, 2010

Industry Classification (ISIC, version 3.1)		Number of plants	Employment, in 1000 workers	Employment Share, %	Sale, 10 billion rial	Sale Share, %
	Sum:	11,612	888	100%	1,265,055	100%
15	Manufacture of food products and beverages	2309	149.27	16.80	170819	13.50
16	Manufacture of tobacco products	1	0.15	0.02	207	0.02
17	Manufacture of textiles	877	72.91	8.21	41317	3.27
18	Manufacture of wearing apparel; dressing and dyeing of fur	103	6.98	0.79	2323	0.18
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	134	5.18	0.58	2830	0.22
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	78	5.22	0.59	4120	0.33
21	Manufacture of paper and paper products	255	16.11	1.81	11889	0.94
22	Publishing, printing and reproduction of recorded media	149	10.39	1.17	4393	0.35
23	Manufacture of coke, refined petroleum products and nuclear fuel	95	10.31	1.16	354697	28.04
24	Manufacture of chemicals and chemical products	739	54.93	6.18	70294	5.56
25	Manufacture of rubber and plastics products	725	44.07	4.96	34865	2.76
26	Manufacture of other non-metallic mineral products	2391	139.74	15.73	89578	7.08
27	Manufacture of basic metals	524	56.04	6.31	132799	10.50
28	Manufacture of fabricated metal products, except machinery and equipment	885	65.65	7.39	51648	4.08
29	Manufacture of machinery and equipment n.e.c.	832	66.56	7.49	55915	4.42
30	Manufacture of office, accounting and computing machinery	30	5.64	0.64	6275	0.50

31	Manufacture of electrical machinery and apparatus n.e.c.	411	36.76	4.14	35767	2.83
32	Manufacture of radio, television and communication equipment and apparatus	58	6.77	0.76	5615	0.44
33	Manufacture of medical, precision and optical instruments, watches and clocks	136	10.96	1.23	7766	0.61
34	Manufacture of motor vehicles, trailers and semi-trailers	501	95.06	10.70	164382	12.99
35	Manufacture of other transport equipment	125	13.87	1.56	9866	0.78
36	Manufacture of furniture; manufacturing n.e.c.	244	15.60	1.76	7614	0.60
37	Recycling	10	0.31	0.03	77	0.01

Note: Panel A shows Statistical summary of the cleaned and trimmed data. Panel B shows aggregate statistics per industries, for a selective year (2010). The Statistics Center of Iran assigns plants to industries based on their outputs and activities. Each plant belongs to one specific industry, specified by a 4-digit isic code (version 3.1). Cleaning procedure is explained in the text (see Data section). Statistical multiplier is implemented in aggregations. To deflate sale, value added and payment, we use PPI reported by the Center of Statistics in Iran and measured for each of the 2 digit industries. For investment and capital, price indeces are obtained from the Central Bank. The Data source is Iran's Manufacturing Plants Data Bank, provided by Statistical Center of Iran.

Table 2. Exporting on Plant Outcomes; Ordinary and Weighted Least Squares 2004-2012

	Dependent Variables↓	Explanatory variable: *Export Status* Un-weighted (1)	Un-weighted # of observation	Weighted (2)	Weighted # of observation
	Size Measures:				
1	Log(Labor)	0.970*** (62.2)	111,707	0.117*** (5.4)	67,029
2	Log(real Value Added)	1.391*** (61.4)	110,756	0.189*** (5.9)	66,618
3	Log(real sale)	1.431*** (64.5)	104,000	0.248*** (7.6)	66,026
4	Log(real total Payments to Labor)	1.678*** (62.8)	111,652	0.363*** (12.3)	67,004
5	Log(real Investment)	1.408*** (39.3)	79,924	0.388*** (7.7)	48,565
6	Log (Energy in BTU)	1.241*** (53.0)	111,653	0.202*** (8.4)	66,990
	Productivity Measures:				
7	Log TFP (measured by method of Levinsohn-Petrin)	0.488*** (35.6)	107,958	0.0839*** (4.1)	66,618
8	Log(real Value Added/Labor)	0.425*** (32.0)	110,756	0.0743*** (3.8)	66,618
9	Log(real Sale/Labor)	0.478*** (35.5)	104,000	0.137*** (7.1)	66,026
10	Log(real total Payments/Labor)	0.709*** (38.6)	111,652	0.246*** (8.7)	67,004
12	Log(real Investment/Labor)	0.458*** (15.1)	79,924	0.293*** (5.9)	48,565
13	Log(Energy in BTU/Labor)	0.271*** (16.7)	111,653	0.0859*** (3.7)	66,990

Note: Table shows coefficient of export dummy in the following model: Plant outcome$_t$ = export status$_t$ +X$_t$ +error$_t$. Dependent variables are in logarithmic values. OLS estimator is used in column 1; and Weighted Least Square is used in column 2. Weights are obtained from 1st stage logit model of exporting$_{t-1}$ on plants characteristics$_{t-1}$, and averaged for each plant over different years. Independent variable of interest is export status; other control variables are year dummies, dummy for private management (vs. state), industry as dummies for 4 digit ISIC codes. Robust t-statistics are in parentheses. † ***significant at 0.01 level. **significant at 0.05 level. *significant at 0.10 level. Data source is Iran's Manufacturing Plants Data Bank.

