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Total factor productivity and export performance of Tunisian manufacturing firms

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Abstract

Using data on Tunisian manufacturing firms, this paper analyzes the causal relationship between firm's total factor productivity and export market participation during 2000–2012. We find out a causal link from high productivity to presence in foreign markets, as predicted by a recent literature on international trade with heterogeneous firms. We apply the propensity score matching in order to examine whether the presence in international markets enables firms to achieve further productivity improvements through learning-by-exporting effects. We found a causal relationship in both direction.in this sense, more productive firms become exporters and exporting promote the productivity of Tunisian firms.

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1. Introduction

Firm performance depends on factors such as capital accumulation, adoption of new technologies, and management capabilities, which are influenced by the investment climate, including trade liberalization (Tybout, 2003). Empirical studies since the 1980s (Krugman, 1987; Rodrik, 1991; Grossman & Helpman, 1999) show that trade liberalization and export promotion enhance productivity. Exporting firms generally exhibit higher productivity and growth in employment and output compared to non-exporters (Bernard & Jensen, 1999, 2004). Two main hypotheses link exporting and productivity. The self-selection hypothesis posits that more productive firms are likelier to export (Clerides et al., 1998; Bernard & Jensen, 1999, 2004; Haidar, 2012), implying their performance does not necessarily change post-entry. In contrast, the learning-by-exporting hypothesis suggests that exporting fosters productivity growth via knowledge transfer, advanced technologies, management practices, and economies of scale in foreign market[1].

In addition to the seminal contributions of Bernard and Jensen (1999, 2004) and the heterogeneous firm model of Melitz (2003), more recent empirical studies continue to document the link between exporting and productivity. For instance, Bernard et al. (2020) highlight persistent heterogeneity in export participation across firms, while Jensen et al. (2021) provide new evidence on the productivity gains associated with trade. At a more country-specific level, Wagner (2020) examines the role of soft power in shaping Germany's exports, Jitsutthiphakorn (2021) shows how innovation and firm productivity affect export survival in ASEAN developing countries, and Vieira and Silva (2021) analyze the drivers of export performance in BRICS economies.

Although a substantial empirical literature has examined the relationship between productivity and exports across various countries, to the best of our knowledge, no firm-level study has investigated this nexus in the Tunisian context. This paper aims to fill this gap by examining the exporting behavior of Tunisian manufacturing firms within the framework of Tunisia's recent liberalization policy. Studying the Tunisian context is particularly significant for several reasons. In recent decades, Tunisia has undergone profound and rapid changes in its economic environment, accompanied by reforms affecting all sectors of the economy, with a particular focus on manufacturing. With the rise of globalization and heightened international competition, openness and trade liberalization have become imperative for Tunisia. As one of the cornerstones of its economic strategy since the implementation of the Structural Adjustment Program, the open-door policy has been considered a necessary condition to reestablish a trajectory of high and sustained growth[2]. One of the key mechanisms for achieving this objective involves the promotion of exports. Furthermore, as Tunisia transitions from a protected economy to a market-oriented economy, Tunisian firms—serving as drivers of economic growth—must adapt to liberalization and face competition from foreign firms that are often better structured and more competitive.

This paper aims to investigate the direction of causality between trade and firm productivity. Our analysis builds on the seminal model of heterogeneous firms developed by Melitz (2003). This framework shows that only the most productive firms can overcome the fixed costs of exporting, while less productive firms remain in the domestic market or exit, leading to aggregate productivity gains through resource reallocation.

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[1] This argument may be of particular relevance for firms from small domestic markets.

[2] Tunisia has signed free trade agreements with the European United States, the US, and Arab countries

Using data from 2,358 Tunisian manufacturing firms over the period 2000–2012, we assess the validity of the self-selection and learning-by-exporting hypotheses with respect to total factor productivity (TFP). TFP is estimated using the Olley and Pakes (1996, henceforth OP) method to address simultaneity between unobserved productivity shocks and input choices. To our knowledge, these issues have not previously been explored in the Tunisian context using microeconomic panel data of such granularity.

The remainder of this article is organized as follows. Section 2 presents the estimation of total factor productivity (TFP). Sections 3 and 4 discuss, respectively, the results from the learning-by-exporting model and those obtained using propensity score matching. Finally, Section 5 concludes with key findings and policy implications.