Table 3: Average Marginal Effects of Plants' Characteristics on Export Status, Pooled Logit, 2004-2012

	Dependent variable: dummy for export
Log($labor_{t-1}$)	0.0157*** (14.39)
Log(real $sale_{t-1}$)	0.00627*** (7.081)
Log(TFP_{t-1})	0.00315*** (3.351)
Log(total payments to $labor_{t-1}$)	0.00668*** (10.55)
Dummy for private management (vs. state)	0.0194*** (7.976)
Log(exchange rate in free $marke_{t-1}$)	9.65e-07*** (2.823)
Industry dummies (2dgt isic)	Yes
Year dummies	Yes
Observations	67,117

Note: Table shows average marginal effects from estimations of exporting on explanatory variables. In all the columns, the dependent variables is dummy for export status (1 if export value>0), logit model is used, and explanatory variables include dummies for year, 2-digit ISICs and constant term. The first column is within 87,894 observations (after cleaning and exclusion of always exporters and exiters). The p-scores of this regression are used in the first round of trimming. The second column is within the same observation, except for exclusion of observations with p>0.3 or p<0.01, estimated in the first column. The p-scores of this regression are used in 2nd round of trimming. The third column reports the marginal effects within the final data (with 28,172 observations), which are survived after data cleaning and two rounds of trimming. Robust t-statistics are in parentheses. ***significant at 0.01 level. **significant at 0.05 level. *significant at 0.10 level. The original dataset is Iran's Manufacturing Plants Data Bank, 1382-1390.

Table 4: Impact of Exporting on Size Variables

Panel A: Impact of Exporting on Size

$$Performance_{i,t} = \alpha\, Export_{i,t} + X'\beta + d_i + \varepsilon_{i,t}$$

Dependent variable→ Explanatory variable ↓	Weighted by P-Score					
	Log(Labor)	Log(real Value Added)	Log(real Sale)	Log(real total Payments to Labor)	Log(real Investment)	Log(Energy in BTU)
Export status	0.1207*** (7.460)	0.1206*** (3.355)	0.207*** (7.107)	0.153* (1.884)	0.351*** (7.829)	0.113*** (3.544)
Log(Labor)		0.890*** (43.22)	0.849*** (39.19)	0.822*** (12.13)	0.743*** (20.05)	0.595*** (23.06)
Year dummies	Y	Y	Y	Y	Y	Y
Observations	97,731	96,970	93,920	71,094	97,695	97,683
R-squared	0.017	0.200	0.216	0.045	0.126	0.081
Number of plants	17,744	17,744	17,744	16,928	17,744	17,743

Panel B: Impact of Exporting on Growth of Size

$$\Delta Performance_{i,t} = \alpha\, Export_{i,t} + X'\beta + d_i + \varepsilon_{i,t}$$

Dependent variable→ Explanatory variable ↓	Weighted by P-Score					
	ΔLog (Labor)	ΔLog(real Value Added)	ΔLog(real Sale)	ΔLog(real total Payments to Labor)	ΔLog(real Investment)	ΔLog (Energy in BTU)
Export status	0.098*** (3.65)	0.114** (2.285)	0.174*** (4.393)	0.232** (2.341)	0.281*** (4.243)	0.0736* (1.767)
Log(Labor)		0.545*** (12.74)	0.508*** (11.64)	0.327*** (2.984)	0.383*** (5.933)	0.323*** (8.269)
Year dummies	Y	Y	Y	Y	Y	Y
Observations	70,707	69,732	66,638	42,753	70,667	70,641
R-squared	0.002	0.053	0.065	0.008	0.038	0.015
Number of plants	17,744	17,701	17,448	14,065	17,743	17,738

Note: Tables show the impact of exporting on different measures of plants' size. In Panel B, dependent variables are first differenced. All models are weighted. Weights are obtained from 1st stage logit model of $exporting_{t-1}$ on plants' $characteristics_{t-1}$, and averaged for each plant over its lifetime. Dependent variables are in logarithmic values. Explanatory variables that are not shown here are dummy for private management, and year dummies. Plants' fixed effects are excluded through demeaning. T-statistics are robust and clustered on 2digit ISIC codes. *** Significant at 0.01 level. ** Significant at 0.05 level. * Significant at 0.10 level. Data source is Iran's Manufacturing Plants Data Bank.

Table 5: Impact of Exporting on Productivity Measures

Panel A: Impact of Exporting on Level of Productivity

$$Performance_{i,t} = \alpha\ Export_{i,t} + X'\beta + d_i + \varepsilon_{i,t}$$

Dependent variable→ Explanatory variable ↓	Weighted by P-Score					
	Log TFP (measured by Levinsohn-Petrin)	Log(real Value Added/ Labor)	Log(real Sale/ Labor)	Log(real total Payments/ Labor)	Log(real Investment/ Labor)	Log(Energy in BTU/ Labor)
Export status	0.157*** (3.401)	0.121*** (3.355)	0.207*** (7.107)	0.351*** (7.829)	0.153* (1.884)	0.113*** (3.544)
Log(Labor)	0.121*** (3.597)	-0.110*** (-5.341)	-0.151*** (-6.989)	-0.257*** (-6.946)	-0.178*** (-2.631)	-0.405*** (-15.67)
Year dummies	Y	Y	Y	Y	Y	Y
Observations	96,190	96,970	93,920	97,695	71,094	97,683
R-squared	0.016	0.038	0.054	0.055	0.013	0.038
Number of plants	17,744	17,744	17,744	17,744	16,928	17,743

Panel B: Impact of Exporting on Growth of Productivity

$$\Delta Performance_{i,t} = \alpha\ Export_{i,t} + X'\beta + d_i + \varepsilon_{i,t}$$

Dependent variable→ Explanatory variable ↓	Weighted by P-Score					
	ΔLog TFP (measured by Levinsohn-Petrin)	ΔLog(real Value Added/ Labor)	ΔLog(real Sale/ Labor)	ΔLog(real total Payments/L abor)	ΔLog(real Investment/ Labor)	ΔLog(Ener gy in BTU/ Labor)
Export status	0.189** (2.414)	0.101** (2.229)	0.159*** (4.592)	0.269*** (4.231)	0.228** (2.349)	0.0620 (1.504)
Log(Labor)	-0.0298 (-0.616)	-0.202*** (-5.810)	-0.247*** (-7.845)	-0.364*** (-5.864)	-0.419*** (-4.107)	-0.424*** (-12.51)
Year dummies	Y	Y	Y	Y	Y	Y
Observations	52,227	52,299	53,306	53,258	53,237	52,227
R-squared	0.235	0.220	0.696	0.225	0.221	0.235
Number of plants	14,441	14,445	14,551	14,547	14,544	14,441

Note: Tables show the impact of exporting on different measures of plants' productivity. In Panel B, dependent variables are first differenced. All models are weighted. Weights are obtained from 1st stage logit model of $exporting_{t-1}$ on plants' $characteristics_{t-1}$, and averaged for each plant over its lifetime. Dependent variables are in logarithmic values. Explanatory variables that are not shown here are dummy for private management, and year dummies. Plants' fixed effects are excluded through demeaning. T-statistics are robust and clustered on 2digit ISIC codes. *** Significant at 0.01 level. ** Significant at 0.05 level. * Significant at 0.10 level. Data source is Iran's Manufacturing Plants Data Bank.

Table 6 Distributed Lags of the Impact of Exporting on Size and Productivity

Panel A: Impact of Exporting on Size Growth, with Fixed Effect

	Weighted by P-Score				
Dependent variable→ Explanatory variable↓	ΔLog(Labor)	ΔLog(real Value Added)	ΔLog(real Sale)	ΔLog(real total Payments to Labor)	ΔLog(real Investment)
Dummy for 1st year and more	0.0452** (2.183)	0.164*** (2.738)	0.253*** (5.414)	0.383*** (5.055)	0.306** (2.349)
Dummy for 2nd year and more	-0.0952*** (-3.377)	-0.156 (-1.538)	-0.261*** (-3.403)	-0.303*** (-2.729)	-0.251 (-0.899)
Dummy for 3rd year and more	-0.0310* (-1.698)	-0.0168 (-0.217)	0.0252 (0.413)	-0.0608 (-0.628)	0.0424 (0.236)
Log(Labor)	0.750*** (31.49)	0.549*** (13.02)	0.513*** (11.99)	0.392*** (6.108)	0.331*** (3.058)
Year dummies	Y	Y	Y	Y	Y
Observations	70,707	69,732	66,638	70,667	42,753
R-squared	0.413	0.055	0.071	0.043	0.009
Number of plants	17,744	17,701	17,448	17,743	14,065