2. Production function estimation and TFP measurement

The first step in our analysis consists to construct a measure of productivity from the estimation of a production function according to the Olley and Packes (1996) approach. To describe this approach briefly, suppose that the production function is a Cobb Douglas. Over panel data, the retained model takes the following form:

$$y_{it} = \alpha + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + v_{it} \qquad (1)$$

Where, y_{it}, k_{it} and l_{it} are respectively, the output logarithm (or added value), capital stock and the number of employees; the β_k and β_l are respectively capital and labor elasticity. The error term consists of two parts: a common error term v_{it} specific to econometric models and ω_{it} is unobserved state variable which represents productivity shocks affecting firm i at time t. ω_{it} is observed only by the firm and acts as an input that affects the output as well as capital and employment. This leads to an endogeneity bias, since entrepreneurs' input choices depend on productivity shocks experienced by the firm. Such dependence implies a potential correlation between unobserved productivity shocks and firms' input decisions, which are therefore not exogenous. To overcome this problem, we use in this paper the semiparametric estimator introduced by Olley and Pakes (1996)[3], OP. Once the production function parameters have been estimated, one can infer the TFP using the following formula:

$$\hat{\omega}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} \qquad (2)$$

The data used in this paper were drawn from the National Annual Survey Report on Firms (NASRF), conducted by the Tunisian National Institute of Statistics (TNIS). Each year, TNIS collects unbalanced-sheet data on a sample of firms with 10 or more employees from the Tunisian Business Register (RNE). The sample covers virtually all formal sectors across all regions of the country and is representative of the population of firms, stratified by size, sector, and region. After cleaning, the dataset resulted in an unbalanced panel of 14,736 observations for 2,358 firms[4]. Table I and Table II provide some descriptive statistics. The

3 OP address the simultaneity problem by developing a two-step estimator of the production function. In the first step, they estimate $\hat{\beta}_l$ and the joint effect of all state variables, under the assumption that labor input adjusts instantaneously to productivity shocks. In the second step, the coefficients on the observable state variables are identified using the orthogonality condition between capital and the innovation in productivity, based on the assumption that capital adjusts only slowly in response to productivity shocks (see Olley and Pakes, 1996, for details).

4 The data were cleaned in several steps. First, we removed firms with fewer than six employees, since the survey only covers firms above this threshold. Second, we excluded observations with negative values for key variables such as value added, investment, or capital stock. Finally, to mitigate the influence of extreme outliers, we winsorized all continuous variables at the 1st and 99th percentiles. This widely used procedure

average percentage of exporters in total firms is 47.2%. The firms that change their export status from non-export to export (entrant) and from export to non-export (quitter) constitute an average of 4.54% and 3.22% of all firms, respectively, across time.

Table I: Export patterns of manufacturing firms.

Year	Number of firms	Exporters (%)	Entrants (%)	Exiters (%)
2000	1353	47.23	3.88	3.22
2001	1408	49.79	3.49	3.27
2002	1059	57.03	4.02	2.7
2003	865	59.15	5.74	2.79
2004	853	58.85	4.63	2.99
2005	981	56.4	4.88	3.12
2006	1098	51.44	5.19	3.27
2007	1211	56.4	4.88	3.12
2008	1236	51.44	5.19	3.27
2009	1308	51.62	4.69	3.38
2010	1195	50.6	4.06	3.27
2011	1211	51.37	4.28	3.42
2012	958	46.24	4.11	3.65

Table II: Descriptive Statistics of Exporters and Non-exporters

	Unit of measurement	Exporters	Non-exporters	Allwayes exporters	Never	Quitters	New exporters
Ln(TFP)	Index	4.634	3.741	4.831	3.412	3.745	4.723
Labor productivity	in TND	16858	11458	17376	14208	14355	15866
R&D expenditure	In TND	25321	16961	28912	12306	11540	19316
FDI	%	48.37	6.925	57.38	2.19	11.13	28.20
Skill	Proportion	0.1467	0.1612	0.1235	0.21	0.155	0.1602
Investment	In TND	425165	321658	45673	23612	30915	41177
Average Wage	In TND	9863	7438	9857	7380	7476	9895
Firm size	Number	153	88	160	67	126	92
Capital Intensity	TND per worker	41854	38547	42617	39266	40073	41912
Export intensity	%	0.446	-----	0.562	-----	0.252	0.33
Firm age	years	15	16	14	17	9	8

Table II shows that, on average, exporting firms exhibit higher TFP, labor productivity, and capital intensity than non-exporting firms. They also allocate more resources to research and development (R&D). Moreover, there is a notable difference in the proportion of skilled labor between exporters and non-exporters. While exporting firms pay higher average wages, this does not necessarily imply a greater reliance on skilled labor. Additionally, foreign investors (FDI variable) display a stronger preference for exporting firms.

Table III presents the parameter estimates of the Cobb-Douglas production function using various estimation methods: ordinary least squares (OLS), firm-level fixed effects (FE), random effects (RE), and the semi-parametric method of Olley and Pakes (OP). In all specifications we included dummies for "never exporters", "always exporters", "new exporters" and "quitters". This allows us to account more explicitly for heterogeneity in export status when computing TFP. Note that in the case of FE and RE, we replace ω_{it} in Equation (1) by ω_i, where ω_i denotes individual firm effects. Across all methods employed, all coefficients are statistically significant. At the bottom of Table III, we report three panel-

reduces the distortive impact of a small number of extreme observations while preserving the overall structure and representativeness of the data.

specific tests: the tests for the absence of fixed effects, the presence of random effects, and the Hausman test, which determines whether fixed or random effects are more appropriate.

Table III: Parameter estimates of production function

	OLS	**FE**	**RE**	**OP**
Const.	5.16 (0.170)	5.73 (0.533)	4.84 (0.118)	
LnK	0.319 (0.976)	0.312 (0.0316)	0.459 (0.0222)	0.427 (0.0492)
LnL	0.693 (0.0410)	0.426 (0.0227)	0.466 (0.0398)	0.64 (0.0793)
Trend	0.034 (0.0081)	0.029 (0.0057)	0.029 (0.0088)	0.033 (0.0156)
Always Exporter	0.14 (0.037)	0.11 (0.0180)	0.161 (0.0192)	0.10 (0.020)
New Exporter	0.033 (0.028)	0.048* (0.025)	0.042 (0.020)	0.055 (0.022)
Quitter	-0.012 (0.026)	-0.035 (0.023)	-0.029 (0.021)	-0.031 (0.019)
Industry dummy	yes	no	yes	yes
Fisher Test : OLS vs FE		7.81 [0.000]		
BP LM Test : OLS vs RE			6426 [0.000]	
Hausman Test : FE vs RE			712.88 [0.000]	
R^2	0.79	0.78	0.77	0.88
Num. Obs	12,214	12,214	12,214	11,152

Values in parentheses represent the standard errors of the estimated coefficients: For the tests of absence of fixed effects, random effects and the Hausman test we report the p-value; Num. Obs indicate the number of observations.

The results of these tests indicate the presence of unobservable heterogeneity in our model, which is controlled for by individual firm effects[5], and there is an instantaneous correlation between productivity and the production factors, which are therefore not exogenous[6]. Hence, only the FE estimator is unbiased and consistent. However, this specification explicitly assumes that productivity is time-invariant, which is open to criticism. Moreover, the FE estimator ignores variability between firms, and therefore the estimates lack their permanent or structural dimension.

We find that the capital coefficient tends to increase while the labor coefficient tends to decrease when moving from OLS to OP. These results support the notion that OLS typically overestimates β_l—suggesting a positive correlation between labor and productivity, which

[5] Results of the two firsts tests conclude clearly to the rejection of null hypothesis of no fixed effects and random specific effects.

[6] The results of Haussman test conclude that the null hypothesis of orthogonality errors should be rejected.

leads to an upward bias in the labor coefficient when using OLS—and usually underestimates β_k (see Levinsohn and Petrin, 2003, for further details).

Intuitively, if a firm has prior knowledge of its productivity level (ω_{it}) when making input decisions, endogeneity arises because labor quantities will be determined based on these prior beliefs about productivity. Consequently, a positive productivity shock is likely to lead to increased use of variable inputs, introducing an upward bias in the labor elasticity (De Loecker, 2010). Compared to OLS estimates, accounting for the simultaneity between inputs and productivity slightly reduces the labor coefficient, thereby correcting the upward bias present in OLS estimates.