Panel B: Impact of Exporting on Productivity Growth, with Fixed Effect

	Weighted by P-Score				
Dependent variable→ Explanatory variables↓	ΔLog TFP (measured by Levinsohn-Petrin)	ΔLog(real Value Added/ Labor)	ΔLog(real Sale/Labor)	ΔLog(real total Payments/ Labor)	ΔLog(real Investment/Labor)
Dummy for 1st year of exporting	0.230** (2.501)	0.118** (2.129)	0.204*** (4.920)	0.383*** (5.055)	0.272** (2.136)
Dummy for 2nd year	-0.140 (-1.425)	-0.0612 (-0.618)	-0.167** (-2.204)	-0.303*** (-2.729)	-0.167 (-0.610)
Dummy for 3rd year	0.0226 (0.299)	0.0136 (0.180)	0.0559 (0.928)	-0.0608 (-0.628)	0.0698 (0.399)
Log(Labor)	-0.0279 (-0.583)	-0.202*** (-5.740)	-0.245*** (-7.720)	0.392*** (6.108)	-0.418*** (-4.121)
Year dummies	Y	Y	Y	Y	Y
Observations	69,658	69,732	66,638	70,667	42,753
R-squared	0.008	0.019	0.030	0.043	0.008
Number of plants	17,701	17,701	17,448	17,743	14,065

Note: Panel A and B show the impact of exporting on growth rates of different measures of size and productivity. All models are weighted. Weights are obtained from 1st stage logit model of $exporting_{t-1}$ on plants $characteristics_{t-1}$, and averaged for each plant over its life time. Dependent variables are in logarithmic values. Independent variables are dummies for year of exporting≥1; year of exporting≥2, year of exporting≥3. Explanatory variables that are not shown here are dummy for private management, and year dummies. Plants' fixed effects are excluded through demeaning. T-statistics are robust and clustered on 2digit ISIC codes. *** Significant at 0.01 level. ** Significant at 0.05 level. * Significant at 0.10 level. Data source is Iran's Manufacturing Plants Data Bank.

Table 7: Robustness to the Impact of Exporting on Size and Productivity

Panel A: Growth Rate of Size

Dependent variable→	Reported coefficients belong to "Export status"					
	ΔLog (Labor)	ΔLog(real Value Added)	ΔLog(real Sale)	ΔLog(real total Payments to Labor)	ΔLog(real Investment)	ΔLog (Energy in BTU)
1. Baseline (Table4, Panel B)	0.0116 (0.644)	0.114** (2.285)	0.174*** (4.393)	0.232** (2.341)	0.281*** (4.243)	0.0736* (1.767)
2. No Weighting	-0.0580*** (-5.811)	0.00832 (0.341)	0.0540** (2.471)	0.234*** (3.043)	0.151*** (4.390)	0.0171 (0.627)
3. Add Y_{t-1} as an explanatory variable	0.111*** (5.242)	0.0955*** (2.845)	0.162*** (5.790)	0.314*** (3.702)	0.296*** (5.998)	0.0950*** (2.809)

Panel B: Growth Rate of Productivity

Dependent variable→	Reported coefficients belong to "Export status"					
	ΔLog TFP (measured by Levinsohn-Petrin)	ΔLog(real Value Added/ Labor)	ΔLog(real Sale/ Labor)	ΔLog(real total Payments/Labor)	ΔLog(real Investment/Labor)	ΔLog(Energy in BTU/ Labor)
1. Baseline (Table5, Panel B)	0.189** (2.414)	0.101** (2.229)	0.159*** (4.592)	0.269*** (4.231)	0.228** (2.349)	0.0620 (1.504)
2. No Weighting	0.0522** (2.098)	0.0658*** (2.806)	0.110*** (5.221)	0.209*** (6.176)	0.280*** (3.686)	0.0751*** (2.694)
3. Add Y_{t-1} as an explanatory variable	0.154** (2.234)	0.0950*** (2.825)	0.160*** (5.723)	0.295*** (5.987)	0.314*** (3.702)	0.0948*** (2.801)

Note: Tables show the robustness of cross comparisons (Panel B) of Tables 4 and 5. Only the coefficient of *export status* is reported. Each cell shows a different regression. The first row is the baseline results. Second row excludes weighting. Third row adds $performance_{t-1}$. T-statistics are robust and clustered on each plant. *** Significant at 0.01 level. ** Significant at 0.05 level. * Significant at 0.10 level. Data source is Iran's Manufacturing Plants Data Bank.