Figure 1: Comparing Means: TFP by Subgroup

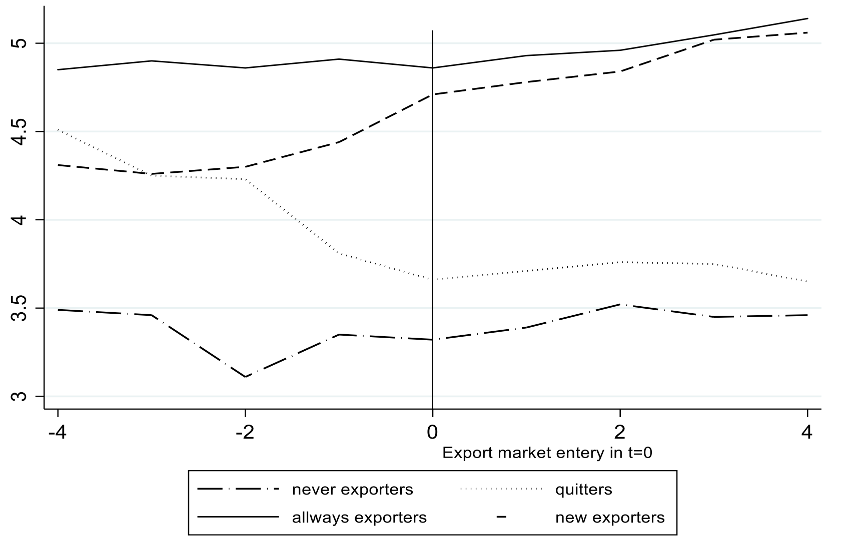

Figure 1 depicts the trajectory of TFP, as estimated from Equation (2), for different groups of firms. Notably, there are significant pre-export productivity differences among domestic firms, switchers, and exporters. Moreover, new exporters begin with productivity levels substantially higher than those of continuing non-exporters, yet still significantly below those of continuing exporters. Notably, the productivity levels of future exporters rise markedly two periods prior to entry into export markets. This upward trend continues for two periods after market entry, with their productivity levels approaching those of continuing exporters. These findings suggest that more productive firms self-select into exporting and that exporting further enhances productivity.

We observe a dramatic decline in the productivity of firms that exit the export market, particularly during the $t-2$ to $t=0$ periods. After $t=0$, their productivity levels become comparable to those of domestic firms and follow a similar trend. These findings once again support the theoretical prediction that less productive firms are more likely to exit the export market.

3. Learning-by-exporting (LBE) hypothesis

Once the production function parameters and TFP are estimated, we proceed to study the interdependence between export behavior and productivity by examining two hypotheses: self-selection into the export market and learning by exporting. The standard method for testing the effect of learning-by-exporting is to analyze the impact of lagged export status on productivity. To this end, we examine changes in TFP as a function of the probability of exporting and a set of control variables linking TFP to specific firm characteristics. Indeed, TFP estimates from Equation (2) could be biased if capital and labor are correlated with exporting behavior. To address this, Equation (3) includes firm-level controls that account for factors potentially correlated with both inputs and export performance, thereby mitigating bias in the estimated β coefficients. The retained model is specified as follows:

$$\begin{aligned} Ln(TFP_{it}) = \beta_0 + \beta_1 Exp_{it-1} + \beta_2 FDI_{it-1} + \beta_3 \ln(Wage_{it}) + \beta_4 \ln(skill_{it-1}) \\ + \beta_5 \ln(Tic_{it-1}) + \beta_6 \ln(R\&D_{it-1}) + \beta_7 \ln(IntCap_{it-1}) + \beta_8 \ln(size_{it}) \\ + \beta_9 \ln(age_{it}) + \beta_{10} \ln(size_{it})^2 + \beta_{11} \ln(age_{it})^2 + \varepsilon_{it} \end{aligned} \tag{3}$$

Exp is a dummy equal to 1 if firm i exported at time $t-1$, and FDI equals 1 if foreign participation in the firm's capital was at least 10% at $t-1$. $R\&D$ denotes research and development expenditure, while $Tic, Skill$, and Int_cap measure investment in information and communications technology, the share of technical and administrative staff, and capital intensity, respectively. We also control for firm age (in years since the firm began operation) and $size$ (proxied by the number of employees), along with their squares. These firm-level controls are included in Equation (3) to account for factors potentially correlated with both input choices and export performance, thereby mitigating bias in the estimated β coefficients.

The estimation of Equation (3) faces two main challenges in practice. The first concerns the relationship between productivity and FDI. Foreign investors may initially target firms operating in the most productive and best-performing sectors. In this case, a positive correlation between FDI and productivity may reflect a self-selection effect, with foreign investors favoring the most productive local firms. The second challenge concerns the relationship between productivity and exports. Only the most productive firms may be able to enter the export market due to sunk entry costs and financial constraints. Consequently, a positive correlation between productivity and exports may reflect a self-selection effect in the foreign market. To mitigate potential simultaneity and selection biases, we consider the lagged variables by one period.

The parameter estimates of Equation (3) are reported in Table IV. The four specifications in this table were designed to mitigate simultaneity and reverse causality between productivity, exports, and FDI. To this end, we rely on lagged explanatory variables, which allow us to more convincingly capture the causal impact of past export status and foreign participation on current productivity. Specification (1) excludes lagged export status as a benchmark, specification (2) excludes lagged FDI for robustness, specification (3) includes all lagged controls and represents our baseline model, while specification (4) restricts the sample to non-switchers to control for biases arising from frequent changes in export status. For this reason, we did not estimate specifications with contemporaneous controls, as they would be more prone to simultaneity bias and could confound correlation with causality. Given the presence of firm-specific heterogeneity and potential heteroscedasticity in the data, we estimate Equation (3) using a fixed-effects model with FGLS[7]. We conclude that the estimation results are robust across all four specifications. The coefficients remain remarkably consistent, indicating that our findings are not sensitive to changes in sample composition or model specification.

We focus essentially on the results reported in colon (3). The first lesson drawn from this table is that lagged export status has a positive and statistically significant effect on TFP. Past export status increases productivity by 7.57% (or $(exp(0.073) - 1) \times 100)$), confirming that exporting firms are, on average, more productive than non-exporters. This

[7] For all specifications considered, Table IV presents only the FGLS estimates of the fixed-effects model.

result underscores the significance of an export-related effect that positively influences the productivity of firms engaged in international markets. In fact, exporters become more efficient as they adopt new technologies and learn new production methods

Table IV: Parameter estimates of Learning-by-exporting hypothesis

	(1)	(2)	(3)	(4)
Exp	_	0.082	0.073	0.134
		(0.042)	(0.0391)	(0.0265)
FDI	0.124	_	0.131	0.112
	(0.0345)		(0.0472)	(0.0416)
$Ln(wage)$	0.191	0.206	0.200	0.223
	(0.0253)	(0.0236)	(0.0222)	(0.0228)
$Ln(Skill)$	0.025	0.018	0.015	0.014
	(0.009)	(0.0077)	(0.0053)	(0.0054)
$Ln(Tic)$	0.004	0.005	0.006	0.028
	(0.0011)	(0.0012)	(0.0018)	(0.009)
$Ln(R\&D)$	0.003	0 .002	0.006	0.006
	(0.0008)	(0.001)	(0.0019)	(0.0028)
$Ln(Intcap)$	-0.147	-0.135	-0.141	-0.129
	(0.011)	(0.009)	(0.008)	(0.006)
$Ln(Size)$	-0.123	-0.120	-0. 115	-0.116
	(0.0137)	(0.0133)	(0.0107)	(0.0098)
$Ln(Age)$	-0.264	-0.253	-0.353	-0.341
	(0.0835)	(0.0593)	(0.0806)	(0.0843)
$Ln(Size)^2$	0.018	0.021	0.021	0.042
	(0.0137)	(0.0142)	(0.0153)	(0.019)
$Ln(Age)^2$	0.061	0.069	0.070	0.078
	(0.0113)	(0.0109)	(0.0111)	(0.0128)
Industry dummy	yes	yes	yes	yes
Const	5.63	5.60	5.69	5.56
	(0.0912)	(0.0926)	(0.0917)	(0.0871)
OLS *vs.* FE test	3.62	4.71	4.33	4.69
	[0.000]	[0.000]	[0.000]	[0.000]
OLSvsRE	35.76	44.92	36.42	37.38
	[0.000]	[0.000]	[0.000]	[0.000]
Hausman test :	42.90	38.26	77.29	64.46
FE *vs* RE	[0.000]	[0.000]	[0.000]	[0.000]
R^2	0.68	0.71	0.75	0.77
Num. Obs	11,152	11,152	11,152	9,826

Values in parentheses represent the standard errors of the estimated coefficients: For the tests of absence of fixed effects, random effects and the Hausman test we report the p-value; Num. Obs indicate the number of observations.

Indeed, exporters become more efficient in the presence of foreign competition. Exporting firms experience greater productivity gains than firms operating solely in the domestic market. This result is consistent with findings from Castellani (2002), Girma et al. (2004), Bernard and Jensen (2004), Melitz (2003), Delgado et al. (2002), and more recently Sharma (2017) and Sikdar and Mukhopadhyay (2018). According to these studies, trade liberalization generates significant competitive pressure, compelling firms to enhance productivity to remain competitive in the export market. Strong export growth can lead to increased productivity, either through the exploitation of economies of scale, as access to new markets allows firms to produce at lower cost, or through learning effects associated with exporting.

Note that the sample contains three groups of firms: the always-exporting firms, the firms that have never exported, and the firms that switch to the export market. The presence of the latter groups of firms disturbs the estimation results. In the last column of Table IV (specification (4)), we report the estimation results of the same model while considering only the non-switcher firms. The effect of export status on TFP proved significantly greater than in the previous case. This effect increased by over 89%.

The direct effect of foreign participation in the social capital of firms, as measured by the coefficient associated with the FDI variable, is positive and statistically significant. Foreign investment in a firm's capital increases productivity by 14% (or $(\exp(0.131) - 1) \times 100$). Moreover, we find a positive and significant impact of human capital on productivity. In this study, we use the proportion of skilled workers as a proxy for human capital. This result indicates that firms with higher proportions of skilled workers tend to be more productive. This finding is consistent with theoretical and empirical models of human capital and growth, which posit that the knowledge and skills embodied in human capital directly raise productivity and enhance a firm's ability to develop and adopt new technologies.

Spending on research and development appears to have a positive and significant impact on TFP. A 10% increase in R&D expenditure induces a 0.6% increase in TFP. Indeed, a firm's own R&D improves its performance in two ways: it provides temporary monopoly power that widens the cost–price margin, and it enhances the firm's productivity. Mansfield (1965, 1969) argues that knowledge, which can be created and accumulated through the R&D investment of a firm or industry, becomes available for product innovations or improvements in the production process, thus constituting an important source of productivity gains[8].

We find that both firm $size$ and age have a negative impact on TFP. Consequently, younger and smaller firms exhibit higher productivity than older and larger firms [9]. When controlling for the convex relationship between firm age, size, and productivity by including their squared terms, only the squared term of age has a positive and statistically significant effect on TFP at the 1% level. This result suggests that new firms, which are generally less productive and smaller than established firms, require time to reach a certain age, after which their productivity may increase due to learning effects. Thus, up to a certain age, younger firms are more productive than older ones, but beyond this threshold, older firms become more productive than younger firms. These findings also indicate that the oldest small firms are more productive than larger firms.

4. Propensity score matching and robustness check

Linear regressions used to test the hypothesis of learning by exporting cannot account for selectivity bias. Consequently, this method may produce biased estimates of the effects of exports on productivity. As we have explained, participation in foreign markets can be influenced by a firm's past productive performance, meaning that only firms that are already performing well choose to enter these markets.

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8 Griliches and Lichtenberg (1984) state that firms carry out R&D in order to design new products which will provide more value per unit of resources used, or new processes which will reduce the resource requirements of existing products. This dual role of R&D, leading to both product and process innovation, has been further emphasized in subsequent works such as Nelson and Winter (1982), Cohen and Levinthal (1989, 1990), and Hall, Mairesse and Mohnen (2010).

9 Note that there are various arguments about the impact of firm size on productivity. In fact, it is claimed that large firms could be more efficient in production, more productive, benefit from economies of scale, and have easier access to credit. On the other hand, it is emphasized that small firms may be more efficient because, usually, young and small firms are more flexible and better able to adapt to new market conditions.

Estimating the effect of learning by exporting without accounting for self-selection can yield unreliable results. To address this issue, we employ the propensity score matching method based on the nearest-neighbor principle. This approach allows for consistent comparisons between exporters and non-exporters in our sample in terms of TFP levels and growth rates. This technique has been applied in numerous studies, including Arnold and Hussinger (2005) and Haidar (2012), to analyze whether participation in international markets enables firms to achieve further productivity improvements[10].

Our aim is to assess the causal effect of a treatment (exporting) on the treated group (exporting firms). The propensity score matching method involves pairing each exporting firm with one or more non-exporting firms from the control group based on this score. The propensity score is defined as the conditional probability of receiving the treatment (export), given a set of firm-specific characteristics. In the first step, we estimate a Probit model in which the probability of entering or exiting export markets is expressed as a function of the lagged values of the logarithm of TFP, $FDI, R\&D$ expenditure, skilled labor, capital intensity, firm age and $size$ as well as industry and year dummies.

The averages of the outcome variable, productivity, and its growth rates for exporters (the treated group) and non-exporters (the control group) are presented in the fourth and fifth rows of Table V. In the sixth row, we report the average difference in the outcome variable between these two groups for the unmatched sample. This represents a simple mean comparison between exporters and non-exporters.

Table V: Matching Results

	Treated	Controls	*Diff. of sample means*	*ATT (std. dev.)*
Outcome Variable: TFP				
Unmatched Sample	N= 3,816	N=1024	0.859	
Matched Sample	N= 3,486 4.736	N=1024 3.979		0.56 (0.070)
Outcome Variable: TFP growth 1 year later				
Unmatched Sample	N=1735	N=743	0.046	
Matched Sample	N=1248 0.113	N=743 0.078		0.035 (0.032)
Outcome Variable: Cumulative TFP growth 2 years later				
Unmatched Sample	N=1402	N=656	-00215 (0.00158)	
Matched Sample	N=1148 0.159	N=656 (0.137)		0.021 (0.024)

From this table, we find that, for the unmatched sample, exporters are on average more productive. This difference in TFP levels is statistically significant. In the case of the matched sample, when examining the average treatment effect on the treated (ATT), the difference remains significant compared to the bootstrapped standard error of approximately 0.070, although the effect of exporting decreases from 0.859 to 0.56. Hence, we conclude that, after controlling for the selection bias induced by non-random sample selection, the effect of exporting on productivity remains significant.

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10 The advantage of this method is that it does not need to assume a functional form for the equation; while the regression can always get biased estimates due to poor specification.

As an additional robustness check, we estimate a Heckman selection model (Heckman, 1979) to address the potential self-selection of firms into export markets. The model is estimated in two steps. In the first stage, a probit equation explains the probability of exporting for all firms. In the second stage, TFP is regressed on the set of covariates for exporting firms only, while including the inverse Mills ratio derived from the first stage to correct for selection bias[11]. The results confirm our main findings[12]: exporting firms exhibit significantly higher productivity, and the inverse Mills ratio is statistically significant, indicating that self-selection matters. Overall, the Heckman estimates corroborate the causal link between exporting and productivity that we documented with propensity score matching.

This result contradicts findings from several studies that did not detect an export effect on productivity. Various explanations have been proposed to account for this phenomenon. A positive and significant correlation between current productivity and export status is not necessarily attributable to the export effect. Productivity can be serially correlated, meaning that current productivity is influenced by past market experience even in the absence of a learning-by-exporting effect. Moreover, unobservable characteristics may affect both export activity and productivity, leading to a correlation between the two. Additionally, the observed effect may reflect learning by exporting or the reallocation of resources in favor of exporting firms.

When we consider productivity growth one year after entering the export market, as well as the cumulative two-year growth rate reflecting productivity gains after periods of exporting, the difference is no longer significant, both in the matched and the unmatched sample. Hence, upon entering the export market, a firm does not, on average, achieve more rapid productivity gains than non-exporting firms one or two years later.

Note that this result can be attributed to several factors. Firstly, foreign offshore companies are largely disconnected from their local environment. These enclaves hinder technological diffusion to other firms operating in the onshore sector. Additionally, Tunisian firms that engage in partial exporting face several constraints compared to offshore companies, such as difficulties in accessing financing, exposure to anti-competitive practices in the domestic market, and rigid redundancy procedures. Consequently, they are unable to benefit from the positive spillovers associated with entry into the export market, which would otherwise enhance their productivity.

Secondly, it should be noted that liberalization reforms were in their initial stages during this period, implying significant structural adjustments in manufacturing activities that had previously been shielded from competition. At that time, the liberalization program was still in its early phase for finished products, while trade reforms primarily targeted inputs and equipment until the late 1990s. This gradual liberalization process extended over time. Consequently, during the period under study, firms engaged in partial exporting faced minimal competition in the domestic market and had little incentive to enhance productivity.

Another explanation is that Tunisia has specialized in products and industries with limited positive externalities. Since the trade liberalization agreement with the European Union in 1996, Tunisian firms have continued to rely on importing high-tech goods from EU countries. Rather than fostering effective technology transfer to the domestic economy,

[11] Following common practice in the absence of valid exclusion restrictions, the set of explanatory variables is the same in both the selection and outcome equations, so identification relies on distributional assumptions.

[12] Due to space constraints, we do not report the full table of results in this paper; however, these results are available from the authors upon request.

many firms have taken the shortcut of incorporating imported high-value components into their export products. While importing advanced inputs can itself generate productivity gains through learning-by-doing in assembly processes, supplier search, or contract negotiation, these effects appear to have been limited in the Tunisian context. Consequently, this pattern has likely constrained the long-term growth of firm productivity.

5. Conclusion

Using a panel of Tunisian manufacturing firms observed over the period 2000–2012, we examine the impact of trade liberalization on firm productivity to identify the nature of the relationship between productivity and export status at the firm level. The analysis of this relationship in the Tunisian context is particularly revealing. To this end, we first compute TFP by estimating the Cobb-Douglas production function while controlling for simultaneity bias. Second, we test the learning-by-exporting hypothesis by evaluating the impact of historical export status on current TFP.

The first set of results indicates that, on average, exporting firms are more productive than non-exporting firms. We also find a positive and significant impact of lagged export status on productivity; however, this result should be interpreted with caution.

In fact, linear regressions used to test the learning-by-exporting hypothesis cannot account for selectivity bias. This method may produce biased estimates of the effect of exports on productivity. For robustness checks, we therefore employed a propensity score matching technique to enable consistent comparisons between exporters and non-exporters in our sample with respect to TFP levels and growth rates. The results show that, once selection into the treatment group is properly controlled for, TFP differences between exporters and non-exporting firms remain significant. In other words, we find a causal effect in both directions: from exporting to TFP and from TFP to exporting. This effect disappears when we consider growth rates over one or two years after the start of export activities.

To enhance productivity growth through the liberalization process, Tunisia needs to advance structural reforms, such as building institutions to address procurement issues and promote innovation. Stimulating innovation in a more competitive environment requires the use of various instruments, including fiscal policy, technical assistance, development institutions fostering innovation, and support for intellectual property protection, among others.

With a more open policy environment and increased competition, Tunisian industries must prioritize building capacities for technology production rather than relying on imports to bridge the technology gap. Achieving growth targets in Tunisia depends on enhancing the contribution of TFP. This objective necessitates the development of human resources through a robust education and training system to support technological adoption and stimulate innovation, as well as the creation of an environment conducive to more efficient resource utilization.

References

Arnold, J.M and K. Hussinger (2005) "Export behavior and firm productivity in German manufacturing: A firm-level analysis" *Review of World Economics* 141(2), 219-243. DOI **:** 10.1007/s10290-005-0026-8**.**

Bernard, A.B and B.J. Jensen (1999) "Exceptional exporter performance: cause, effect, or both?" *J Int Econ* 47(1), 1-25. DOI **:** 10.1016/S0022-1996(98)00027-0

Bernard, A.B and B.J. Jensen (2004) “Why some firms export” *Rev Econ Stat* 86(2), 561–569. DOI : 10.1162/003465304323031111

Bernard, A.B and J. Wagner (1997) “Exports and success in German manufacturing” *Weltwirtschaftliches Archiv 133*(1), 134-157. DOI : 10.1007/BF02707680

Castellani, D. (2002) “Export behavior and productivity growth: Evidence from Italian manufacturing firms” *Rev World Econ* 138(4), 605–628. DOI : 10.1007/BF02707654

Ciarli, T., Coad, A and A. Moneta (2023). *Does exporting cause productivity growth? Evidence from Chilean firms*. Structural Change and Economic Dynamics, 66, 228-239 DOI :10.1016/j.strueco.2023.04.015

De Loecker, J. (2010) “A note on detecting learning by exporting” NBER working paper number 16548. DOI : 10.3386/w16548

Delgado, M.A., Farinas, J.C and S. Ruano (2002) “Firm productivity and export markets: A non-parametric approach” *Journal of international Economics* 57(2), 397-422. DOI : 10.1016/S0022-1996(01)00154-4

Girma, S., Greenaway, D and R. Kneller (2004) “Does exporting lead to better performance? A microeconometric analysis of matched firms” *Rev Int Econ* 12(5), 855-866. DOI : 10.1111/j.1467-9396.2004.00486.x

Griliches, Z and F.R. Lichtenberg (1984) “R&D and productivity growth at the industry level: Is there still a relationship?” In R&D, patents, and productivity (pp. 465-502). University of Chicago Press. DOI : 10.7208/9780226308920-024

Grossman, G.M and E. Helpman (1999) “Competing for endorsements” *American Economic Review* 89(3), 501-524. DOI : 10.1257/aer.89.3.501

Haidar, J.I. (2012) “Trade and productivity: Self-selection or learning by exporting in India” *Economic Modelling* 29 (5), 1766–1773. DOI : 10.1016/j.econmod.2012.05.005

Helpman, E., Melitz, M. J. and S.R. Yeaple (2004). Export versus FDI with heterogeneous firms. *American economic review* 94(1), 300-316. DOI : 10.1257/000282804322970814

Jitsutthiphakorn, U. (2021) “Innovation, firm productivity, and export survival: Firm-level evidence from ASEAN developing countries” *Journal of Economic Structures* 10(1), 22. DOI : 10.1186/s40008-021-00251-7

Krugman, P. (1987) “The narrow moving band, the Dutch disease, and the competitive consequences of Mrs. Thatcher: Notes on trade in the presence of dynamic scale economies” *Journal of development Economics* 27(1-2), 41-55. DOI : 10.1016/0304-3878(87)90005-8

Levinsohn, J and A. Petrin (2003) “Estimating production functions using inputs to control for unobservables” *The review of economic studies 70*(2), 317-341. https://doi.org/10.1111/1467-937X.00246

Melitz, M.J (2003). “The impact of trade on intra-industry reallocations and aggregate industry productivity” E*conometrica*, *71*(6), 1695-1725.

Olley, S and A. Pakes (1996) “The Dynamics of productivity in the telecommunications equipment industry” *Econometrica* 64(6), 1263–1297. DOI : 10.2307/2171831

Rodrik, D. (1991) “Policy uncertainty and private investment in developing countries” *Journal of Development Economics* 36(2), 229-242. DOI : 10.1016/0304-3878(91)90034-S

Sharma, C. (2017) “Do firms learn more from exporting to the developed markets? *Empirical Evidence of Indian Firms*” *Global Economy Journal* 17 (1), 20170005. DOI : 10.1515/gej-2017-0005

Sikdar, C and K. Mukhopadhyay (2018) “Assessment of R&D and its impact on Indian manufacturing industries TFP” International Journal of Computational Economics and Econometrics 8(2), 207-228. DOI : 10.1504/IJCEE.2018.091042

Tybout, J.R. (2003) “Plant-and firm-level evidence on ‘new’trade theories” *Handbook of international trade* 1(1), 388-415. DOI : 10.1002/9780470756461.ch13

Vieira, F.V and C.G da Silva (2021) “What drives export performance in the BRICS countries? An ARDL investigation” *Economics Bulletin*, 41(2), 686-695.

Wilhelmsson, F and K. Kozlov (2007) “Exports and productivity of Russian firms: In search of causality” *Economic Change and Restructuring* 40(4), 361-385. DOI : 10.1007/s10644-008-9038-4